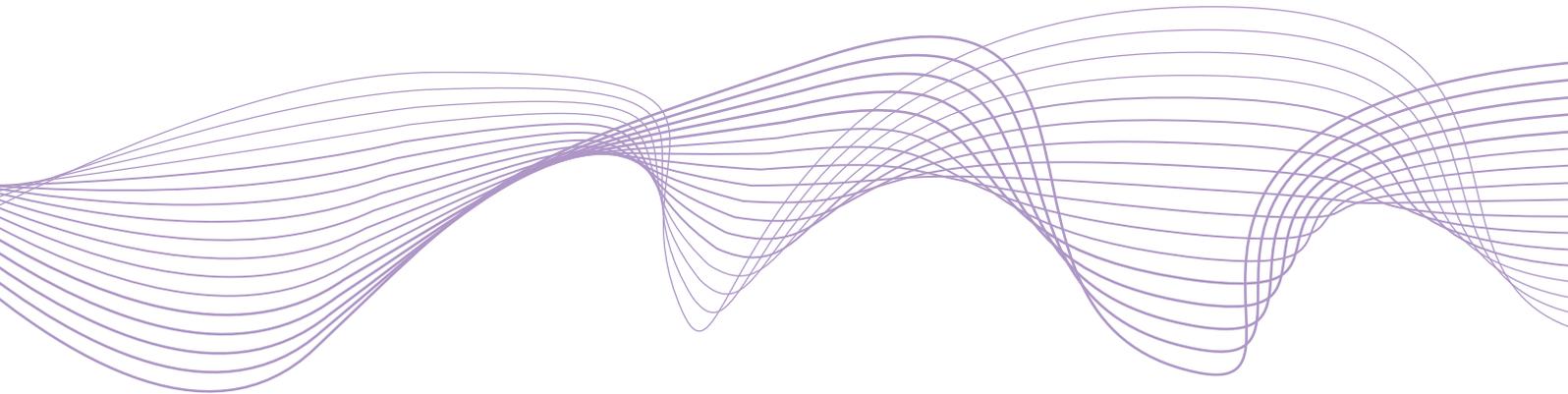


Working Paper Series

No 128 / December 2021

Banking networks and economic growth: from idiosyncratic shocks to aggregate fluctuations

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Abstract

This paper explores the transmission of non-capital shocks through banking networks. We develop a methodology to construct non-capital (idiosyncratic) shocks, using labor productivity shocks to large firms. We document a change in the relationship between foreign idiosyncratic shocks and domestic economic growth between 1978 and 2000. Contemporaneous changes in banking integration drive this phenomenon as geographically diversified banks divert funds away from economies experiencing negative shocks towards other unaffected economies. Our GIV estimates suggest that a 1% increase in bank loan supply is associated with a 0.05-0.26 pp increase in economic growth. Lastly, this can potentially explain the Great Moderation.

Keywords: financial intermediation; growth; deregulation; cross-border spillovers; idiosyncratic shocks; credit; the Great Moderation

JEL classification: E32; E44; F36; G21; G28; O47; R11; R12

1 Introduction

The objective of this paper is to explore the transmission of non-capital (real) shocks through banking linkages. Understanding how shocks that materialize inside and outside of the banking sector transmit across geographies is critical to deepening our understanding of how the typology of shocks is a key determinant of macroeconomic consequences. In both standard international real business cycle models and banking models, greater financial integration can result in the synchronization of business cycles when banking shocks are the prime source of aggregate fluctuations, and desynchronization of business cycles when non-banking shocks are the prime source of aggregate fluctuations.¹ While a large body of empirical work has studied the transmission of bank capital shocks through banking networks, it has yet to address how non-capital shocks propagate through banking networks.² In this paper, we provide empirical evidence that geographically diversified banks divert funds away from economies experiencing negative non-capital shocks, and towards other unaffected economies. This suggests that the transmission of non-capital shocks through banking networks results in *negative* comovement of business cycles, consistent with theoretical predictions. Thus, we present a mechanism through which banks act as potential aggregators of idiosyncratic shocks to understand the origins of aggregate fluctuations.

Specifically, we develop and empirically implement a test of how non-capital shocks, *idiosyncratic shocks*, hereafter, are transmitted through banking linkages. We develop a simple statistical model that links foreign idiosyncratic shocks with domestic economic growth through banking networks. Idiosyncratic shocks can affect future returns on capital, but do not affect bank capital contemporaneously. We use this model to derive an empirically testable relation between foreign idiosyncratic shocks, the strength of banking networks, and domestic economic growth. The basic insight in the model comes from the distinction between bank capital shocks and non-capital shocks. While bank capital shocks directly affect the *aggregate* amount of loanable funds, non-capital shocks affect the *relative* lending share across geographies, keeping the total stock

¹In their theoretical work, [Perri and Quadrini \(2018\)](#) show that with banking integration, endogenous shocks related to the banking sector may result in the synchronization of business cycles, whereas exogenous country-specific shocks originating outside of the banking sector may cause desynchronization of business cycles among interconnected economies. Other related works that highlight the two competing mechanisms include [Holmstrom and Tirole \(1997\)](#), [Morgan, Rime, and Strahan \(2004\)](#), [Kalemli-Ozcan, Papaioannou, and Perri \(2013\)](#), and [Kalemli-Ozcan, Papaioannou, and Peydró \(2013\)](#).

²Several papers have exploited periods of macroeconomic downturns to understand the transmission of bank capital shocks through banking networks. Such works among others include [Peek and Rosengren \(2000\)](#); [Khwaja and Mian \(2008\)](#); [Schnabl \(2012\)](#); [Chodorow-Reich \(2014\)](#); [Huber \(2018\)](#).

of funds fixed. Specifically, if a banking network spans two economies, domestic and foreign, foreign negative idiosyncratic shocks may boost the domestic loan supply and subsequent domestic economic growth. This implies that geographic diversification of banks in the presence of non-capital shocks reduces the covariance of business cycle fluctuations across geographies. However, banking networks make domestic and foreign economies more vulnerable to foreign idiosyncratic shocks, increasing the variance of business cycle fluctuations in both economies. Ultimately, if the reduction in covariance dominates the increase in variance, aggregate volatility declines.

The cleanest natural experiment to test the transmission of shocks through bank networks requires an exogenous shock to the banking network and measurement of non-capital shocks. Dissolution of regulatory barriers to geographic expansion of banks in United States from 1980s through 1990s provides such an environment with plausibly exogenous shocks to the banking network. State-level fluctuations are constructed using labor productivity shocks to large firms headquartered in that state after partialling out industry-wide labor productivity shocks as in [Gabaix \(2011\)](#). We focus on state-level fluctuations, constructed from labor productivity shocks to large firms for two reasons. First, these shocks are geographically isolated, lack temporal dynamics, and are firm-specific events. Second, state-level fluctuations that are constructed from labor productivity shocks to large firms are unlikely to be related to bank-capital shocks, as large firms are less reliant on banks as a source of external financing ([Gertler and Gilchrist \(1994\)](#); [Kashyap, Lamont, and Stein \(1994\)](#)). In addition, idiosyncratic shocks may alter banks' expectations of future economic growth of the state. Hence, the geographic isolation, lack of temporal dynamics, orthogonality to contemporaneous bank capital and ability to predict future economic growth make idiosyncratic shocks prime candidates for measuring non-capital shocks.

For illustration of the mechanism that connects idiosyncratic shocks to economic growth through banking network, consider the following microcosm of our empirical setting. There are only two states in the economy: Illinois and Indiana. Prior to deregulation, Illinois and Indiana are connected through a non-banking channel, namely, an exports/imports channel. Suppose that in this fictionalized world, Illinois' greatest exports are free-market economists and Indiana's greatest exports are conservative politicians. If a new bill is passed allowing banks operating exclusively in Illinois to operate in Indiana and vice versa, the two states will now be connected by a banking channel in addition to the existing non-banking channel. Our focus is on how the transmission

of shocks between Illinois and Indiana changes upon passage of this new bill. For example, if a localized fire destroys all economics textbooks in the largest printing house in the state of Illinois, how will Indiana's economy be affected in the presence of banking linkages? We hypothesize this negative idiosyncratic shock will hurt Illinois' labor productivity as economists may need to reinvent several basic theories for their work and lose easy access to existing research. Banks will note that due to reduced labor productivity, returns to capital in Illinois will be lower as economists will use a portion of their capital to reinvent knowledge. As a result, banks will divert their loan supply to Indiana, thereby increasing investment in Indiana and fostering positive economic growth. This reductive example is intended to illustrate the mechanism that connects foreign (Illinois) shocks to domestic (Indiana) growth in the presence of a banking linkage between the two entities.

We begin with aggregate analysis showing that idiosyncratic shocks in state j were positively correlated with economic growth in state i during the late 1970s and early 1980s. This implies that a good (bad) news for state j was also a good (bad) news for state i , suggesting that states behaved as complements during that period. However, the relation monotonically reversed post 1984, i.e., good (bad) news for state j became bad (good) news for state i , suggesting that states behaved as substitutes after this period. We attribute this changing relation between idiosyncratic shocks in state j and economic growth in state i to banking integration between the two states.

In a difference-in-differences (DID) framework, combining the state pairwise banking integration natural experiment with the measurement of non-capital shocks, we show that a one standard deviation negative idiosyncratic shock, $\Gamma_{j,t-1}$, in state j increases economic growth in state i by 0.05-0.19 pp after the state pair (i, j) is integrated via a banking linkage.³ This estimation is based on the assumption that the linkages between states are equally strong across all state-pairs. Taking into account the strength and the direction of real linkages between states by considering imports and exports, we find that a one standard deviation negative $\Gamma_{j,t-1}$ increases economic growth in state i by 0.13-0.19 pp post banking integration.

The effect of idiosyncratic shocks in state i on economic growth in state j operates via changes in bank loan supply. We employ an instrumental variable (IV) strategy similar in spirit to the granular IV methodology presented in [Gabaix and Koijen \(2020\)](#). Using idiosyncratic shock, $\Gamma_{j,t-1}$, in state j combined with banking integration as an instrument for bank lending in state i ,

³The DID estimator is relative to the pre-integration economic growth level.

we estimate a 0.05-0.26 pp increase in economic growth in state i following a 1% increase in bank loan supply. The relevance of the instrument stems from the assumption that different states, when integrated, compete for bank lending and geographically diversified banks allocate funds away from geographies experiencing negative idiosyncratic shocks, increasing loan supply in unaffected states. This assumption is verified in the first stage regression. The exclusion restriction is satisfied under the assumption that the covariance of loan demand between the state-pair (i, j) does not change around the same time as banking deregulation between the state-pair. Alternatively, the exclusion assumption is also satisfied if the covariance in loan demand is sticky relative to changes in the covariance in loan supply around the timing of banking integration. We note that even if this assumption is violated, it will bias our test to finding a null result if the ex-ante covariance in loan demand is positive, which is likely to be the case as states behaved as complements before banking deregulation.

We present additional results supporting that the effect operates through the banking channel. We verify that banks *did* expand across state lines post banking integration, and, the heterogeneity in the baseline estimate across states can be explained by the degree to which out of state banks expanded in a state following banking deregulation. Additionally, the effect of impact following deregulation develops slowly over time. This result is consistent with the idea that while a law can be passed in a day, the establishment of actual banking infrastructure, acquisition of private information by banks, and formation of banking relations develops over time.

Exploring the underlying mechanism, we dissect the anatomy of idiosyncratic shocks to argue that the effect propagates through the transmission of geographically isolated non-capital shocks by banks. First, consistent with the argument that the geographic expansion of banks provides diversification benefits to banks as long as shocks are not correlated across geographies, we show that the effect is driven by shocks with low spatial correlation. Second, banking integration increases banking competition. Persistent shocks matter more in the pre-integration period when banks enjoy monopoly (Petersen and Rajan (1994)), whereas banks become more sensitive to temporally isolated shocks in a competitive environment (Diamond (1984)). Consistent with this view, we find the effect is larger in magnitude for shocks that exhibit little temporal dynamics. Third, we examine the sign of the shock. While we attempt to construct shocks that have a low likelihood of being correlated with bank capital shocks, we cannot completely rule out this correlation. We

find our effect is smaller in magnitude when shocks are negative. Negative shocks are likely to affect banks' total amount of loanable funds by pushing banks closer to their constraint, and hence, are unlikely to be transmitted across state boundaries in the hypothesized fashion. To support our conclusions, we also replicate our baseline table, constructing state-level idiosyncratic shocks using only positive firm-level shocks and find similar effects.

Additionally, we examine the reallocation of funds by banks across firms, hypothesizing that firms which are more dependent on banks as a source of external financing drive the aggregate response in economic growth across states. We use age as a proxy for external finance dependence and show that younger firms are more responsive to foreign idiosyncratic shocks after banking integration. Specifically, we find that younger firms exhibit greater sensitivity of debt growth, sales growth, market-to-book ratio, and work-in-progress inventory growth to foreign idiosyncratic shocks, relative to older firms after banking integration. Thus, our findings corroborate the hypothesis that firms which are more bank-dependent drive the aggregate response in economic growth.

We provide external validity to the mechanism using a dynamic stochastic general equilibrium (DSGE) model that connects foreign non-capital shocks to domestic economic growth via banking integration. The model features international business cycles where global banks intermediate funds between savers, households and consumers, and borrowers (firms). In the model, global banks divert funds away from an economy that suffers a negative non-capital shock towards the unaffected economy in a financially integrated system. We use this model to replicate our empirical results. The data simulated from the model shows that with increasing banking integration the relation between domestic economic growth and shocks in foreign country changes from positive to negative when foreign shocks are non-capital shocks. However, with increasing banking integration the relation between domestic economic growth and shocks in foreign country become more positive when foreign shocks are bank capital shocks. Moreover, we show that the empirical results obtained in the paper are more consistent with the model when we set the spatial correlation between non-capital shocks to zero and vanishes when this correlation is one, implying that banks benefit from geographic diversification if the shocks they face can be geographically diversified.

We argue that this phenomenon can explain the decline in aggregate volatility during the period of relative quiescence in macroeconomic volatility starting from 1984 referred to as "The Great

Moderation.” When the correlation between shocks and economic growth across states becomes negative, aggregate fluctuations are temperate. Theoretically, the effect of banking integration with idiosyncratic shocks on aggregate volatility is ambiguous. The geographic diversification of banks in the presence of non-capital shocks can reduce the covariance of business cycle fluctuations across geographies, but increase the variance of business cycle fluctuations. The latter effect develops because banking integration makes domestic growth more vulnerable to foreign shocks. We use the model to quantitatively analyze the two competing effects. The calibrated model yields two key results. First, the covariance declines with banking integration. Second, the decline in covariance dominates the increase in individual variance resulting in an aggregate decline in volatility. Hence, this paper proposes an alternative theory explaining The Great Moderation. We document how simultaneous changes taking hold in the banking system during the 1980s and 1990s increased the overall role of banks in intermediating shocks between states. The presence of new cross-state intermediaries altered the transmission of shocks across state lines, and allowed for greater diversification, reducing aggregate volatility in the economy. Banking reforms provide a mechanism to explain why the overall US economy did not react to exogenous shocks during the Great Moderation as strongly as in previous periods.

We conduct a battery of robustness tests to ensure the validity of our results. First, we conduct a parallel trend analysis to show that the result is not driven by pre-trends before deregulation. Second, we conduct a placebo test in which we randomize the timing of banking integration and show that the results disappear when using randomly created deregulation dates. This indicates that the precise timing of banking deregulation is important. Additionally, we argue that the results are unlikely to be driven by geography based measurement error in the idiosyncratic shock, nor, are they sensitive to the methodology adopted to construct idiosyncratic shocks. Lastly, we show that the results are unlikely to be driven by cross-state migration, during the sample period.

1.1 Related Literature

The main contribution of this work is identifying the novel mechanism through which idiosyncratic shocks affect economic growth. This paper attempts to overcome a major challenge of identifying non-capital shocks, real shocks, that are orthogonal to bank capital, and studying their transmission through banks within an economy. We draw from studies on the measurement and importance

of idiosyncratic shocks, granular residuals, and networks in generating aggregate fluctuations. Specifically, our work is related to [Gabaix \(2011\)](#), [Carvalho and Gabaix \(2013\)](#), [Di Giovanni, Levchenko, and Mejean \(2014\)](#), [Carvalho and Grassi \(2019\)](#), and [Acemoglu et al. \(2012\)](#). Further, drawing insights from [Gabaix and Koijen \(2020\)](#), we use our set-up to directly study how foreign shocks affect domestic economic growth by changes in the credit supply. We provide causal evidence that foreign idiosyncratic shocks affect domestic bank loan supply, which in turn, impacts economic growth. Hence, this paper speaks directly to the first order diversification function of banks in an economy as posited in [Diamond \(1984\)](#). Moreover, in distinction to past work which has studied the relation between bank lending on economic growth, we do not rely on single systematic shock to generate variation, but a series of idiosyncratic shocks which do not largely impact bank capital.⁴

Our work is closest in spirit to [Kalemli-Ozcan, Papaioannou, and Peydró \(2013\)](#) and [Morgan, Rime, and Strahan \(2004\)](#). In a cross-country study, [Kalemli-Ozcan, Papaioannou, and Peydró \(2013\)](#) find a strong negative effect of banking integration on output synchronization, conditional on global shocks and country-pair heterogeneity. We contribute to this work by *empirically* identifying the underlying mechanism that the negative effect of banking integration on output synchronization occurs in the presence of non-capital shocks. [Morgan, Rime, and Strahan \(2004\)](#) find that the volatility of a state's economic growth declines as banks in that state become more integrated with banks in other states. Furthermore, they note that fluctuations in states integrated by banks tend to converge. This is attributed to shocks to bank capital as the dominant source of aggregate fluctuations. Our findings do not contradict [Morgan, Rime, and Strahan \(2004\)](#). We contribute to [Morgan, Rime, and Strahan \(2004\)](#) by distinguishing non-capital shocks from bank capital shocks. We structurally isolate non-capital shocks. Our empirical design captures the effect of shocks that are not borne out of contemporaneous shocks to collateral or capital, rather, banks' future expectations of local economic growth. The specific nature of state pairwise deregulation allows us to document how banks transfer non-capital idiosyncratic shocks across geographies post integration through the loan supply channel.

Our paper provides a critical link in the discussion on the Great Moderation by proposing

⁴In recent papers on credit supply shocks, the literature has used extreme events like the Great Recession of 2007 and the European Crisis to argue that systematic shocks to banking capital affect the real economy ([Peek and Rosengren \(2000\)](#); [Khwaja and Mian \(2008\)](#); [Schnabl \(2012\)](#); [Chodorow-Reich \(2014\)](#); [Huber \(2018\)](#)) or shocks to large borrowers of banks ([Amiti and Weinstein \(2018\)](#)).

an alternative explanation.⁵ We show how idiosyncratic shocks interact with structural reforms in banking and transmit across state lines. Our primary mechanism for the reduction in volatility of aggregate fluctuations operates via a decline in the covariance of economic growth across states, post banking deregulation. Using a DSGE model, we show that with increasing banking integration, the relation between domestic economic growth and foreign shocks becomes more negative when non-capital shocks are the primary source of aggregate fluctuations. While banking integration increases the volatility of economic growth in both the domestic and foreign economies, it decreases the covariance between the two in the presence of non-capital shocks. Our estimation results indicate that the decline in the covariance between the economies dominates the increase in volatility of individual economies. Hence, our findings help explain the decline in aggregate volatility during the period referred to as the Great Moderation.

This paper is organized as follows. Section 2 outlines the theoretical framework. Section 3 discusses the institutional details of banking deregulation. Section 4 describes the data, construction and properties of idiosyncratic shocks. Section 5 presents key results. Section 6 outlines and presents evidence in support of the underlying mechanism. Section 7 presents robustness results. Section 8 presents a discussion on the linkage between our results and the Great Moderation and section 9 concludes.

2 Framework

This section develops a simple framework where the transmission of non-capital shocks to domestic economic growth depends on banking linkages. Let there be $i, j \in I$ states and $k \in K$ banks. Banks can operate across states. For simplicity, we assume that there are no other linkages between states except banking linkages. Bank lending growth is defined as a sum of aggregate shock, a bank specific capital shock, local and foreign shocks. We interpret these foreign shocks as shocks to expected future returns on capital that are uncorrelated with the bank capital shocks and other fundamental shocks.

$$\frac{\Delta l_{it}^k}{l_{i,t-1}^k} = a_t + \eta_t^k + v_{it} - \sum_{\substack{j \in I \\ j \neq i}} \frac{l_{j,t-1}^k}{l_{i,t-1}^k} v_{jt} \quad (1)$$

⁵We direct the readers to [Davis and Kahn \(2008\)](#) for a survey of previous studies that offer explanations for the Great Moderation.

Equation 1 defines the bank lending growth function where, l_{it}^k is the lending of bank k in state i at time t , $\frac{\Delta l_{it}^k}{l_{i,t-1}^k}$ denotes bank lending growth, and $\frac{l_{j,t-1}^k}{l_{i,t-1}^k}$ refers to the lending depth of bank k in state j . a_t denotes aggregate shocks with variance σ_a^2 . η_t^k denotes shocks to bank capital which affects banks' loan supply ability. The variance-covariance matrix of these shocks is $\Sigma_\eta = \sigma_\eta^2 \mathbf{1}$, where $\mathbf{1}$ denotes the identity matrix. The bank lending policy function so far is similar to the one employed in [Landier, Sraer, and Thesmar \(2017\)](#), and assumes the presence of active, within-bank internal capital markets that generate commonality in lending growth between states conditional on bank capital shocks. The innovation is the addition of domestic, v_{it} , and foreign shocks, v_{jt} , which are uncorrelated with shocks to bank capital and aggregate shocks. We make two additional assumptions. First, banks have a fixed amount of loanable funds, and, states compete for them. Therefore, local shocks enter equation 1 with a positive sign whereas foreign shocks enter with a negative sign. This assumption is similar in spirit to [Stein \(1997\)](#) which emphasizes the critical role of internal capital markets in the transfer of funds, within conglomerates, towards the most deserving projects. Second, we assume that the impact of these shocks is proportional to the lending depth of the bank. This assumption articulates the importance of banking relations, i.e., banks respond more to these shocks when they are deep in the economy. The variance-covariance matrix of v_{it} is given by $\sigma_v^2 \mathbf{1}$, where $\mathbf{1}$ denotes an identity matrix. We make additional assumptions that include $\mathbb{E}[a_t \eta_t^k] = 0$; $\mathbb{E}[a_t v_{it}] = 0 \forall i \in I$; $\mathbb{E}[\eta_t^k v_{it}] = 0 \forall i \in I$ and $\forall k \in K$; $\mathbb{E}[v_{jt} v_{it}] = 0 \forall i \neq j$.

Economic growth in state i can be described by the equation 2, where we posit that lending shocks affect economic growth – $\mu > 0$ and $\frac{\Delta y_{it}}{y_{i,t-1}}$ refer to economic growth. ε_{it} are fundamental shocks to economic growth, i.e., shocks that are unrelated to credit growth shocks. The variance of these shocks is given by σ_ε^2 and $\mathbb{E}[\varepsilon_{it} \varepsilon_{jt}] = 0 \forall i \neq j$, $\mathbb{E}[\varepsilon_{it} a_t] = 0$ and $\mathbb{E}[\varepsilon_{it} v_{jt}] = 0$.

$$\frac{\Delta y_{it}}{y_{i,t-1}} = \mu \frac{\Delta l_{it}}{l_{i,t-1}} + \varepsilon_{it} \quad (2)$$

Combining equation 1 and 2 with the accounting identity $\Delta l_{it} = \sum_{k \in K} \Delta l_{it}^k$ gives the following

equation:

$$\frac{\Delta y_{it}}{y_{i,t-1}} = \mu \{ a_t + v_{it} + \sum_{k \in K} \eta_t^k \frac{l_{i,t-1}^k}{l_{i,t-1}} - \sum_{j \neq i} v_{jt} \sum_{k \in K} \left(\frac{l_{i,t-1}^k}{l_{i,t-1}} \times \frac{l_{j,t-1}^k}{l_{t-1}^k} \right) \} + \varepsilon_{it} \quad (3)$$

where, $\sum_{k \in K} \frac{l_{i,t-1}^k}{l_{i,t-1}} \times \frac{l_{j,t-1}^k}{l_{t-1}^k}$ denotes the sum of the depth of each bank k in state j ($j \neq i$) multiplied with the relative importance of bank k in state i , capturing the extent of banking integration between state i and j . Equation 3 shows that economic growth in state i is positively related to the aggregate shocks, capital shocks, and domestic shocks and negatively related to foreign shocks. While the effect of bank capital shocks increases as the reliance on that bank for external funding increases, the foreign shocks negatively affect domestic economic growth depending on the banking integration between the foreign and the domestic economy. A key testable implication from equation 3 is that foreign idiosyncratic shocks negatively affect domestic economic growth via banking linkages. This forms the basis of our empirical strategy, combining measurement of foreign shocks and exogenous shocks to banking linkages between the domestic and the foreign economy.

3 Institutional Details

This section describes the natural experiment of state pairwise banking deregulation that dissolved regulatory barriers, enabling cross-border banking expansion from the 1980s through the 1990s. The experiment has previously been employed in [Michalski and Ors \(2012\)](#) and [Landier, Sraer, and Thesmar \(2017\)](#), and provides for a clean identification of exogenous changes in banking linkages across states.

The McFadden Act of 1927 prohibited interstate branching by permitting national banks to branch only within the state in which they were based. These prohibitions remained in place until the 1980s, at which point, the banking sector underwent significant changes. Deregulation occurred in a staggered fashion across states, and continued until 1994. There are three main classes of reforms that occurred during this period on the basis of reciprocity: national non-reciprocal, national reciprocal, and bilateral reciprocal. First, national non-reciprocal reforms allowed banks from all other states to enter its banking market. Overall, 33.8% of state-pairs deregulated in this form. Second, national reciprocal reforms permitted interstate banking deregulation between

states that also passed similar national reciprocal reforms. 21.6% of state-pairs engaged in national reciprocal form of deregulation. 8.8% of state-pairs chose the third form of deregulation via bilateral reciprocal agreements between state-pairs. We direct the readers to [Michalski and Ors \(2012\)](#) and [Amel \(1993\)](#) for additional details on banking deregulation. The era of banking deregulation in the United States ended with the enactment of Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) of 1994, which allowed banks to branch across all state lines.

State pairwise banking deregulation provides an exogenous source of variation in banking linkages across states in equation 3. Our identifying assumption is that these state-pairwise banking deregulation agreements are not correlated with unobserved heterogeneity in economic growth comovement, implying that states did not cherry-pick the states with which they deregulate based on pre-existing linkages in economic growth. This is likely to be true as only 8.8% of all state-pairs deregulated via bilateral agreements whereas all other states deregulated nationally either voluntarily or forcibly in 1994. [Michalski and Ors \(2012\)](#) argue that interstate trade share and flows were not a driver for banking deregulation ruling out pre-existing comovement in economic growth as a result of trade linkages between states. Additionally, we control for any geographic patterns of deregulation through fixed effects. Further, on the political economy of these reforms, [Kroszner and Strahan \(1999\)](#) document that deregulation was influenced by lobbying activity from small firms and banks. However, there is limited evidence that either of these agents are responsible for the expansion in credit supply post deregulation.⁶

Another key assumption is that the removal of regulatory barriers following deregulation resulted in actual geographic expansion of banks across state lines. A survey of existing literature suggests that this is a reasonable assumption. [Berger, Kashyap, and Scalise \(1995\)](#) document that interstate branching increased the percentage of deposits held by out-of-state BHCs in a typical state from 2% to 28% between 1979 and 1994. [Morgan, Rime, and Strahan \(2004\)](#) document a 14-17 pp increase in interstate banking activity post deregulation. In an identical setting, [Landier, Sraer, and Thesmar \(2017\)](#) show that the average adjusted lending co-Herfindahl of banking assets across state-pairs increases post banking integration. We independently replicate this result using an alternate dataset on gross banking assets held by out-of-state banks used in [Berger, Kashyap, and](#)

⁶[Mian, Sufi, and Verner \(2020\)](#) document that the credit supply expansion following banking deregulation primarily affected real economic activity through the household demand channel. [Rice and Strahan \(2010\)](#) do not find any effect of banking deregulation on the net borrowings of small firms. Moreover, large banks were responsible for the credit supply expansion post banking deregulation ([Demsetz and Strahan \(1997\)](#), [Stiroh and Strahan \(2003\)](#)).

[Scalise \(1995\)](#) in appendix B. We document that the share of gross domestic banking assets owned by out-of-state banks grew from $\approx 7\%$ in 1979 to $\approx 35\%$ in 1994 and this growth is explained by banking integration.

4 Data

Our data set is the balanced panel of all US state pairs (i, j) from 1978 to 2000. It contains data on real GDP growth rate for state i , a measure of idiosyncratic shock for state j , a binary variable that takes a value of 1 for periods after which state i permitted entry from banks in state j , all and commercial loans issued in state i , and 1977 state pairwise commodity flow data. We use four key sources of data: annual state-level real GDP growth rate from the Bureau of Economic Analysis (BEA), state-level annual bank lending data from the Call Reports, data on dates of state pairwise deregulation dates, data on total and directional commodity flows from the 1977 Commodity Flow Survey (CFS) dataset compiled by [Michalski and Ors \(2012\)](#), and, idiosyncratic shocks constructed using Compustat data.

4.1 Bank Lending Data

We measure both the total amount of commercial lending, and all lending for each state and year, using the annual *Consolidated Report of Condition and Income* (call reports). We compute the total loan supply by aggregating all new loans, and commercial and industrial loans at the BHC-state-level. This aggregation methodology assumes that commercial banks do not operate outside the border of the state in which they are located. [Morgan, Rime, and Strahan \(2004\)](#) and [Landier, Sraer, and Thesmar \(2017\)](#) argue that this is a reasonable approximation before the enactment of IBBEA in 1994.

4.2 Idiosyncratic Shocks

Idiosyncratic shocks measure non-capital shocks originating in a specific geography and are orthogonal to bank capital shocks and other fundamental shocks. Construction of state-level idiosyncratic shocks requires annual sales and employment numbers along with information on headquarter location and industry. This information is sourced from Compustat. We narrow our focus to US

companies, headquartered in one of the 50 states or DC.⁷ ⁸ We eliminate firms operating in heavily regulated industries such as oil and gas extraction, finance, and utilities. Our analysis is limited to firms that have data on both employment and sales. The firm-level data is used to construct our measure of state-level idiosyncratic productivity shocks.

4.2.1 Construction of Idiosyncratic Shocks

In this section, we describe the process for constructing idiosyncratic shocks. We follow a methodology similar to [Gabaix \(2011\)](#) to construct state-level idiosyncratic shocks. Labor productivity (z_{kt}^s) of firm k headquartered in state s at time t is measured as the natural logarithm of the ratio of sales and employees. It is assumed that the sales and employees of firm k originate in the state in which they are headquartered.⁹ We define labor productivity shock to firm k in state i as $g_{kt}^{(i)}$ where $g_{kt}^{(i)} = z_{kt}^{(i)} - z_{k,t-1}^{(i)}$.

We construct state-level idiosyncratic shock using a two-step process. First, we regress firm-level productivity shocks on industry-year fixed effects (θ_{mt}) based on the 4 digit SIC industry code to which the firm belongs. We then compute firm-level residuals from this regression. These residuals (ε_{kt}^i) are devoid of any industry-wide systematic shocks. Under the assumption that all firms have uniform loading on industry-wide systematic shocks, this methodology generates firm-level idiosyncratic shocks. [Gabaix \(2011\)](#) argues that this measure is a better control for industry-wide real price movements and disturbances, providing a better approximation to the ideal firm-level idiosyncratic shocks, in comparison to accounting for solely year fixed effects. In the next step we aggregate firm-level idiosyncratic shocks for the largest K firms. A firm is defined as large based on its Compustat sales. We sort firms based on sales for each state, and narrow our focus to the top K firms in each state. For aggregation, each firm-level idiosyncratic shock is Domar weighted by its sales to total nominal GDP. We denote these state-level idiosyncratic shocks

⁷Compustat backfills headquarter location with the latest headquarter information, leading to error in the coding of firms that moved. However, the incidence of the relocation of firm headquarters is extremely rare for our sample period as noted by [Cohen, Coval, and Malloy \(2011\)](#). Nevertheless, we manually correct for changes in headquarter location.

⁸As a robustness test, we redo the baseline analysis after dropping the states of South Dakota and Delaware, given their explicit focus on attracting credit card companies. Our baseline estimate is quantitatively similar despite the exclusion of these two states (see appendix section [F.6](#)).

⁹This assumption may result in a geography-based measurement error problem. We refer the readers to section [7.3](#) for a detailed discussion on this issue.

as Γ_{it} computed as follows:

$$g_{kt}^{(i)} = \theta_{mt} + \varepsilon_{kt}^{(i)} \quad (4)$$

$$\Gamma_{it} \equiv \sum_{\substack{k=1 \\ k \in i}}^K \frac{S_{k,t-1}^{(i)}}{Y_{t-1}} \varepsilon_{kt}^{(i)} \quad (5)$$

Γ_{it} is used as our main measure of the idiosyncratic shock at the state-level, we refer to this measure as Γ_{it}^{ind} . We construct state-level shocks, Γ using top 10 firms in each state.¹⁰

4.2.2 Properties of Idiosyncratic Shocks

We begin by describing the cross-sectional distribution of idiosyncratic shocks, Γ . Figure 1a reports the cross-sectional distribution of Γ from 1978 through 2000 across states and suggests that there is wide heterogeneity in the average magnitude and sign of these shocks across states. States such as Texas, North and South Carolina, Florida, and New York etc. received on average negative shocks during the sample period. Whereas, states such as California, Washington, Illinois, Michigan etc. experienced on average positive shocks.

Gabaix (2011) argues that in modern economies dominated by large firms, idiosyncratic shocks to these firms can lead to nontrivial aggregate shocks. First, we show that idiosyncratic shocks are indeed granular in the sense of Gabaix (2011). We verify the dominance of large firms in each state in appendix C.1, showing that top 10 firms by sales in a state account for at least 50% of sales by all firms in that state.¹¹ Second, we verify that these shocks predict future economic growth. Figure 1b presents the pooled binscatter plot of idiosyncratic shocks and subsequent annual economic growth in a given state. The line is upward sloping, with a β of 0.67 from the pooled regression, significant at the 1% level, and a model R^2 of 7%. We redo this regression at the state level and estimate an average (median) β of 0.71 (0.83) with a model R^2 of 13% (11%).¹² Hence,

¹⁰In section 7.1 we discuss the sensitivity of our results to alternative construction methodology such as altering the value of K , allowing Γ_{it} to have a factor structure with heterogeneous exposures, etc.

¹¹A related concern is that a large firm in one state may be small relative to a large firm in another state. This does not seem to pose a threat to our construction of state-level shocks as long as the firms used to construct these shocks are large relative to the state economy they are headquartered in. However, it does raise concern over the assumption whether large firms in a given state that are smaller relative to firms in other states, and are less dependent on banks for external financing. We compare the bank debt to total debt for firms across states and do not find meaningful difference in the ratio across states, see appendix C.8.

¹²We supplement this descriptive analysis by showing the comovement in the series of idiosyncratic shocks and subsequent annual economic growth for selected states in appendix C.2.

these shocks exhibit predictability of future economic growth at the state level.¹³

Next, we examine the temporal persistence among shocks. Figure 1c reports the kernel density of the coefficients of a state-wise AR(1) process for Γ . While, the AR(1) estimate exhibit heterogeneity the majority of mass is bunched around zero. The average AR(1) estimate for a pooled regression has a value of -0.092. This indicates on average low degree of persistence among these shocks. Furthermore, the impulse response functions from an AR(1) and AR(3) model report that idiosyncratic shocks exhibit short-lived temporal dynamics or absence of long-run temporal dependence (see appendix C.3).

Lastly, we examine the spatial correlation between state-level idiosyncratic shocks. Figure 1d plots the kernel density of the state-pairwise R^2 computed by running simple OLS regression of idiosyncratic shocks in state i on state j . Despite some heterogeneity, the mass of model R^2 is concentrated around zero with an average value of 0.046 (dashed red line). This suggests that the state-level idiosyncratic shocks are local and do not explain idiosyncratic shocks in other states.

4.2.3 Why use these shocks?

The idiosyncratic shocks constructed as in section 4.2.1, help identify the effect of geographically isolated non-capital shocks. We focus on idiosyncratic productivity shocks for three reasons. First, the shocks are geographically isolated and do not exhibit long-run temporal dependence. Second, the shocks predict future economic growth. Hence, they may alter banks' expectations of future economic growth in a state. Third, these shocks are constructed using large firms which do not primarily rely on bank credit for external funding (Gertler and Gilchrist (1994), Kashyap, Lamont, and Stein (1994)). We verify this assumption by comparing the ratio of bank debt to total debt for the sample of firms used in constructing the state-level idiosyncratic shocks (shock firms) to all other firms in the S&P Capital IQ database. The median (mean) bank debt to total debt ratio for shock firms is 23.63% (30.35%), compared to a value of 44.63% (48.03%) for other firms. See appendix C.4. Hence, state-level idiosyncratic shocks constructed from labor productivity shocks to large firms present themselves as prime candidates for the measurement of geographically isolated shocks. with limited long-run temporal dynamics that do not affect bank capital contemporaneously.

¹³Shocks to large firms in a state predict future economic growth via two channels. First, large firms are often connected to other firms via input-output linkages in a state. Hence, any shocks to the large firms are likely to be transmitted to other firms in that economy. Second, large firms are often the largest employers in a region. Hence, any shock to large firms can result in employment shocks.

4.2.4 A Narrative Analysis of Idiosyncratic Shocks

In this section, we use a narrative-driven approach to study how firm-level labor productivity shocks used to construct state-level shocks can be attributed to firm-specific events. We delineate the top three firms per state-year with the largest magnitude of temporally adjusted labor productivity as *significant* observations. For each significant firm-year observation, we identify historical events from the website fundinguniverse.com.¹⁴ This is further supplemented with information from Businessweek Archives and ABI/INFORM Collection, and, the historical archives of annual reports sourced from ProQuest.

The hand-collected information reveals that the majority of firm-specific events are related to restructuring activity within a firm, hostile takeover attempts, leveraged buyouts, litigation, scandals, mergers and acquisitions, other corporate governance issues, discovery and release of new products. Table 2 presents a selected sample of the most economically and methodologically interesting firm-level productivity shocks. A key insight from the narrative analysis of firm-level events that contribute to state-level idiosyncratic shocks is that observation of these events does not require access to private information.

4.3 Data Description

Table 1 reports the summary statistics for the variables of interest in this study from 1978-2000. The median annual change in GDP is 3.3% (mean is 3.25%). The 25th and 75th percentiles for GDP growth are 1.4% and 5.3% respectively. The granular residual has a median of 0.000. The 25th and 75th percentiles are -0.053 and 0.059. The idiosyncratic shock is centered ~ 0 on average, and the distribution is symmetric. The table also reports the log of annual commercial and industrial lending, and total lending. The average values for these are 16.65 and 18.13, respectively. The standard deviation is 1.33 and 1.26, respectively.

5 Results

This section documents the aggregate trend in the comovement of economic growth in state i and idiosyncratic shocks in state j . We show that the comovement is driven by banking integration

¹⁴The website fundinguniverse.com sources its information on company history and significant events from various volumes of International Directory of Company Histories.

between state-pairs. Using an instrumental variable strategy, we document that the effect develops through shocks to loan supply.

5.1 Comovement in Economic growth and Idiosyncratic Shocks

We first document the relation between economic growth in state i and idiosyncratic shocks in state j . Figure 2a displays the evolution of the relation between GDP growth in state i and idiosyncratic shocks in state j over time. We plot the estimated β 's from five-year forward rolling regressions of $\Delta gdp_{i,t}$ on $\Gamma_{j,t-1}^{Avg}$, $\Delta gdp_{i,t} = \alpha + \beta \Gamma_{j,t-1}^{Avg} + \varepsilon_{i,t}$ from 1978 through 1995, where $\Gamma_{j,t-1}^{Avg}$ is the average of $\Gamma_{j,t-1}^{ind}$ for all other states. The magnitude of β exhibits a monotonically declining trend from 1978 until 1991. The estimated value decreases from a value of ~ 1 in 1978 to a value of ~ -1 in 1991.¹⁵ The average β for the 1978-1986 period is positive, 0.28, and the average β is negative for 1986-1994, 0.39.¹⁶ This implies that states behaved as complements before 1986 and as substitutes thereafter.

The secular decline in the nature of cross-border spillovers from 1978-1994 motivates further examination into the underlying factors driving the change. The time period in which the relation between economic growth in state i and idiosyncratic shocks in state j exhibits a monotonic change, coincides with the period in which the US banking industry underwent structural reforms. We study this in a rigorous manner, providing prima facie evidence that the change in the relation between economic growth in state i and idiosyncratic shocks in state j is attributable to geographic banking integration. Figure 2b plots the point estimate obtained from the state pairwise regression between GDP growth in state i and idiosyncratic shocks in state j from two subsets. *Pre* refers to a sample of all state-pairs before banking integration. *Post* refers to a sample of all state-pairs after banking integration. Point estimates are plotted with the 90% confidence interval obtained by two-way clustering of the standard errors at state i and state j level. The estimate for the pre period is positive in magnitude but statistically insignificant, whereas, the estimate for the post period is negative and statistically significant. The difference in magnitude between the two estimates is -0.046, statistically significant at the 5% level. Moreover, this difference is stable across different

¹⁵The only exception to this trend is the year 1979 which exhibits a large positive deviation from the trend. This can potentially be explained by the fact that 1979 was the year of oil crisis due to decreased oil output in the wake of the Iranian Revolution. Since oil was crucial to production and households at that time, a large systematic oil shock can explain the extremely large positive correlation estimated for 1979.

¹⁶The year 1979 is not included in the calculation of averages. The t-statistic associated with the difference in the average beta for the two periods is 4.50.

quantiles of ΔGDP (see appendix D.1). Next, we turn to more sophisticated specification(s) to attribute the change in the relation between economic growth in state i and idiosyncratic shocks in state j to geographic banking integration.

5.2 Baseline Result

Motivated by the aggregate trend in the comovement of economic growth in state i and idiosyncratic shocks in state j and its proximate timing with banking deregulation in the US, we examine if this aggregate trend can be explained by banking integration across state-pairs. To this end, we estimate a difference-in-difference specification as in equation 6. Our baseline specification estimates a regression at the (i, j, t) level where each observation corresponds to a state-pair (i, j) at time t .

$$\Delta GDP_{it} = \beta_0 Post_{i,j,t} \times \Gamma_{j,t-1}^{ind} + \beta_1 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{it}, i \neq j \quad (6)$$

where ΔGDP_{it} denotes real GDP growth for state i , $\Gamma_{j,t-1}^{ind}$ denotes state-level idiosyncratic shock for state j , and $Post_{i,j,t}$ is a binary variable taking a value of 1, if banks in state j are allowed to expand operations in state i . α_{ij} denotes state-pairwise fixed effects controlling for all time invariant state-pair specific heterogeneity such as distance. θ_{jt} captures time-varying heterogeneity for state j . We do not include the level term for $\Gamma_{j,t-1}^{ind}$ as it is absorbed within θ_{jt} . We also control for $\theta_i \times t$ denoting linear trend specific to state i .¹⁷ ε_{it} denotes the idiosyncratic term in the baseline specification. This regression equation is estimated at state-pair level as the variable $Post_{i,j,t}$ exhibits variation at state-pair level. Additionally, the state-pair level regression allows us to control for time-varying characteristics for the origin state of idiosyncratic shocks and any time invariant heterogeneity at the state-pair level. As the regression is estimated at the state-pair level, the regression error term is likely to exhibit correlation at the state-pair level. Hence, the regression standard errors are estimated by two-way clustering at the state i and state j levels.¹⁸

Table 3 reports the estimates of the state-level impact of idiosyncratic shocks on GDP growth

¹⁷The inclusion of state $_i$ specific linear trend does not violate the identification issues raised in Borusyak and Jaravel (2017), as the unit of treatment in our analysis is state-pair. Regardless, our results are robust to the exclusion of $\theta_i \times t$.

¹⁸The estimation of the baseline specification at the state-pair level is conceptually based on the framework in section 2 and has several advantages including controlling for state-pair heterogeneity and state $_j$ time-varying heterogeneity. However, each state $_i$ appears 50 times in the regression sample each year using the granular residual of each state $_j$ as a regressor at a time, which can potentially induce correlation in the error term across states. Apart from estimating the standard errors by two-way clustering at state $_i$ and state $_j$ level, we address this concern by aggregating the baseline specification 6 across all j and estimating a regression using the state $_i$ -year as the unit of observation and using $\sum_{j \neq i} Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ as the key independent variable. Appendix table F.1 reports these results.

before and after banking integration of the state-pair. Column (1) reports the baseline specification devoid of any fixed effects. The point estimate of interest is the interaction term of *Post* and Γ . The interaction term is negative and statistically significant at the 5% level. The negative point estimate indicates that a negative idiosyncratic shock in state j is related to an increase in economic growth in state i after banking integration of state i and j , relative to pre banking deregulation. Column (2) adds year fixed effects to the specification in column (1). The point estimate of the interaction term decreases as well as the estimated standard error of the point estimate. The estimate remains negative and statistically significant at 1% level. The following columns (3) to (6) sequentially add fixed effects to the specification in column (1). Despite the addition of fixed effects, the point estimate of the interaction term is negative and statistically significant at 1% level. Column (6) estimates the specification in equation 6. Economically, the baseline estimate of column (6) indicates that a one standard deviation (0.3) negative $\Gamma_{j,t-1}^{ind}$ increases economic growth in state i by 0.05 pp post banking integration.¹⁹

5.2.1 Parallel Trends Assumption: Assessment of Pre-Trends

A necessary condition for identification is the parallel-trends assumption, which states that the relation between economic growth and idiosyncratic shocks in other states would have followed common trends across states before and after banking deregulation, had the deregulation shock not happened. Absent deregulation, the potential outcome is unobserved, rendering direct testing of this assumption impractical. However, we can assess whether the “treated” states and “control” states trended in parallel prior to the shock. With parallel pre-trends, we attribute any divergence in the trend post banking deregulation to banking deregulation itself – not any other possible concurrent shocks or alternative explanations. Under this identifying assumption, the relation between economic growth in one state and idiosyncratic shocks in another, present a valid counterfactual had the states not deregulated. Figure 3 proposes a visual assessment of whether pre-trends prior to deregulation are parallel, and, if deregulation altered the relation between economic growth and idiosyncratic shocks in other states. Figure 3 plots the estimated coefficients β_k and the 90%

¹⁹All non-binary variables in table 3 are standardized to mean 0 and variance 1. The effect is estimated by multiplying the point estimate of β_0 in column (6) with the standard deviation of GDP growth rate. Effect of 1 sd $\Gamma = \beta_0 \times \sigma_{\Delta GDP} = 0.0164 \times 3.254 = 0.0534$

confidence interval from the following equation:

$$\Delta GDP_{it} = \sum_{k=-5, k \neq -1}^{k=+5} \beta_k Time_{i,j,t}(=k) \times \Gamma_{j,t-1}^{ind} + \sum_{k=-5, k \neq -1}^{k=+5} \lambda_k Time_{i,j,t}(=k) + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{it}, \quad i \neq j$$

which includes a set of leads and lags of the deregulation between states i and j interacted with state-level idiosyncratic shocks in state j . The excluded category is one year before deregulation. The estimated coefficients of β_k measure the relation between economic growth and idiosyncratic shocks in other states in years before and after deregulation relative to the relation one year before deregulation. The relation between economic growth and idiosyncratic shocks in other states prior to deregulation is not different from the relation one year before deregulation. However, there is a change in the relation between economic growth and idiosyncratic shocks in other states with deregulation. Though it is not statistically significant for $t = 0$ and $t = +1$, the downward jump is economically relevant. The relation becomes statistically significant for all $t \geq 3$. After this point, the change in the relation is statistically significant, stable, and remains economically relevant. Hence, we reject the hypothesis that the change in the relation between economic growth and idiosyncratic shocks in other states is driven by pre-trends before deregulation. If anything, the limited trend from $t = -3$ to $t = -1$ is positive, decreasing the likelihood that pre-trends drive our result.

5.2.2 Weighted Estimation

The estimates produced from our baseline analysis are predicated on the assumption that the strength of banking linkages are equal across state-pairs. Given that banking linkages are likely to differ across state pairs, we estimate a weighted specification of our baseline regression. In this specification, we assume that the strength of banking linkages is proportional to the strength of non-banking real linkages. [Michalski and Ors \(2012\)](#) argues that this is a reasonable assumption since banks which are present in two regions charge the appropriate risk premiums for trade-related projects between these markets, whereas higher rates are charged for projects involving shipments to markets where banking linkages are absent. Hence, we hypothesize that accounting for non-banking linkages will produce point estimates of larger magnitude, relative to the equal-weighted

assumption.

Table 4 reports the results from a weighted estimation. We compute the share of exports from state i to state j , and the share of imports coming from state j to state i using the 1977 Commodity Flow Survey Data. The share measures the magnitude and the direction of real linkages from i to j . Columns (2) and (3) weight each observation by the share of exports and imports respectively. We also report the equal-weighted regression for comparison in column (1). The estimates in column (2) and (3) are negative and statistically significant – similar to column (1). In terms of magnitude, a one standard deviation $\Gamma_{j,t-1}$ shock increases economic growth in state i by 0.13-0.19 pp post banking integration. This estimate is larger than the baseline estimate of 0.05 pp. Hence, by accounting for the strength of banking linkages using non-banking linkages, we find a larger effect of idiosyncratic shocks in state i on economic growth than in state j post banking integration.

5.3 Instrumental Variable Strategy

Thus far, we have established that banking integration changes the relation between economic growth in state i and idiosyncratic shocks in state j . In principle, strong evidence should show that the result operates via changes in loan supply. To demonstrate this mechanism, we turn to instrumental variable (IV) strategy. The IV strategy employed is similar in spirit to the “granular” IV of [Gabaix and Koijen \(2020\)](#). This section presents the IV framework, results and a discussion on the validity of the exclusion restrictions.

5.3.1 Framework

This section describes the theoretical framework underlying our IV strategy for identifying the relation between bank lending and economic growth. We denote the growth rate in state i ($j \neq i$) as g_i . g_i is a function of L_i , the loan supply in state i , U_i and U_j , unobserved characteristics for each state in the state-pair (i, j) , $\phi_{i,j}^{NB}$, denotes the integration of state-pair (i, j) via non-banking channels, and ϵ_i , an idiosyncratic component in state i . The loan supply, L_i is a function of the g_i and g_j , growth rates for each state in the state-pair (i, j) , $\phi_{i,j}^B$, denoting the banking integration of state-pair (i, j) , V_i and V_j which denote unobserved characteristics for each state in the state-pair (i, j) , and η_i , an idiosyncratic component in state i . The growth rate, g_i , and the loan supply, L_i , are assumed to be as in equation 7 and 9 respectively yielding equation 8 and 10 under the assumption

of separability.²⁰

$$g_i = f(L_i, U_i, g_j, U_j, \phi_{i,j}^{NB}, \epsilon_i) \quad (7)$$

$$= f_1(L_i) + f_2(U_i, \epsilon_i) + f_3(g_j, \phi_{i,j}^{NB}, U_j) \quad (8)$$

$$L_i = h(g_i, g_j, \phi_{i,j}^B, V_i, V_j, \eta_i) \quad (9)$$

$$= h_1(g_i, \eta_i, V_i) + h_2(g_j, \phi_{i,j}^B, V_j) \quad (10)$$

This system of equations is plagued by a major source of endogeneity, namely, simultaneity bias, as both the growth rate and loan supply are jointly determined in equilibrium. We address this concern using an IV strategy. The loan supply is instrumented by Γ_j , idiosyncratic shocks to large firms in state j , and, $\tilde{\phi}_{i,j}^B$, exogenous shocks to the banking integration of state-pair (i, j) . Specifically, we assume that the instrument has the form: $L_i = m[\Gamma_j, \tilde{\phi}_{i,j}^B] \equiv z_{i,j}$. Assuming the validity of the exclusion restriction and relevance of the instrument, yields the moment condition, $\mathbb{E}[\{g_i - f(L_i, 0, 0, 0, 0, 0)\}z_{i,j}] = 0$. We project $h_2(\cdot)$ using $z_{i,j}$ onto $f_1(\cdot)$ to identify the effect of loan supply shocks on economic growth. We instrument for bank loan supply in state i , $\log(l_{i,t})$, with the interaction term of idiosyncratic shocks, $\Gamma_{j,t-1}$, in state j , and the timing of when state i permits banks in state j to branch within state i , $Post_{i,j,t}$.²¹ We estimate the effect of shocks to loan supply on economic growth via a two stage least square estimation (2SLS) in the following setup where equation 11 and 12 represent the first and the second stage respectively.²²

$$\log(l_{i,t}) = \alpha_2 + \beta_2 \Gamma_{j,t-1} \times Post_{i,j,t} + \beta_3 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \epsilon_{it} \quad (11)$$

$$\Delta gdp_{i,t} = \alpha_1 + \beta_1 \hat{\log}(l_{it}) + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \mu_{it} \quad (12)$$

5.3.2 Identifying Assumptions

The identification relies on two key assumptions: relevance and exclusion. The relevance of the instrument stems from the assumption that different states compete for bank lending, and

²⁰ f is separable in, f_1 , f_2 , and f_3 which depend on observable characteristics in state i (L_i), unobserved and idiosyncratic components in state i (U_i, ϵ_i), and state-partner (j) components ($g_j, \phi_{i,j}^{NB}, U_j$), as in equation 8. h is separable in two functions, h_1 and h_2 which depend on state i characteristics (g_i, η_i, V_i), and state-partner (j) characteristics ($g_j, \phi_{i,j}^B, V_j$) as in equation 10

²¹ $\log(l_{i,t})$ refers to new commercial and industrial (C&I) loans given by all banks in state i during time t , capturing the flow of new loans.

²²Note that the estimation is run at the state-pair level. Therefore, for each pair we estimate the shocks to loan supply in state i coming from state j and use the projected loan supply from the first stage to estimate β_1 in the second stage.

geographically diversified banks allocate funds away from geographies experiencing negative non-capital shocks, increasing the loan supply in other states. This assumption is verified in the first stage in which we show that there is substitution of lending away from states that experience negative non-capital shocks, and towards unaffected states.

The exclusion restriction requires that the instruments do not affect economic growth via any channel other than the loan supply channel. Assuming shocks in state j do not effect loan demand in state i would guarantee exclusion, however, this assumption seems implausible as the state-pair is likely to have a non-zero covariance in loan demand via non-banking channels such as trade, input-output linkages, etc. The *weak identification assumption* is that the covariance is stable in magnitude around the timing of banking integration. This allows for loan demand in state i to fluctuate in response to idiosyncratic shocks in state j , but guarantees identification of the pure loan supply effect in the difference-in-differences setup of the first stage. Moreover, if the covariance in loan demand is assumed to be time-invariant, the state-pair fixed effect controls for fluctuations in loan demand. Another relatively *weaker identification assumption* assumes that the covariance in loan demand between two states is sticky relative to loan supply around the deregulation event between the two states.²³ This allows for covariance in loan demand to change post deregulation, but imposes that changes in the covariance of loan supply between two states are more immediate than changes in the covariance of loan demand.²⁴ Furthermore, we discuss violation of the exclusion restriction in appendix section D.2, and argue that violation of the restriction is likely to bias the estimates towards a null effect because states behave as complements on aggregate in the absence of banking linkages.

5.3.3 2SLS Estimation Results

Table 5 reports the first and the second stage estimates. The results indicate that after banking integration, if state j experiences a negative idiosyncratic shock, state i will experience an increase in bank lending, delivering an increase in economic growth in state i .

The first stage estimation regresses loan supply in state i on idiosyncratic shocks in state j , and banking linkage between state i and j . The point estimate of interest is the coefficient β_2 ,

²³We refer to this assumption as the weaker identification assumption and the previous assumption as the weak identification assumption.

²⁴The extant literature seems to be consistent with this assumption. The quantity correlation increases by 1.4% as implied by Michalski and Ors (2012), while price correlation increases by 3.2% as implied by Landier, Sraer, and Thesmar (2017) following pairwise banking integration indicating demand covariance responds slowly relative to the loan supply channel.

the interaction term of $\Gamma_{j,t-1} \times Post_{i,j,t}$. The point estimate reported in column (1) is negative and statistically significant at 5% level. The negative estimate of β_2 indicates that a negative idiosyncratic shock in state j increases the loan supply in state i after banking deregulation of state i and j . In column (3) we control for time-varying regional demands for the state-pair. Additionally, we control for the state-pair level time-invariant heterogeneity through state-pair fixed effect. This specification is related to our weak identification assumption in which we allow the covariance in loan demand between the two states to be non-zero but time-invariant. Under this assumption, β_2 captures the pure effect of the loan supply channel. The point estimate of the interaction term in column (3) is smaller relative to the estimate in column (1). The standard error of the estimate also shrinks substantially from column (1) to column (3), while the model R^2 jumps from 3% to 94% between these two columns. The drop in magnitude from column (1) to column (3) can be attributed to β_2 in column (1), capturing the effect of both loan demand and loan supply channels. In column (5), we control for any time-variant shocks in state j and a linear trend in state i . The point estimate of β_2 remains negative and increases in magnitude relative to the estimate in column (3). In column (7) we control for idiosyncratic shocks in state i as well as the lagged idiosyncratic shocks in both state i and j to better identify the pure effect of the loan supply channel. The point estimate of the interaction term of deregulation and idiosyncratic shocks in state j is negative and statistically significant at the 5% level, at least. The estimates from column (1), (3), (5) and (7) indicate that after banking integration, if state j experiences a negative idiosyncratic shock, state i will experience an increase in bank lending through the loan supply channel.

In the second-stage, we regress the projected loan supply from the first-stage on economic growth. The point estimate of interest is β_1 , the coefficient of $Log(C\&I - Loan_{i,t})$. The point estimate is positive and statistically significant. The point estimate of $Log(C\&I - Loan_{i,t})$, reported in column (4), estimates the loan supply effect on economic growth under the weak identifying assumption. The magnitude of the point estimate is higher than the magnitude estimated in column (2). The increase in magnitude can be attributed to controlling for the covariance in loan demand. If states are complements on aggregate, non-banking channels are likely to transmit the idiosyncratic shocks across states; a negative shock in state j will reduce the loan demand in state i , biasing the effect of loan supply in state i , projected using shocks in state j , on economic growth in state i downwards. The first stage associated with column (4) controls for the covariance in loan demand

under the weak identifying assumption. This could potentially explain the increase in the magnitude of β_1 from column (2) to column (4). Column (6) controls for all shocks in state j and linear trends in state i . The point estimate of β_1 in column (6) is still positive and statistically significant at 5% level. Column (8) controls for lags of idiosyncratic shocks in state i and j . The estimate of β_1 reported in column (8) is also positive and significant.

5.3.4 Discussion on the Magnitude of Estimate

Economically, the results indicate that a 1% increase in bank lending through the loan supply channel increases economic growth by 0.05-0.26 pp. The existing literature presents point estimates of similar or higher magnitudes. Most recently, [Herreño \(2020\)](#) estimates that a 1 percent decline in aggregate bank lending supply reduces aggregate output by 0.2 percent. [Herreño \(2020\)](#) estimates the aggregate effect using a general equilibrium model that incorporates multi-bank firms, relationship banking, endogenous credit dependence, and bank market power. The model is calibrated using estimates reported in [Huber \(2018\)](#). While the [Huber \(2018\)](#) employment elasticity to bank lending estimate applies to Germany, its magnitude is quantitatively similar to the estimate presented by [Chodorow-Reich \(2014\)](#) for the United States and by [Bentolila, Jansen, and Jiménez \(2018\)](#) for Spain.

The estimated magnitude of the effect of loan supply on economic growth is lower than the magnitude presented in the literature so far. This could be driven by the fact that prior work uses negative shocks to banks to identify changes in loan supply. Our lower estimate can be explained if positive and negative shocks are likely to effect loan supply asymmetrically, i.e., banks respond to negative shocks more aggressively than they respond to positive shocks. This is likely to be the case if banks exhibit loss aversion, i.e., banks prefer avoiding losses to acquiring equivalent gains.²⁵

5.4 Heterogeneous Treatment Effects

Thus far, we have presented the average effect for the sample across all states. [De Chaisemartin and d'Haultfoeuille \(2020\)](#) argue that linear regressions estimate weighted sums of the average treatment effects (ATE) in each group and period, with weights that could be negative. This may produce a negative estimate, though all the ATEs are positive. This section documents the heterogeneous

²⁵While loss aversion has been documented among several investor classes, there is little evidence of banks exhibiting loss aversion. In a recent panel survey of investors from a large bank in UK, [Merkle \(2019\)](#) documents evidence of loss aversion over anticipated outcomes.

effects of banking integration across states, and, argues that majority of the ATEs are negative. However, the estimates exhibit a great degree of heterogeneity indicating that states are affected differently by banking integration. We show that a significant portion of this heterogeneity can be explained by the extent of new entry by out of state banks following banking integration.

Figure 4 reports the results from the state-wise estimation of the baseline specification. The estimated coefficients from the state-level regressions exhibit a great degree of heterogeneity across states. The majority of state-specific estimates (75%) are negative. 45% of these negative estimates are statistically significant at the 90% level of confidence.²⁶ Less than 18% of these estimates have a positive magnitude. The mean value of the estimates is -0.0444, and the standard error of the average estimate is 0.0086. Furthermore, the mean value is negative and lower than the baseline estimate of -0.0164. To characterize the distribution of the state estimates, the 10th percentile of the estimates is -0.1073 and the 90th percentile is 0.0327. For illustration, California, Maine, Maryland and South Carolina exhibit β values in the 10th percentile range, while Indiana, Washington and Vermont exhibit β values below the 10th percentile value. The estimates for all of these states are statistically significant at 90% level. Conversely, Wyoming, Idaho, New Mexico, Connecticut, Utah and Alaska exhibit estimates above the 90th percentile value. Apart from Idaho and Utah, the majority of these estimates are statistically insignificant at 90% level. Massachusetts and Louisiana exhibit estimates numerically very close to zero.²⁷

5.4.1 What explains the heterogeneity in state-level estimates?

In this section we discuss reasons for heterogeneity in the state-level estimates. We attempt to explain this heterogeneity using two key variables - (1) the median timing of deregulation, i.e., early versus late-deregulation states, and (2) the degree of penetration by out-of-state banks.

We analyze the growth in the share of gross domestic assets owned by out-of-state MBHCs for early and late deregulators based on the median deregulation year for each state. We define all states with a median deregulation year before 1991 as *early deregulation states* and all other states as *late deregulation states*.²⁸ Figure 5 shows that the average share of gross domestic assets owned

²⁶Note that these regressions are small sample estimations, and hence lack power in the estimation of standard errors.

²⁷We direct readers to appendix section D.3 for alternative methodologies to compute the effect for each state. In these exercises, a single state-pair is compared before and after treatment. This is immune to the Borusyak and Jaravel (2017) critique that the estimate is biased when the control sample diminishes over time, or post treatment outcomes in one unit are used as the control for another unit. We also document that the estimates produced using alternative methodologies are highly correlated with the estimates presented here, see appendix figure D.2b.

²⁸1991 is the median value for all states.

by out-of-state MBHCs grew steadily from 6% in 1979 to 47% in 1994 for early deregulation states, whereas the average share of gross domestic assets owned by out-of-state MBHCs grew modestly from 7% in 1979 to 29% in 1994 for late-deregulation states. The heterogeneity in the banking response by late and early deregulators has earlier been documented by [Mian, Sufi, and Verner \(2020\)](#) for inter- and intra-state banking deregulation. Here, we document a similar heterogeneity for state-pairwise banking deregulation.

The findings discussed in the previous paragraph suggest that the majority of out-of-state banking expansion occurred in early deregulation states. Assuming that changes in banking expansion flow from changes in banking regulation, we hypothesize that the negative and larger magnitude β estimates from the baseline regression are from states with earlier dates of regulation. Figure 6a reports the scatter plot of state-level estimates and median deregulation year. Consistent with our hypothesis we find that the state-level estimate decreases and approaches zero as the median deregulation year increases. Exploring this issue further, Figure 6b plots the scatter plot of state-level estimates with the change in share of gross domestic assets owned by out-of-state MBHCs. As expected, the best fit line is downward sloping, indicating that the large negative state-level estimates are correlated with states that experienced the largest growth in share of gross domestic assets owned by out-of-state banks.

Table 6 reports the results from the regression of state-level coefficients on median deregulation year and a quadratic function of the change in the share of gross domestic assets owned by out-of-state MBHCs from 1979 through 1994. The median deregulation year explains around 13% of the variation in the state-level estimate. Moreover, the positive sign of the point estimate indicates a one year increase in the median deregulation year, increases the state-level point estimate by 0.008.²⁹ Hence, states that deregulated later are associated with greater state-level estimates, β . This estimate is statistically significant and relevant as the point estimate is 0.12 times the standard deviation of the state-level estimates discussed in section 5.4. The quadratic function of the share of gross domestic assets owned by out-of-state MBHCs over the years 1979 and 1994 explains roughly 20% of the variation in the estimate. While the linear term is insignificant, the squared term is statistically significant at the 1% level and enters the regression with the expected negative sign. An increase in the change in out-of-state banking asset share decreases the point estimate of

²⁹ $\Delta\beta_s = 0.1237 \times \sigma_{\beta_s} = 0.1237 \times 0.061 = 0.008$.

the coefficient. Taken together, the median deregulation year and change in out-of-state banking assets explain ~25% of variation in the state-level estimates.

6 Mechanism

In this section, we explore how non-capital shocks are transmitted through banks. On the banking side, we show that the effect of deregulation develops slowly over time, consistent with the idea that actual banking linkages and relationships develop over time. On the typology of shocks, we show that the effect is pronounced for shocks that are more likely to be geographically isolated, exhibit less temporal persistence, as well as, shocks that are less likely to effect bank capital. We supplement the empirical analysis with the theoretical model of [Kalemli-Ozcan, Papaioannou, and Perri \(2013\)](#) to show that the underlying mechanism of the baseline result is driven by geographic diversification of non-capital shocks following banking integration.

6.1 Long-run Effect

We consider the dynamic effect of the impact over time. *Impact* is defined as the year in which state i permits banks from state j to expand in its territory. For each state, we estimate the effect of the impact over time by constructing time windows of varying length around the event. [Figure 7](#) reports the plot of these estimates for different time horizons. A time horizon or window of x in this plot indicates that for each state-pair, we include observations for x years before and after the year of banking integration. The size of the windows are reported on the x-axis. For each time horizon, the point estimate for the interaction term is estimated as in baseline specification [6](#), and, the estimated coefficients are plotted on the y-axis along with the 95% confidence interval. The figure shows that the point estimate develops slowly over time and stabilizes after five years of banking integration. This finding aligns with the hypothesis that the effect is established through banking linkages. While a law can be passed in a day, the implementation of banking linkages across borders ([D'Acunto et al. \(2018\)](#)) and establishment of relations can take time ([Chodorow-Reich \(2014\)](#)). Diverging trends between states before deregulation cannot drive these results as we find parallel trends, discussed in section [5.2.1](#).

6.2 Effect by properties of Shocks

In this section, we show that the effect is pronounced for shocks that are more geographically isolated, exhibit low temporal persistence, and, are less likely to effect bank capital. Examination of how these properties contribute asymmetrically to the baseline effect lends credence to our conjecture that the effect develops through transmission of non-capital shocks via banking integration.

How do non-capital shocks transmit to the economy through banking integration? First, geographic expansion of banks provides diversification benefits as long as shocks are not correlated across geographies. Second, banking integration increases banking competition. Prior to deregulation, banking markets were concentrated and banks could forego rents in one period with the expectation of recouping and profiting in future periods as in [Petersen and Rajan \(1994\)](#). In this period, persistent shocks mattered more for credit supply, whereas temporally isolated shocks had little effect. Post integration, however, lending markets became more competitive. Therefore, in the absence of any commitment between the lender and the borrower, lending contracts were designed such that banks could at least break even each period as in [Diamond \(1984\)](#). Hence, shocks with low temporal dynamics matter more post integration. Table 7 reports results based on cross-state spatial correlation (column 1) and temporal persistence (column 2) of the shock. *Low R^2* takes a value of 1 if the squared correlation of the shock between states i and j , where $i \neq j$, is below the median value. *Low-AR(1)* takes a value of 1 if the AR(1) coefficient for the state i is between the first and the third quartile values. The results in column (1) indicate that post integration, economic growth in state i increases (decreases) more when negative (positive) shocks in state j are geographically isolated. Results in column (2) show that post integration, economic growth in state i increase (decreases) more when negative (positive) shocks in state j exhibit low temporal correlation. The results seem to be dominant for shocks that lack temporal dynamics and spatial structure strengthening our conjectures regarding the mechanism behind the baseline results.

While we attempt to construct shocks that have a low likelihood of being correlated with bank capital shocks, we cannot completely rule out this correlation. Hence, we study how the transmission varies with the sign of the shock. We posit that negative shocks are likely to affect banks' total amount of loanable funds by pushing banks closer to their constraint, and hence, are

unlikely to be transmitted across state boundaries in the hypothesized fashion. Consistent with this hypothesis, see column (3) table 7, we find our effect is smaller in magnitude when shocks are negative. Further, we replicate our baseline table, constructing state-level idiosyncratic shocks using only positive firm-level shocks, shown in appendix table F.2.

6.3 Firms and Growth

Thus far, the results indicate that banks allocate funds away from economies experiencing negative shocks towards unaffected economies. In this section, we further examine the reallocation of funds by banks across firms. We hypothesize that firms which are more dependent on banks as a source of external financing drive the aggregate response in economic growth across states. We use age as a proxy for external finance dependence. Prior work has shown that firm age is a key determinant of external financing needs and bank dependence (Hadlock and Pierce (2010)).

We show that younger firms are more responsive to foreign idiosyncratic shocks after banking integration. We segment firms into “young” and “old” based on median firm age across all firms. The differential response of “young” and “old” firms is presented in Table 8. Consistent with our hypotheses, we find that younger firms are more responsive to idiosyncratic foreign shocks after deregulation. We study debt growth in column 1, sales growth in column 2, market-to-book ratio in column 3, and work-in-progress inventory growth in column 4. After accounting for firm and industry-year fixed effects, we find that a one standard deviation idiosyncratic shock in state j is associated with a 0.75 sd increase in debt growth, 0.47 sd increase in sales growth, 0.46 sd increase in market-to-book ratio, and 0.89 sd increase in work-in-progress inventory, for young firms relative to old firms after banking integration. Hence, these findings corroborate our hypothesis that firms which are more dependent on banks as a source of external financing drive the aggregate response in economic growth.

6.4 Model

In this section, we briefly discuss the theoretical model presented in Kalemli-Ozcan, Papaioannou, and Perri (2013), and exploit this model to show that the underlying mechanism, connecting shocks to growth, is driven by financial integration. The model allows us to do a counterfactual analysis, to examine the changing relation between economic growth in state i and non-capital shocks in

state j based on the ex-ante correlation of non-capital shocks. This counterfactual analysis helps us examine the validity of the exclusion restriction discussed in section 5.3.2.

6.4.1 Overview

In the model, there are two countries, e.g., *home* and *foreign*, each with two segments with size λ and $1 - \lambda$ respectively. The λ segments (segment 2) of each country are financially integrated, while the $1 - \lambda$ segments are financially separate (segment 1), i.e., a $1 - \lambda$ share of the domestic and foreign economies operate in autarky so that banks intermediate only between households and firms in that $1 - \lambda$ segment, respectively. In each segment of each country, there are households which supply labor to firms, and, borrow and save with banks. Firms pay dividends and wages to the households, and make investment decisions. It is assumed that firms need to pay workers before they realize sales, hence, firms must fund their working capital needs via external funding provided by banks. Banks in segment 2 of each country are *global banks*. For illustration of the schema of the economy in the model, we refer to figure 1 of [Kalemli-Ozcan, Papaioannou, and Perri \(2013\)](#).³⁰ The model focuses on two types of stochastic shocks that drive economic fluctuations - (1) standard productivity shock, and (2) banking shocks that affect the value of risky assets held by banks. In particular, we use this DSGE model to study how exogenous changes to financial integration affect the cross-border transmission of shocks. We interpret standard productivity shocks as non-capital shocks and banking shocks as shocks that affect bank capital. In this stylized model, bank lending to firms is risk-free, hence productivity shocks do not affect bank capital – productivity shocks alter the demand for loans of firms experiencing these shocks. We refer the readers to appendix E for in depth discussion on model details such as setup, solution, calibration etc.

6.4.2 Results

We generate synthetic data from the model to study the relation between economic growth in state i (home) and shocks in state j (foreign) as we increase the level of banking integration between the two. We focus on two bundles of shocks: only productivity shocks, and, productivity and bank capital shocks. We run the regression of economic growth in state i on the two sets of shocks in state j for each value of λ and estimate the regression β . Figure 8a presents this result. The key result is that the relation between economic growth in state i and non-capital shocks in state j change with

³⁰This figure is reproduced in appendix figure E.1

the degree of banking integration, λ . For foreign non-capital shocks (blue line), β decreases in the degree of banking integration. For foreign bank capital shocks (red line), β increases in the degree of banking integration. To reiterate, the distinction between the two shocks is that bank capital shocks alter the total supply of capital available for lending whereas non-capital shocks change the relative share of lending by affecting demand.

The diversification benefits of bank geographic expansion of banks may only be realized if shocks being faced by banks are geographically isolated. To test this, we consider two counterfactual scenarios - one where the productivity shocks have zero spatial correlation, $\rho = 0$, and another where productivity shocks are perfectly positively correlated, $\rho = +1$, across geographies. The correlation in productivity shock reflects the strength of the relation between the two states via non-banking linkages such as trade, input/output, etc. Positive correlation in productivity shocks reflects positive correlation in loan demand. Hence, a negative shock in state j reduces loan demand in both states i and j , dampening the loan supply effect. Figure 8b plots this result. The blue and the red lines plot the β for the regression of economic growth in state i and productivity shocks in state j with $\rho = 0$ and $\rho = +1$, respectively. We use this result to make two points. First, the change in β is more pronounced when shocks are geographically diversifiable, $\rho = 0$, as in our mechanism. Second, it is consistent with our identification strategy, in which we argue that as long as states behave as complements with positive demand correlation, on aggregate, due to non-banking channels, our estimation strategy is biased towards finding a null result.

7 Robustness

We conduct a battery of robustness tests to ensure that our results are invariant to alternative measurements of idiosyncratic shocks, geography based measurement error in idiosyncratic shocks, and endogeneity of the banking integration.

7.1 Alternative Measures of Idiosyncratic Shocks

We examine the sensitivity of the results to the methodology adopted in constructing idiosyncratic shocks. To this end, we construct alternative measures of idiosyncratic shocks by altering the construction methodology. First, we use the top 20 and top 30 firms instead of top 10 firms. Second, we use a time-invariant measure of idiosyncratic shocks using a time-series average of shocks in

a state. Third, we adjust idiosyncratic shocks for aggregate temporal shocks instead of industry level temporal shocks. We find that our results are not driven by methodological choices used to construct local idiosyncratic shocks (see appendix table F.3). Fourth, we reconstruct idiosyncratic shocks assuming that the firm-level productivity shocks have heterogeneous, but time-invariant exposure to aggregate macroeconomic shocks. Under this factor structure assumption, residuals constructed from a firm level regression of labor productivity shocks that are adjusted for aggregate industry level shocks are considered to be idiosyncratic. We find that the point estimate for shocks constructed under the factor structure framework are quantitatively similar to our baseline estimates (see appendix table F.7).³¹ Furthermore, we verify that our results are not driven by states where top 10 firms' share of sales is high. We repeat our baseline analysis with alternative samples where we only include states if the top 10 firms account for less than 95%, 90%, 80%, and 70% of all sales and find the point estimate to be insensitive to alternative samples (see appendix table F.4).

7.2 Placebo Test

We conduct a placebo test wherein we randomize the timing of banking integration. This test addresses two concerns. First, it addresses whether the timing of banking integration is meaningful by checking if the results disappear if the timing is randomly selected. Second, it verifies that results are not driven by omitted variable bias (OVB), as long as the structure of omitted variables is identical across state-pairs. A placebo deregulation year is generated for each state-pair (i, j) from a uniform distribution between 1982 and 1994. The baseline specification is estimated using the generated placebo year. We estimate this process 3,500 times. Figure 9 plots the kernel density of the point estimates of $Placebo - Post_{i,j,t} \times \Gamma_{j,t-1}$ obtained from 3,500 Monte-Carlo simulations where we randomize the timing of state-pairwise banking integration. The distribution of the coefficient of the interaction term is centered around zero with a mean and standard deviation of 0.0001 and 0.0076, respectively. The dashed red line indicates the estimated point estimate from our baseline regression in Table 3 with 1.74% of the estimated coefficients of the $Placebo - Post_{i,j,t} \times \Gamma_{j,t-1}$ lying to the left of the dashed line. Hence, we can argue that the timing of banking integration is special and results are unlikely to be driven by omitted variables as long as the structure of such

³¹We refer the readers to appendix F.2 for further discussion on methodology, properties and baseline results using shocks constructed under the factor structure with heterogeneous but time invariant exposure methodology.

variables is identical across state-pairs.³²

7.3 Addressing Geography-based Measurement Error

In the construction of Γ , as in section 4.2.1, we assume that the sales and employment of a firm originate in the same state as where the headquarter is located. This could result in a potential measurement error issue. We argue that this issue is likely to be innocuous for two reasons. First, measurement error is likely to be small. Chaney, Sraer, and Thesmar (2012) note that headquarters and production facilities tend to be clustered in the same state, and, headquarters represent an important fraction of corporate real estate assets. Barrot and Sauvagnat (2016) show that average (median) Compustat firm in their sample have 60% (67%) of its employees at its headquarters. Second, even if the measurement error is large, it is likely to bias the estimate against finding the proposed effect.³³

Nevertheless, we compute two alternative measures of state-level shocks to circumvent the measurement issue and find qualitatively similar results (see appendix section F.4). The first measure is constructed by aggregating annual growth in GDP contribution from each industry within a state, adjusted for the annual aggregate growth in GDP contribution from each industry. This measure is constructed from the BEA data and is immune to geography-based measurement error. The second measure is constructed based on discovery of new oil reserves. These oil discoveries at the state-level are likely to result in positive local idiosyncratic shocks. While both measures alleviate concerns associated with geography-based measurement error, they are plagued by other issues. The value-added shocks are likely to be endogenous to the banking sector, as they include shocks from both large and the small firms. The oil discovery shocks can only be created for a smaller sample of states, resulting in a test with low power. Additionally, the oil discovery shocks are predictable towards the later part of the sample, lessening the predictive power of these shocks even further.³⁴

³²In an alternative placebo test we randomize the idiosyncratic shocks in state j and estimate the coefficient of the interaction term of $Post_{i,j,t} \times Placebo - \Gamma_{j,t-1}$. The results disappear with randomization of Γ ruling out the claim that the results are spurious in nature (see appendix F.3).

³³Assume that a firm, headquartered in state j has majority of its employees and sales in state i , then Γ constructed using our methodology will wrongly attribute the idiosyncratic shock in state i to state j . As shown earlier idiosyncratic shock in state i have a positive correlation with future economic growth. Hence, under such a geography-based measurement error the estimate of the interaction term of Γ and $Post$ will be either positive or zero, biasing our strategy against finding the proposed effect.

³⁴We direct the readers to appendix section F.4.1 and F.4.2 for further discussion of shocks constructed using value-added measure and oil discovery shocks respectively. These sections also report the replication of baseline regression with idiosyncratic shocks constructed using these measures.

7.4 Addressing Concerns Related to Migration

This section addresses concerns of whether the results presented in the paper are driven by inter-state migration, contemporaneous with the state pairwise banking integration. We address this concern in two ways. First, we assume that the tendency to move between state i and state j is likely to be similar or smooth across other states in the same economic regions as state i and state j , respectively. Under this assumption, we augment the baseline specification by including $\text{region}_i \times \text{region}_j \times \text{year}$ fixed effects, and $\text{region}_i \times \text{state}_j \times \text{year}$, where region refers to the BEA economic region of the state. In an alternative test, we randomly form groups of states of different sizes and control for the $\text{random-region}_i \times \text{random-region}_j \times \text{year}$ fixed effects, and $\text{random-region}_i \times \text{state}_j \times \text{year}$ in the baseline specification. We repeat this process of randomization of states into groups 3,500 times and estimate the distribution of the interaction term of the $\text{Post}_{i,j,t}$ and $\Gamma_{j,t-1}^{ind}$. The second test, in contrast to the first test, assumes that the choice set of within US migration is coarsely distributed across space. Appendix F.5 discusses these results and finds that the coefficient of interest is qualitatively and statistically similar to the baseline results. Hence, we can argue that the results discussed in this paper are unlikely to be driven by contemporaneous migration.

8 Great Moderation and Banking Integration

The Great Moderation refers to a period of stable macroeconomic activity starting from the mid 1980s. While several explanations have been proposed to explain the Great Moderation (see, [Davis and Kahn \(2008\)](#)), the three most common hypotheses explaining the Great Moderation are good luck ([Stock and Watson \(2002\)](#)), improvements in monetary policy ([Bernanke \(2004\)](#)), and broad based structural change ([Summers \(2005\)](#)). In this paper, we posit a new hypothesis to explain the relative quiescence in aggregate volatility.

We propose an alternative mechanism that explains the persistence of lower macroeconomic volatility during the Great Moderation. We argue that banking reforms, namely, banking deregulation that took effect during the 1980s and 1990s increased the overall role of banks in intermediating shocks between states. We have shown that during the later 1970s and early 1980s, idiosyncratic shocks in one state are positively correlated with economic growth in another state, suggesting that in the absence of banking linkages, states behaved as complements. However, this monotonically

reversed post 1984, during which states began behaving like substitutes. We have attributed this change in the cross-border transmission of productivity shocks to banking integration. As banks could cross state lines and operate, their investment choice set expanded, allowing them to geographically diversify their portfolio. In other words, prior to banking integration, when shocks in one state were correlated with growth in another, aggregate fluctuations for the overall US economy could be quite large. After banking integration, the negative cross-state correlation allowed banks to ultimately “hedge” their portfolio and reduce risk, lowering the level of aggregate fluctuations. Hence, banking integration provides a mechanism that explains “good luck” and why even large idiosyncratic shocks did not snowball into large aggregate fluctuations. Banking reforms altered the cross-border transmission of shocks, thus, the overall US economy did not react to exogenous shocks during the period of the Great Moderation as strongly as in previous periods.

We exploit the two-country model presented in section 6.4 to show that banking integration can explain the decrease in aggregate volatility. Banking integration affects the variance and covariance of economic growth in/between two geographies.³⁵ The data simulated from the model shows that the covariance in economic growth between the two geographies decreases as banking integration increases, while the variance in economic growth in each geography increases with banking integration. Quantitatively, the decrease in covariance is large enough to offset the increase in variance such that the aggregate economic volatility of the entire system decreases with the increase in banking integration. Figure 10 provides a visual depiction of this result. The variance of the two geographies increases by 22% when λ increases from 0 to 1. The covariance decreases by 240% for the same change in λ . Aggregate volatility decreases by 2% (-2%) with a total of +25% contributed by the variance of the two geographies and -27% contributed from the covariance term. The magnitude of the decline in aggregate volatility is likely to increase as we move from a two-country setup to a multi-country setup; the increase in individual geographic variance is dampened as shocks are distributed by banks over a larger geographic set, while the decline in the covariance is amplified.

³⁵We find similar conclusions on the effect of banking integration on variance and covariance in the extension of simple framework of section 2 presented in appendix section A.1.

9 Conclusion

In this paper, we identify the effect of banking networks on the cross-border transmission of non-capital shocks. We introduce new empirical findings on how non-capital shocks transmit through the economy via banks. Specifically, we provide evidence that geographically diversified banks divert funds away from states that experience negative shocks, and towards unaffected state economies. While the extant empirical literature focuses on the transmission on bank capital shocks, the focus of this paper is on the transmission on non-capital shocks through banking networks. Our results suggest that the transmission of non-capital shocks result in negative comovement of business cycles.

We introduce several new stylized facts in this paper. First, we find that in the late 1970s and early 1980s, idiosyncratic shocks in state j were positively correlated with economic growth in state i , suggesting that two states operated as complements during this period. This relation monotonically changed after 1984 through 1994. Idiosyncratic shocks in state j are *negatively* correlated with economic growth in state i . Second, we attribute this change in relationship to contemporaneous changes in banking linkages across states. In the presence of banking linkages, shocks do not directly transmit cross-border – they are intermediated by banks, providing a mechanism for how non-capital shocks in state j can affect economic growth in state i by changes in the share of bank loan supply across states. Third, we use this empirical set-up to causally estimate the relation between changes in bank loan supply and economic growth. Concretely, we find that a 1% increase in bank loan supply is associated with 0.05-0.26 pp increase in economic growth. Fourth, this mechanism has the potential to explain why the overall economy did not react to exogenous shocks during the Great Moderation as strongly as in previous periods.

Our findings have implications for policymakers in advanced and emerging economies. In recent years, the European Union has proposed and implemented steps towards the creation of a European Banking Union and European Capital Markets Union, part and parcel of a broader Economic and Monetary Union (EMU). These policies are intended to converge the economies of EU states and improve the resiliency of the EMU through a centralized “shock-absorption” system. Our results suggest that a stronger banking union could lead to divergence of economic growth between member states in the presence of non-capital shocks. Our results are also informative to

policymakers in emerging market economies where the banking industry is gradually moving from state ownership to private ownership of banks. In the presence of non-capital shocks and financially integrated banks, there may still be convergence across microeconomics of a country in the presence of welfare-maximizing or monopolistic banks, such as state-owned banks. With a high level of financial integration, moving from welfare-maximizing state-owned banks to profit-maximizing private banks may potentially result in the divergence of microeconomics of a country. We do not claim to settle these debates, but provide another dimension for deliberations while formulating such policies.

Finally, our work highlights how banks can aggregate idiosyncratic shocks in an economy. This aids our understanding of the origins of aggregate fluctuations. Study of the interaction of bank and non-capital shocks and their effects on aggregate fluctuations provides an important avenue of future empirical research that can further the discussion on the nature of cross-border transmission of shocks.

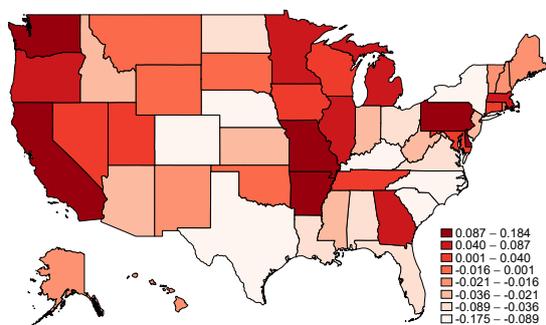
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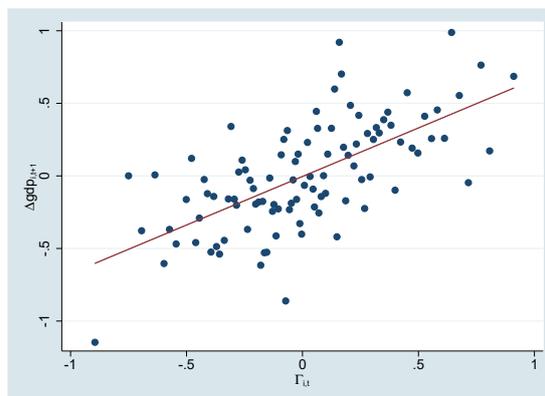
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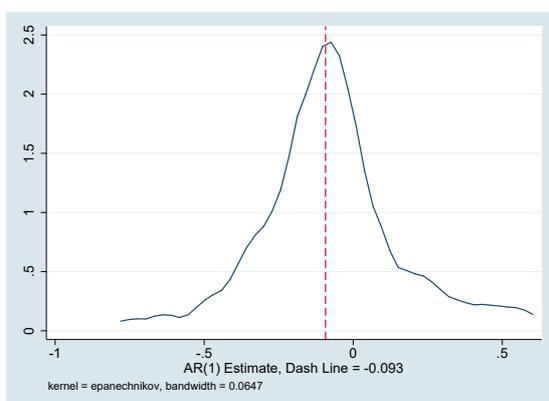
Figure 1: Properties of Idiosyncratic Shocks, Γ



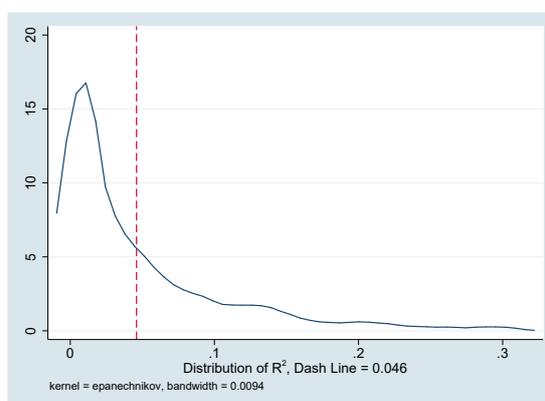
(a) Spatial distribution of Γ



(b) Γ predict subsequent Δgdp



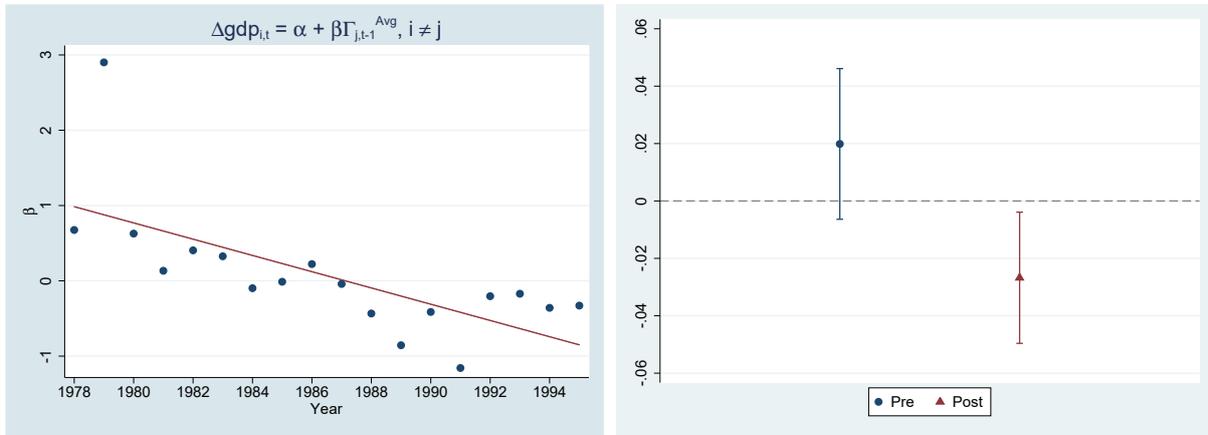
(c) Distribution of state-wise AR(1) estimate for Γ



(d) Distribution of state-pairwise R^2 of Γ

The figure describes the properties of idiosyncratic shocks, documenting their spatial distribution, geographic isolation, temporal non persistence and ability to predict future economic growth. The figure 1a plots the cross-sectional distribution of Γ over US states between 1978 to 1995. We take a time-series average of $\Gamma_{j,t-1}^{ind}$ for each state and use these average values to plot the heat map of the cross-sectional distribution of idiosyncratic shocks. Figure 1b plots the binscatter plot of Γ and subsequent annual economic growth in the same state. State-level idiosyncratic shocks and subsequent annual economic growth are standardized to mean zero and variance of 1. Figure 1c plots the estimated coefficients of the AR(1) term from a state-wise regression. We run time series AR(1) regression for each state and estimate the AR(1) coefficient. The blue line reports the kernel density of AR(1) coefficients obtained from the time series regression. The dashed red line plots the AR(1) estimate obtained from a pooled regression of all states. Figure 1d plots the kernel density of R^2 of Γ for each state-pair. The red dashed line plots the mean value of R^2 . Our data spans a period of 1978 to 2000.

Figure 2: Relation between GDP Growth & Idiosyncratic Shocks

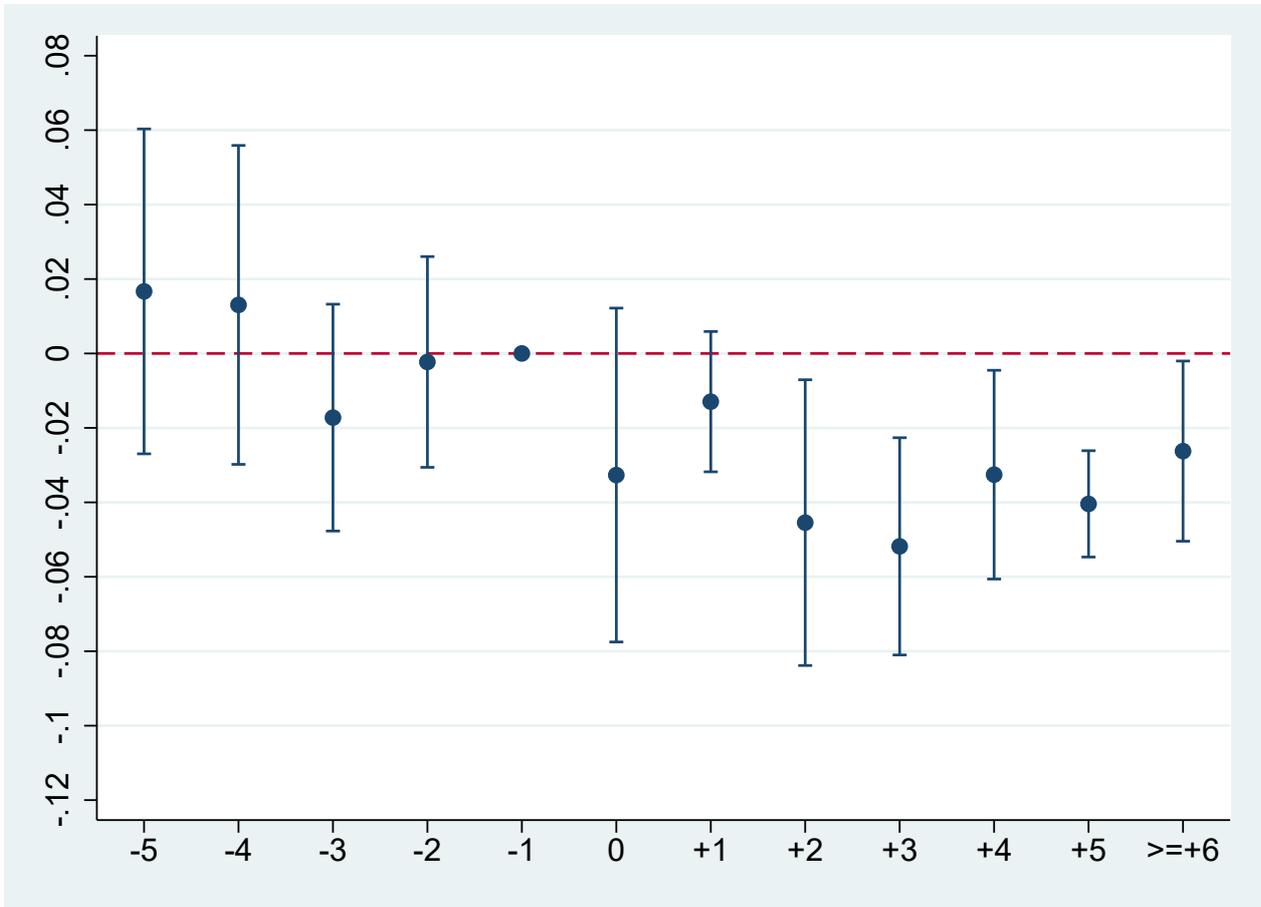


(a) Relation Over Time

(b) Banking Integration

The figure documents the relation between GDP growth in state i and idiosyncratic shocks in state j , where $i \neq j$, - evolution over time and its relation to banking integration. Figure 2a plots the relation between GDP growth in state i and idiosyncratic shock in state j . We run five-year forward rolling regressions of $\Delta gdp_{i,t}$ on $\Gamma_{j,t-1}^{Avg}$ from 1978 to 1995 and estimate the point estimate β . We plot the point estimates of β for each year between 1978 to 1995. Figure 2b plots the point estimate obtained from the regression between GDP growth in state i and idiosyncratic shocks in state j from two subsets. *Pre* refers to a sample of all state-pairs before banking integration. *Post* refers to a sample of all state-pairs after banking integration. 90% confidence intervals are plotted with point estimates. The CI are obtained by two-way clustering the standard errors at state i and state j level. All variables used in regressions were standardized to mean 0 and variance 1.

Figure 3: Parallel Trends Assumption: Assessment of Pre-Trends

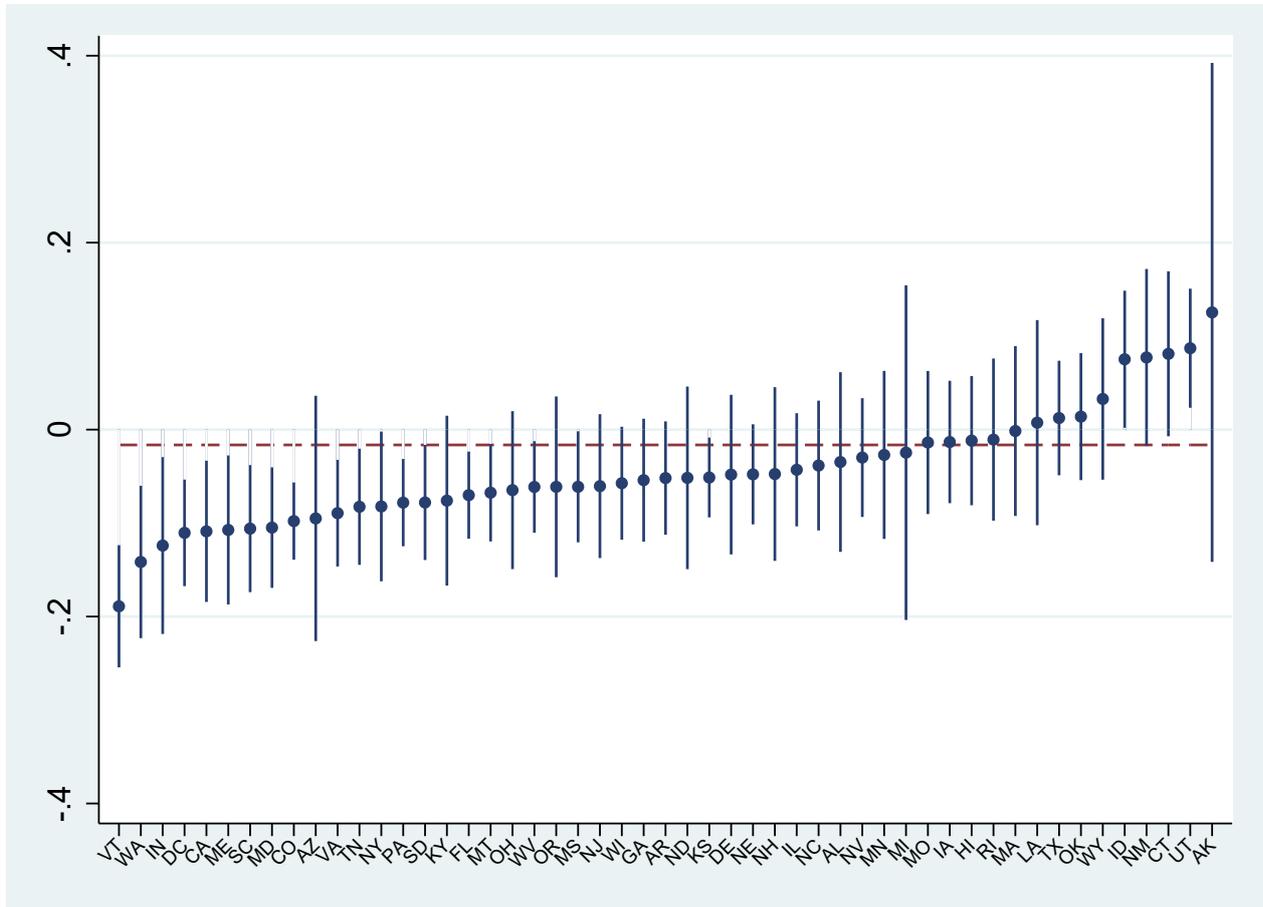


The figure plots the estimated coefficients β_k and the 90% confidence interval from the following equation:

$$\Delta GDP_{it} = \sum_{k=-5, k \neq -1}^{k=+5} \beta_k Time_{i,j,t}(=k) \times \Gamma_{j,t-1}^{ind} + \sum_{k=-5, k \neq -1}^{k=+5} \lambda_k Time_{i,j,t}(=k) + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{it}, i \neq j$$

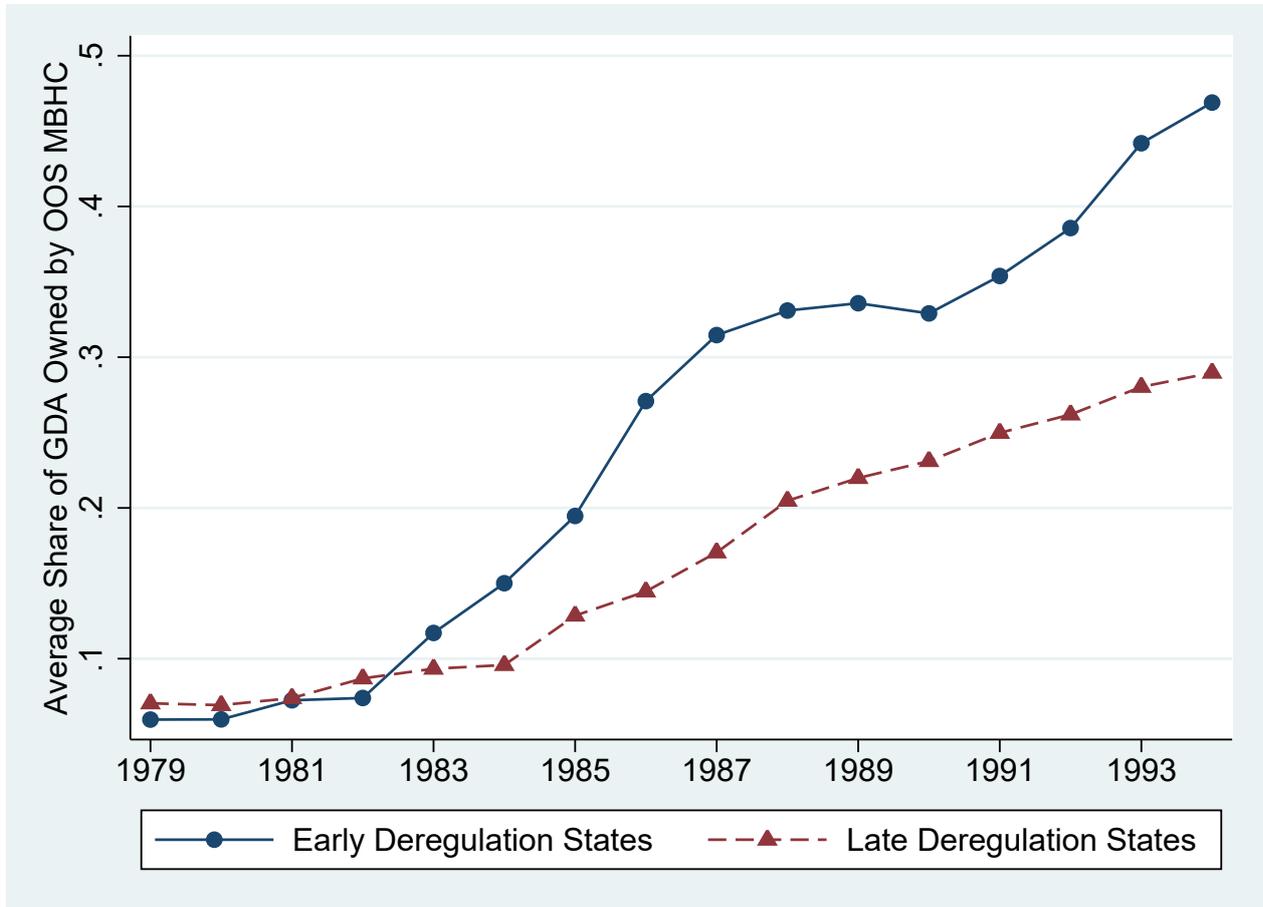
which includes a set of leads and lags of the deregulation between states i and j interacted with state-level idiosyncratic shocks in state j . The excluded category is one year before the deregulation. The 90% error bands are estimated using standard errors two-way clustered at the state i and state j level. All variables used in regressions were standardized to mean 0 and variance 1.

Figure 4: Heterogeneous Treatment Effects



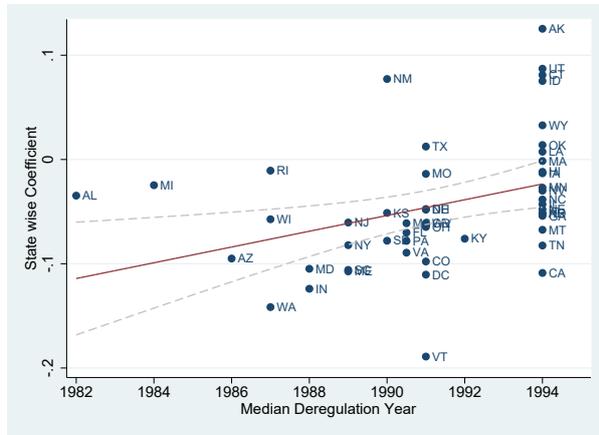
The figure plots the point estimates of the interaction term of post and Γ in the baseline specification for each state, i.e., we run the baseline specification as in table 3 for each state i and estimate the coefficient of the interaction term of post and Γ . The graph also reports the 90% CI associated with each estimate. The 90% error bands are estimated using standard errors two-way clustered at the state _{i} and state _{j} level. The red dashed line reports the baseline estimate from column (6) in table 3.

Figure 5: Out-of-state Banking Expansion in Early and Late-deregulation States

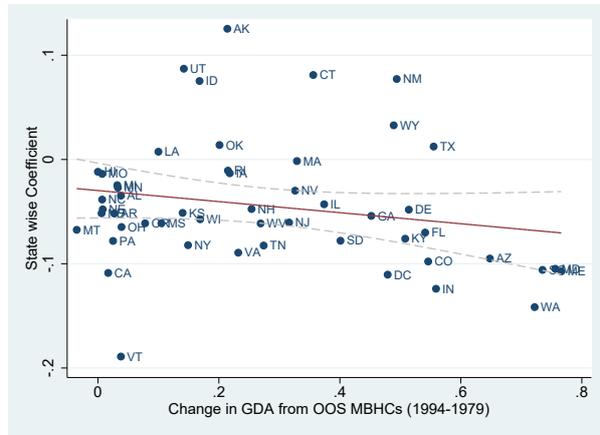


The figure plots the average share of gross domestic banking assets owned by out-of-state MBHCs across early and late-deregulation states. Data on share of gross domestic assets owned by out-of-state MBHCs comes from [Berger, Kashyap, and Scalise \(1995\)](#). Early deregulation states are defined as states that deregulated banking restrictions with at least 50% of other states before 1991, and late-deregulation states are states that deregulated with at least 50% of other states on or after 1991.

Figure 6: State-level estimate, timing of deregulation and out-of-state banking penetration



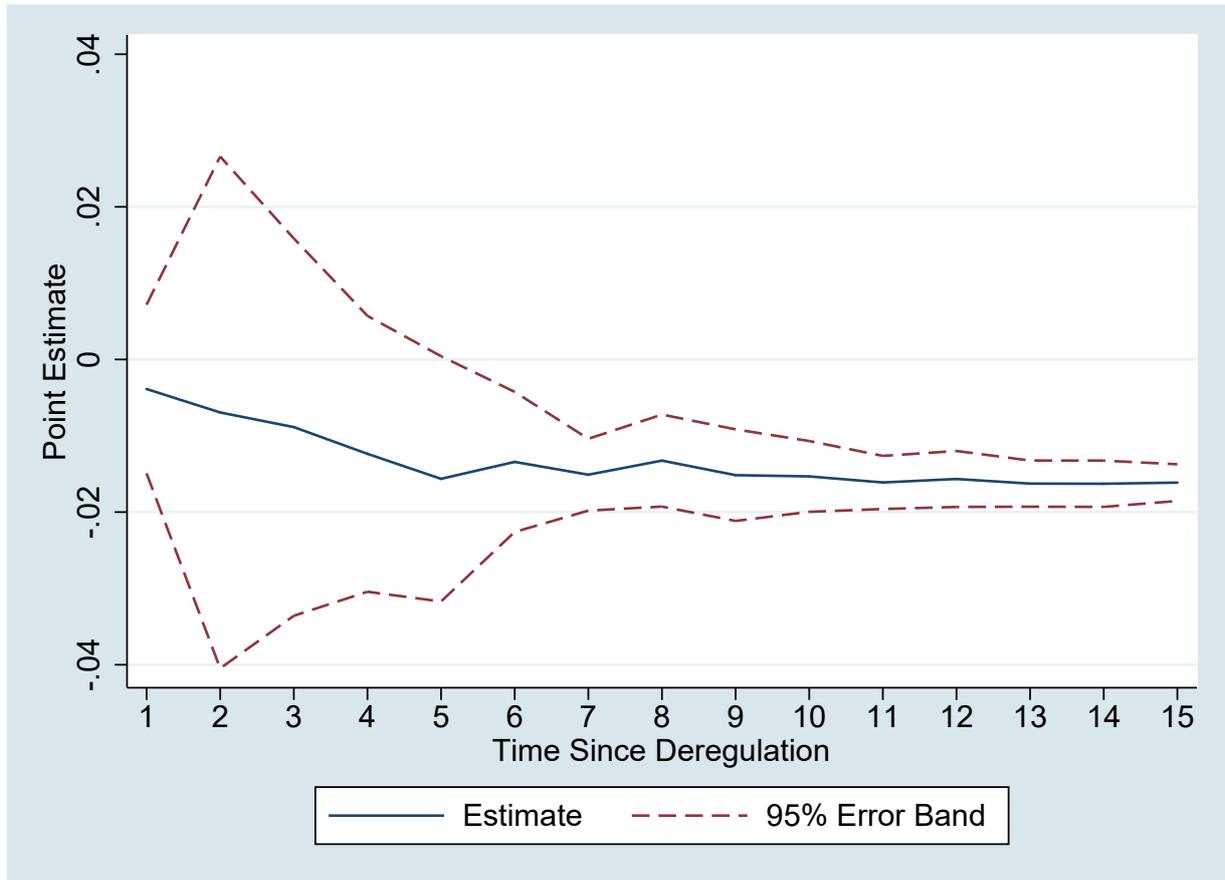
(a) Median Deregulation Year



(b) Change in Gross Domestic Assets Owned by out-of-state MBHCs (1994-1979)

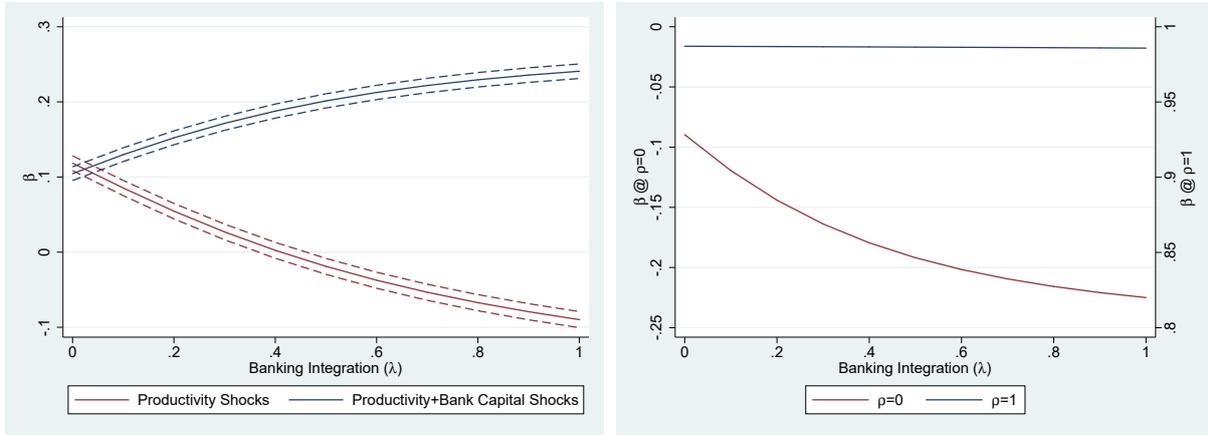
The figure plots the relation between the state-level estimate presented in figure 4 and the median year of deregulation (figure 6a) and the change in the share of gross domestic assets owned by out-of-state MBHCs (figure 6b). The median year of deregulation is set equal to the year when the state has deregulated with at least 50% of other states. Data on share of gross domestic assets owned by out-of-state MBHCs comes from [Berger, Kashyap, and Scalise \(1995\)](#). The change in the share of gross domestic assets owned by out-of-state MBHCs is computed over the years 1979 and 1994.

Figure 7: Long-run Effect



The figure plots the effect of impact f deregulation over time. We define impact as the year in which state i allows banks of state j to enter its territory. For each state we estimate the effect of this impact over time by trimming the data for each state-pair before and after the passage of the law at different time horizons. We consider horizons from 1 through 15 years before and after the law. These different horizons are reported on the X axis. For each horizon we run our baseline specification and estimate the coefficient for the interaction term of Post and Γ . We plot the point estimate for the interaction term of Post and Γ on the Y axis for each time horizon. The 95% error bands are estimated using standard errors two-way clustered at the state $_i$ and state $_j$ level.

Figure 8: Domestic Growth, Foreign Shocks & Banking Integration

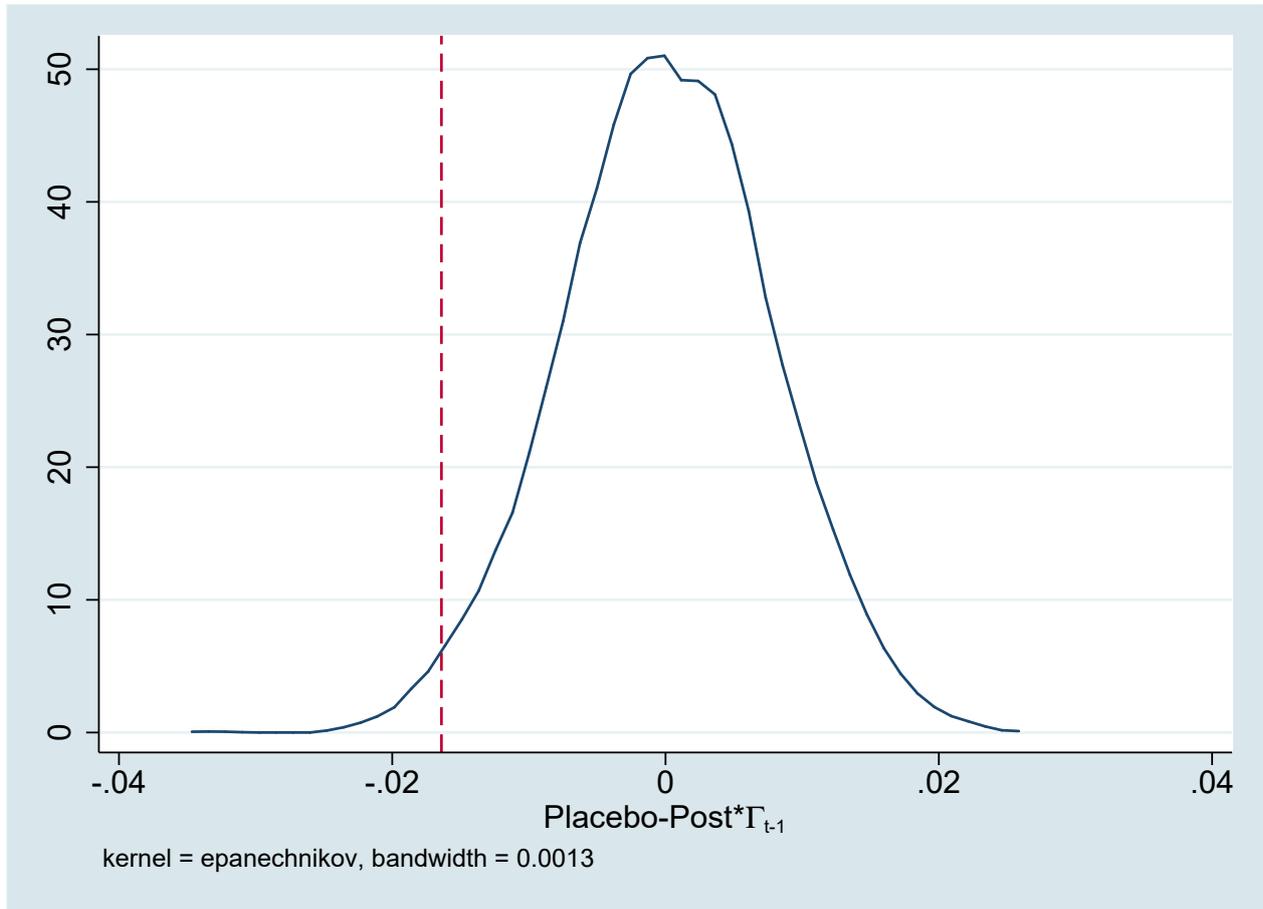


(a) Types of Shocks

(b) Ex-Ante Correlation of Shocks

The figure plots the relationship between domestic growth and foreign shocks for different levels of banking integration. We run the regression $\Delta gdp_{i,t} = \alpha + \beta \Gamma_{j,t} + \varepsilon_{i,t}$ and estimate β for different values of banking integration, λ , between i and j . Figure 8a plots the relationship for different types of shocks - productivity shocks or non-capital shocks and productivity shocks along with bank capital shocks. Figure 8b plots the value of β for different values of $\lambda \in [0, 1]$ based on ex-ante correlation, ρ , of non bank capital shocks between the domestic and the foreign economy. The shocks used in figure 8b are productivity shocks.

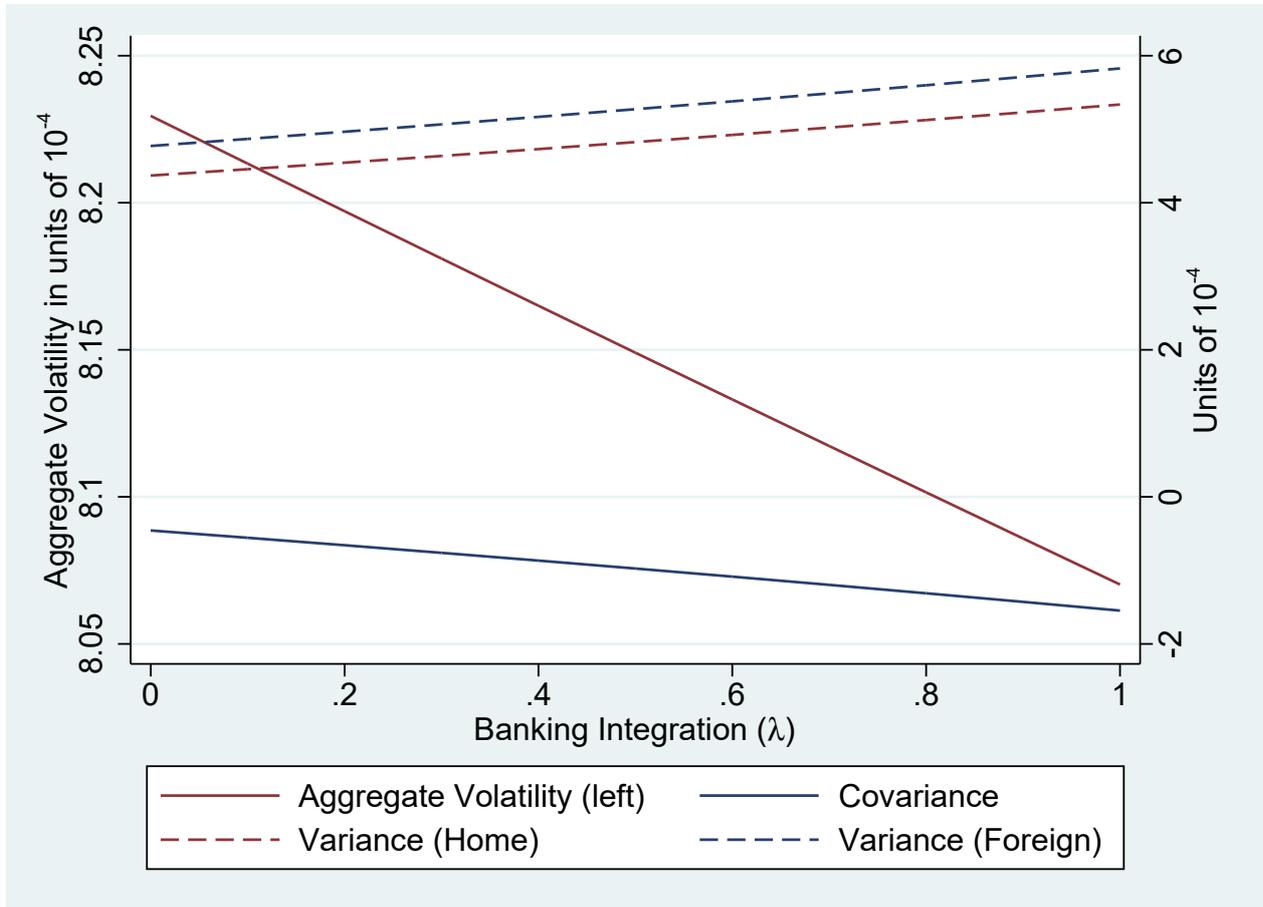
Figure 9: Placebo Test: Randomization of the Timing of Deregulation



| Min | p1 | p5 | p25 | p50 | p75 | p95 | p99 | Max | Mean | St Dev |
|---------|---------|---------|---------|--------|--------|--------|--------|--------|--------|--------|
| -0.0334 | -0.0176 | -0.0127 | -0.0049 | 0.0001 | 0.0051 | 0.0126 | 0.0173 | 0.0245 | 0.0001 | 0.0076 |

The figure plots the kernel density of the point estimates of $Placebo - Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ obtained from the 3,500 Monte-Carlo simulations. We generate a new date of deregulation from a uniform distribution between 1982 and 1994 for each state-pair in every simulation. We call this new deregulation year as placebo year and define the variable $Placebo - Post_{i,j,t}$ based on the placebo year. We run our baseline specification with $Placebo - Post_{i,j,t}$. The table underneath the figure gives the numbers associated with the distribution of the estimates plotted in figure. The dash red line shows the point estimate from column 7 of table 3. There are 1.74% of points to the left of the red-dashed line.

Figure 10: Banking Integration, Variance, Covariance and Aggregate Volatility



The figure plots the variance in economic growth for domestic and home county, the covariance in the economic growth of two countries, and the aggregate volatility of the system for different values of banking integration, λ . For each value of λ we simulate the path of each economy with only productivity shocks such that these shocks have zero spatial correlation and zero persistence and compute the value of variance and covariance of economic growth. Aggregate volatility is computed by adding the variance of economic growth of the two countries and twice the covariance.

Table 1: Summary Statistics

| | N | p25 | Median | p75 | Mean | Std. Dev. |
|------------------|-------|--------|--------|--------|--------|-----------|
| ΔGDP | 1,173 | 1.400 | 3.300 | 5.300 | 3.247 | 3.254 |
| Γ | 1,157 | -0.053 | 0.000 | 0.059 | 0.005 | 0.331 |
| Log (C&I Loans) | 1,173 | 15.618 | 16.526 | 17.388 | 16.651 | 1.334 |
| Log(Total Loans) | 1,173 | 17.295 | 18.036 | 18.923 | 18.132 | 1.261 |

The table reports the number of observations, first quartile, median, third quartile, mean, and standard deviation of observations for the key variable used in our analysis. Our data spans a period of 1978 to 2000.

Table 2: Narrative Analysis of Firm-Level Productivity Shocks

| Year | Firm Name | HQ State | Γ_{it} | $\Gamma_{it} - \mathbb{E}_t[\Gamma_{it}]$ | $\Gamma_{it} - \mathbb{E}_{jt}[\Gamma_{it}]$ | News |
|------|---------------------------------|-------------|---------------|---|--|--|
| 1977 | Whirlpool Corp | Michigan | 14.8% | 0.6919% | 0.5434% | Introduced the first automatic clothes washer and microwave ovens |
| 1978 | The Kroger Co | Ohio | -23.9% | -8.4179% | -7.6038% | FTC crackdown for violation of 1973 trade law. Price patrol cheating scandal. |
| 1979 | Paramount Cocommunications Inc | New York | 23.2% | 2.1942% | 1.9918% | Deal with Teleprompter Corp (largest cable systems operator in US). |
| 1981 | Chevron Corp | California | -0.7% | -3.0755% | -2.9696% | Armaco is nationalized by the Saudi government. |
| 1982 | Savannah Foods & Industries Inc | Georgia | -7.5% | -0.1893% | -0.0020% | Big clients switched to High Fructose Corn Syrup |
| 1983 | Storage Technology Corp | Colorado | -19.0% | -0.6869% | -0.3325% | Loss in market share to IBM due to delay in the product release. |
| 1984 | Skyline Corp | Indiana | -0.6% | -0.0827% | -0.0417% | Internal managerial decision to cut costs to remain debt free. |
| 1985 | Montgomery Ward & Co | Illinois | -9.0% | -2.1164% | -2.0918% | Massive restructuring of the firm after three years of experimentation under former CEO. The firm closed its catalog business after 113 years |
| 1986 | Reynolds Metal Co | Virginia | 6.7% | 0.2358% | 2.7674% | Discovered gold in a bauxite ore |
| 1987 | Eli Lilly and Company | Indiana | 10.3% | 0.3694% | 0.4763% | FDA approves the use of Prozac for treating depression |
| 1988 | Johnson & Johnson | New Jersey | 7.7% | 0.0920% | 0.4588% | Acuvue disposable contact lenses are introduced |
| 1989 | Boeing Co | Washington | -7.6% | -3.1492% | -1.3783% | Boeing jets involved in accidents. Delivery delayed |
| 1990 | Intel Corp | California | 13.0% | 0.4189% | 0.7062% | Intel launches i486 |
| 1991 | Eastman Kodak Co | New York | -1.8% | -0.8057% | -1.1724% | Polaroid's suit against Kodak is settled. Made payment of \$925 million |
| 1993 | Circuit City Stores Inc | Virginia | 7.2% | 0.2308% | 0.2269% | Circuit City launches its new CarMax chain, a retailer of used cars |
| 1994 | Xerox Corp | Connecticut | 14.4% | 2.1486% | 3.2586% | Brand Makeover |
| 1995 | The Black & Decker Corp | Maryland | 10.4% | 0.2561% | 0.4333% | Introduces the VersaPak interchangeable battery system and the SnakeLight flexible flashlight |
| 1996 | Dell Inc | Texas | 17.3% | 0.8928% | 0.5149% | The company begins selling over the Internet |

The table reports the events for a selected sample of firm-year observations between 1977 and 1996. The firm-year observations that we believe to be economically and methodologically most interesting are included in the table. HQ state refers to the name of the state of headquarter of the firm in that year. Γ_{it} refers to the firm level labor productivity shock, $\Gamma_{it} - \mathbb{E}_t[\Gamma_{it}]$ refers to the firm level labor productivity shock adjusted for aggregate labor productivity shocks during the period, and $\Gamma_{it} - \mathbb{E}_{jt}[\Gamma_{it}]$ refers to the firm level labor productivity shock adjusted for aggregate industry labor productivity shocks during the period. $\Gamma_{it} - \mathbb{E}_t[\Gamma_{it}]$ and $\Gamma_{it} - \mathbb{E}_{jt}[\Gamma_{it}]$ have been multiplied by 100 before reporting.

Table 3: Baseline Specification

$$\Delta gdp_{it} = \beta_0 Post_{i,j,t} \times \Gamma_{j,t-1}^{ind} + \beta_1 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{it}, i \neq j$$

| Δgdp_{it} | (1) | (2) | (3) | (4) | (5) | (6) |
|--|-----------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0428** (0.0178) | -0.0026*** (0.0005) | -0.0058*** (0.0012) | -0.0079*** (0.0001) | -0.0177*** (0.0021) | -0.0164*** (0.0007) |
| $\Gamma_{j,t-1}^{ind}$ | 0.0184 (0.0155) | 0.0010*** (0.0002) | 0.0023*** (0.0005) | 0.0031*** (0.0000) | | |
| $Post_{i,j,t}$ | 0.2550*** (0.0641) | 0.0085 (0.0789) | 0.0764 (0.0605) | 0.0769 (0.0470) | 0.0857 (0.0526) | 0.0783 (0.0491) |
| Year FE | | Yes | | | | |
| Region _i -Year FE | | | Yes | Yes | Yes | Yes |
| Region _j -Year FE | | | Yes | Yes | | |
| State _i -State _j FE | | | | Yes | Yes | Yes |
| State _j -Year FE | | | | | Yes | Yes |
| State _i -Linear Trend | | | | | | Yes |
| N | 57,700 | 57,700 | 57,700 | 57,700 | 57,700 | 57,700 |
| R ² | 0.0163 | 0.3094 | 0.5168 | 0.6113 | 0.6114 | 0.6583 |

This table reports the results from the estimation of baseline specification. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10, by sales, firms in state j . The unit of observation in each regression is a state _{i} -state _{j} -year pair. All non-binary variables used in the regression are standardized to mean zero and variance 1. Standard errors reported in parentheses are two-way clustered by state _{i} and state _{j} . * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Weighted Estimation (Weighted by Exports/Imports)

| Δgdp_{it} | (1) | (2) | (3) |
|---|------------------------|-----------------------|-----------------------|
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0164*** (0.0007) | -0.0583** (0.0244) | -0.0397** (0.0156) |
| $Post_{i,j,t}$ | 0.0783 (0.0491) | 0.0452 (0.0767) | 0.0816 (0.0603) |
| Region _{<i>i</i>} -Year FE | Yes | Yes | Yes |
| State _{<i>i</i>} -State _{<i>j</i>} FE | Yes | Yes | Yes |
| State _{<i>j</i>} -Year FE | Yes | Yes | Yes |
| State _{<i>i</i>} -Linear Trend | Yes | Yes | Yes |
| N | 57,700 | 50,838 | 51,312 |
| R^2 | 0.6583 | 0.6946 | 0.6646 |
| Weights | Equal | Export ('77) | Import ('77) |

This table reports the results from the estimation of baseline specification where each observation is weighted by the strength of real linkages. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10, by sales, firms in state j . The regression is weighted by exports and imports. Column (1) presents the baseline regression result of Table 3. Column (2) presents the baseline regression weighted by exports. Column (3) presents the baseline regression weighted by imports. We compute the share of exports going from state i to state j , and the share of imports coming from state j to state i using the 1977 Commodity Flow Survey Data. The share measures the magnitude and the direction of real linkages from i to each j . Each observation in column (2) and (3) is weighted by share of exports and imports respectively. The unit of observation in each regression is a state_{*i*}-state_{*j*}-year pair. All non-binary variables used in the regression are standardized to mean zero and variance 1. Standard errors reported in parentheses are two-way clustered by state_{*i*} and state_{*j*}. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Instrumental Variables Regression

First stage: $\log(l_{i,t}) = \alpha_2 + \beta_2 \Gamma_{j,t-1} \times Post_{i,j,t} + \beta_3 Post_{i,j,t} + \beta_4 \Gamma_{j,t-1} + \varepsilon_{it}$

Second stage: $\Delta gdp_{i,t} = \alpha_1 + \beta_1 \hat{\log}(l_{i,t}) + \mu_{it}$

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|-----------------------|----------------------|----------------------|----------------------|----------------------|-----------------------|------------------------|-----------------------|
| | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage | 1st Stage | 2nd Stage |
| $\log(C\&I - Loan_{i,t})$ | | 1.8751** (0.7221) | | 10.5056* (5.6140) | | 7.5966** (3.1841) | | 4.1409*** (1.3939) |
| $Post_{i,j,t} \times \Gamma_{j,t-1}$ | -0.0492** (0.0211) | | -0.0034* (0.0019) | | -0.0077* (0.0040) | | -0.0067** (0.0031) | |
| $Post_{i,j,t} \times \Gamma_{j,t-2}$ | | | | | | | -0.0082*** (0.0020) | |
| $\Gamma_{j,t-1}$ | 0.0200 (0.0129) | | 0.0000 (0.0003) | | | | | |
| $\Gamma_{j,t-2}$ | | | | | | | 0.9919 (15.3678) | |
| $\Gamma_{(i),t-1}$ | | | | | | | -0.0110 (0.0102) | 0.0469** (0.0217) |
| $\Gamma_{(i),t-2}$ | | | | | | | -0.0206** (0.0085) | 0.0783** (0.0309) |
| $Post_{i,j,t}$ | 0.4169*** (0.0877) | -0.5600 (0.3456) | -0.0424 (0.0532) | 0.4413** (0.1779) | -0.0300 (0.0553) | 0.2729*** (0.0624) | -0.0240 (0.0539) | 0.1595 (0.0958) |
| Region _i -Year FE | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Region _j -Year FE | | | Yes | Yes | | | | |
| State _i -State _j FE | | | Yes | Yes | Yes | Yes | Yes | Yes |
| State _j -Year FE | | | | | Yes | Yes | Yes | Yes |
| State _i -Linear Trend | | | | | Yes | Yes | Yes | Yes |
| N | 50,838 | 50,838 | 50,838 | 50,838 | 50,838 | 50,838 | 50180 | 50180 |
| R ² | 0.0245 | 0.0162 | 0.9364 | 0.6173 | 0.9701 | 0.6946 | 0.9701 | 0.7145 |
| Hansen stat χ^2 pval | | 0.5569 | | 0.7968 | | - | | 0.9206 |

This table presents the estimates of our IV strategy. The first stage regressions reported in Columns (1), (3), (5), and (7) establish a causal relation between bank lending in state i and idiosyncratic production shocks to the top 10 firms in state j after banking integration with varying fixed effects and lags. Columns (2), (4), (6), and (8) report the second stage regression of real GDP growth rate in percentage points on bank lending using the instrumented measures from the first stage. We find that a 1% increase in lending increases economic growth by 0.05 pp (2), 0.26 pp (4), 0.19 pp (6), 0.10 pp (8). The unit of observation in each regression is a state _{i} -state _{j} -year pair. All non-binary variables used in the regression are standardized to mean zero and variance 1. Standard errors reported in parentheses are two-way clustered by state _{i} and state _{j} . * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: State-level Estimates, Deregulation Timing and out-of-state Banking Expansion

| Dep Var: state-level Estimate | (1) | (2) | (3) |
|-------------------------------|----------------------|------------------------|------------------------|
| Median Deregulation Year | 0.1237** (0.0507) | | 0.0846* (0.0456) |
| Δ Asset | | 0.0197 (0.1316) | 0.0532 (0.1411) |
| Δ Asset ² | | -0.4271*** (0.1122) | -0.3639*** (0.1019) |
| N | 51 | 51 | 51 |
| R ² | 13.11% | 19.39% | 24.74% |

The table reports the regression of state-level estimates on median deregulation year, Δ Asset, and Δ Asset². The state-level estimates are constructed by running the baseline specification for each state i separately. The median year of deregulation is set equal to the year when the state has deregulated with at least 50% of other states. Data on share of gross domestic banking assets owned by out-of-state MBHCs comes from [Berger, Kashyap, and Scalise \(1995\)](#). Δ Asset measures the change in the share of gross domestic assets owned by out-of-state MBHCs is computed over the years 1979 and 1994. All non-binary variables used in the regression are standardized to mean zero and variance 1. Robust standard errors reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Asymmetric Effect by Properties of Shock

| Δgdp_{it} | (1) | (2) | (3) |
|---|------------------------|------------------------|------------------------|
| $Low - R^2 \times Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0111*** (0.0006) | | |
| $Low - R^2 \times Post_{i,j,t}$ | -0.0023* (0.0012) | | |
| $Low - AR(1) \times Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | | -0.0073** (0.0033) | |
| $Low - AR(1) \times Post_{i,j,t}$ | | -0.0057*** (0.0019) | |
| $(Neg = 1) \times Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | | | -0.0101 (0.0100) |
| $(Neg = 1) \times Post_{i,j,t}$ | | | -0.0387** (0.0151) |
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0074*** (0.0011) | -0.0121*** (0.0033) | -0.0205*** (0.0045) |
| $Post_{i,j,t}$ | 0.0815 (0.0501) | 0.0812* (0.0484) | 0.0992** (0.0483) |
| Region _i -Year FE | Yes | Yes | Yes |
| State _i -State _j FE | Yes | Yes | Yes |
| State _j -Year FE | Yes | Yes | Yes |
| State _i -Linear Trend | Yes | Yes | Yes |
| N | 54250 | 57700 | 57700 |
| R^2 | 0.6584 | 0.6583 | 0.6583 |

This table presents baseline specification where we dissect the effect by the properties of idiosyncratic shocks in state j . The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10, by sales, firms in state j . The unit of observation in each regression is a state _{i} -state _{j} -year pair. $Low - AR(1)$ takes a value of 1 if the shocks for a state _{j} have an AR(1) estimate between the first and third quartile values. $LowR^2$ takes a value of 1 if the squared correlation of shock in state _{i} with state _{j} with $i \neq j$ is below the median value of R^2 . R^2 between state _{i} and state _{j} are calculated by squaring the correlation coefficient of Γ between each pair and averaging the values over all state _{i} . $Neg = 1$ takes a value of 1 if the shock in state _{j} is a negative shock. All non-binary variables used in the regression are standardized to mean zero and variance 1. Standard errors reported in parentheses are two-way clustered by state _{i} and state _{j} . * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Reallocation of Funds to Bank-Dependent Firms

| | (1) | (2) | (3) | (4) |
|---|---------------------------------------|--|---------------------------|--|
| | $\Delta \text{Ln}(\text{Debt})_{f,t}$ | $\Delta \text{Ln}(\text{Sales})_{f,t}$ | $\frac{M_{f,t}}{B_{f,t}}$ | $\Delta \text{Ln}(\text{Inventory})_{f,t}$ |
| $Young_f \times Post_{i,t} \times \Gamma_{j,t-1}^{avg}$ | -0.7539** (0.3690) | -0.4722* (0.2515) | -0.4601*** (0.1206) | -0.8924** (0.4345) |
| $Post_{i,t} \times \Gamma_{j,t-1}^{avg}$ | 0.5137*** (0.1841) | 0.0857 (0.1753) | -0.0265 (0.1038) | 0.4141* (0.2160) |
| $Young_f \times \Gamma_{j,t-1}^{avg}$ | 0.9111*** (0.2076) | 0.1695 (0.1651) | 0.0531 (0.0683) | 0.7623** (0.3241) |
| $Young_f \times Post_{i,t}$ | 0.0126 (0.1220) | 0.2986*** (0.0974) | 0.4332** (0.1725) | -0.0564 (0.1281) |
| $Post_{i,t}$ | 0.1461* (0.0824) | -0.0572 (0.0702) | 0.0170 (0.0657) | 0.1403* (0.0718) |
| $\Gamma_{j,t-1}^{avg}$ | -0.4733 (0.4289) | 0.0341 (0.2809) | 0.3585 (0.3468) | -0.0446 (0.3504) |
| Firm FE | Yes | Yes | Yes | Yes |
| Industry-Year FE | Yes | Yes | Yes | Yes |
| # Obs | 19,337 | 19,324 | 20,305 | 11,855 |
| R^2 | 0.3102 | 0.4641 | 0.5786 | 0.3297 |
| Mean | 0.0105 | 0.1389 | 3.1658 | 0.0241 |
| Standard Deviation | 0.7757 | 0.3897 | 5.8831 | 0.2718 |

This table presents the results from a firm-level regression of characteristics of firm f , headquartered in state i at time t on the triple interaction term $Young_f \times Post_{i,t} \times \Gamma_{j,t-1}^{avg}$. The triple interaction term measures the response of young firms relative to old firms following a shock in another state after banking integration of the two states. $Young_f$ is a firm level variable that takes a value of 1 if the firm age is less than the median age of all firms and 0 otherwise. $Post_{i,t}$ is a continuous variable between 0 and 1 which denotes the fraction of other states which are integrated with state i , via banking networks, at time t . $\Gamma_{j,t-1}^{avg}$ denotes the average value of idiosyncratic shocks in all other states $j \neq i$. Column (1), (2), (3) and (4) use change in the natural logarithm of total debt, change in the natural logarithm of total sales, market value to book value ratio, and change in the natural logarithm of the work-in-progress inventory, respectively, as the dependent variables. Total debt is defined as the sum of debt in current liabilities and long-term debt. Total sales is defined as the net annual turnover. Market-to-book ratio is defined as the ratio of the sum of the market value of equity and assets to the book value of assets. Work-in-progress inventory is defined as total inventories – work in process. All regressions include firm and industry-year fixed effects. Industry refers to the 4 digit SIC codes. The table includes data on all non-financial and non-utilities firms in Compustat from 1975 through 2000. The last two rows of the table indicate the mean and the standard deviation of the dependent variables. All variables are winsorized at 1% level on both tails, and standardized to a mean of 0 and standard deviation of 1. Standard errors reported in parentheses are clustered by state of the firm headquarters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

For Online Publication:

“Banking Networks and Economic Growth: From Idiosyncratic Shocks to Aggregate Fluctuations”

Appendix A Framework

A.1 Aggregate Effects

In this section we present a simple framework wherein foreign shocks and banking integration increase aggregate volatility by increasing the variance of economic growth of each state, and decreases aggregate volatility by potentially decreasing the covariance in economic growth. We quantify the net effect of these two forces in section 8. Aggregate volatility is the sum of volatility in economic growth of each state and their respective covariance. Hence, we derive the expressions for the variance and the covariance. We begin by re-writing the principal equation derived in section 2.

$$\frac{\Delta y_{it}}{y_{i,t-1}} = \mu \left\{ a_t + v_{it} + \sum_{k \in K} \eta_t^k \frac{l_{i,t-1}^k}{l_{i,t-1}} - \sum_{j \neq i} v_{jt} \sum_{k \in K} \left(\frac{l_{i,t-1}^k}{l_{i,t-1}} \times \frac{l_{j,t-1}^k}{l_{t-1}^k} \right) \right\} + \varepsilon_{it} \quad (\text{A.1})$$

A.1.1 Variance Equation

The variance of economic growth in state i using equation A.1 is given by equation A.2 where, $H_{it} \equiv \sum_{k \in K} \left\{ \frac{l_{i,t-1}^k}{l_{i,t-1}} \right\}^2$, and $H_{kt}^{-i} \equiv \sum_{j \neq i} \left(\frac{l_{j,t-1}^k}{l_{t-1}^k} \right)^2$. Equation A.2 connects domestic economic volatility with banking integration and foreign shocks, wherein the volatility of economic activity in state i increases as banking integration increases.

$$\text{Var} \left[\frac{\Delta y_{it}}{y_{i,t-1}} \right] = \mu^2 \sigma_a^2 + \mu^2 \sigma_\eta^2 \times H_{it} + \mu^2 \sigma_v^2 \left(1 + \sum_{k \in K} \left(\frac{l_{i,t-1}^k}{l_{i,t-1}} \right)^2 \times H_{kt}^{-i} \right) + \sigma_\varepsilon^2 \quad (\text{A.2})$$

A.1.2 Covariance Equation

Next, we employ equation A.1 to derive the covariance equation. For simplicity in notation we present the covariance of economic growth for state 1 and 2 in equation A.3.

$$\begin{aligned} \text{Cov} \left[\frac{\Delta y_{1t}}{y_{1,t-1}}, \frac{\Delta y_{2t}}{y_{2,t-1}} \right] &= \mu^2 \left\{ \sigma_a^2 + \sigma_\eta^2 \left(\sum_{k \in K} \frac{l_{1,t-1}^k}{l_{1,t-1}} \times \frac{l_{2,t-1}^k}{l_{2,t-1}} \right) - \sigma_v^2 \left(\frac{l_{1,t-1} + l_{2,t-1}}{l_{2,t-1}} \right) \left(\sum_{k \in K} \frac{l_{1,t-1}^k}{l_{1,t-1}} \times \frac{l_{2,t-1}^k}{l_{t-1}^k} \right) \right. \\ &\quad \left. + \sigma_v^2 \sum_{j \neq 1,2} \left(\sum_{k \in K} \frac{l_{1,t-1}^k \times l_{j,t-1}^k}{l_{1,t-1} \times l_{t-1}^k} \times \sum_{k \in K} \frac{l_{2,t-1}^k \times l_{j,t-1}^k}{l_{2,t-1} \times l_{t-1}^k} \right) \right\} \quad (\text{A.3}) \end{aligned}$$

The net effect of financial integration on covariance seems ambiguous. However, the negative term associated with financial integration and non-capital shocks is of order 3 whereas the positive term associated with financial integration and non-capital shocks is of order 4. It remains a quantitative question whether the net effect of financial integration and non-capital shocks on covariance is

positive or negative. The overall effect of financial integration will depend on the strength of the covariance term relative to the variance term if the covariance term is net negative. We address these quantitative issues in section 8.

Appendix B Did Banks Expand Across State lines?

The mechanism outlined in this paper relies on the assumption that banks did indeed expand across state lines post banking integration. While state-pairwise banking deregulation simulates the geographic expansion across state lines by diminishing regulatory frictions, the actual expansion is an equilibrium outcome which may not have been affected by the removal of regulatory barriers. In this section, we investigate if banks did expand across state lines.

B.1 Data

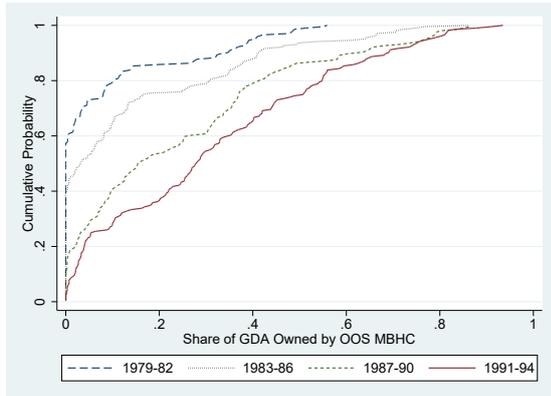
We employ state-level annual data on the share of gross domestic banking assets held by out-of-state Multi Bank Holding Companies (MBHCs). This data comes from [Berger, Kashyap, and Scalise \(1995\)](#). We use the share of gross domestic assets held by out-of-state MBHCs as a proxy for geographic expansion by out-of-state banks. A shortcoming of this measure is that it covers only a subset of all out-of-state banks, namely, out-of-state MBHCs. This suggests that our measure of geographic expansion by out-of-state banks is biased downwards. However, in light of the findings of [Berger, Kashyap, and Scalise \(1995\)](#), which notes that despite the exponential growth of assets in the banking industry between 1979 and 1994, the majority of independent banking organizations (top-tier bank holding companies and unaffiliated banks) disappeared during this time, we surmise that the error caused from mismeasurement is likely small. We use this dataset because unlike the Call Reports dataset employed in [Morgan, Rime, and Strahan \(2004\)](#) and [Landier, Sraer, and Thesmar \(2017\)](#) this dataset does not rely on the assumption that the lending by a bank is exclusively in the state where the bank is headquartered.

B.2 Results

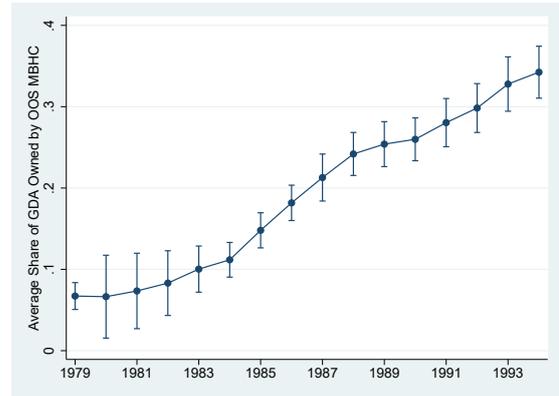
Figure [B.1a](#) reports the cumulative density function (CDF) of the share of gross domestic assets owned by out-of-state MBHCs in each state for four periods between 1979 and 1994. The period of 1979-82 refers to the four years from 1979 to 1982. This is the period before deregulation, during which, ~60% of states did not have any assets held by out-of-state MBHCs. The two periods between 1983 and 1990 (1983-86 and 1987-90), refer to the phase of active deregulation. By the end of 1990, 50% of all states had deregulated with at least 50% of all other states. The period between 1991 and 1994 is the last phase of deregulation before the passage of IBBEA in 1994. From 1979 to 1994, we see that the CDF of the share of gross domestic assets held by out-of-state MBHCs first order stochastically dominates the CDF from the previous period. This is prima facie evidence supporting the hypothesis that geographic expansion of banks occurred contemporaneously with banking deregulation. To further explore the increase in out-of-state banking presence within a given state, we run a regression of the share of gross domestic assets owned by out-of-state MBHCs on time dummies while controlling for state fixed effects. Figure [B.1b](#) plots the yearly margins

and 95% confidence interval from this regression. The share of gross domestic assets owned by out-of-state MBHCs grew from ~7% in 1979 to ~35% in 1994. Growth is relatively flat from 1979 through 1982, and picks up steadily after 1982 with a small period of low growth in the year 1990.

Figure B.1: Geographic Expansion by out-of-state Banks Over Time



(a) CDF plots for share of GDA Owned by OOS MBHCs



(b) Within state temporal variation in share of GDA Owned by OOS MBHCs

The figure plots the temporal variation in the share of gross domestic assets (GDA) owned by out-of-state (OOS) MBHCs. Panel B.1a plots the cumulative distribution function (CDF) for the share of GDA owned by OOS MBHCs. Each line presents the CDF for a four year period between 1979 and 1994. Panel B.1b reports the average share of GDA owned by OOS MBHCs within a state. The estimates are generated by regression the share of GDA owned by OOS MBHCs on year dummies and controlling for state fixed effects. The 95% CI are generated by two-way clustering standard errors at state and year level.

We formally investigate the effect the deregulation timing on the share of gross domestic assets owned by out-of-state MBHCs in Table B.1. For each state, we identify the median deregulation year. Median deregulation year is defined as the year by which that state has deregulated cross-state banking activity with 50% of all other states. The variable $Post_{i,j,t} (=1)$ takes a value of 1 for all yearly observation for a state after the median deregulation year. The point estimate for $Post_{i,j,t} (=1)$ is positive and statistically significant. The $Post_{i,j,t} (=1)$ variable can explain $\approx 11\%$ of variation in the heterogeneity in the share of gross domestic assets owned by out-of-state MBHCs during the sample period. Column (3)-(5) report within state estimator for the $Post_{i,j,t} (=1)$ variable while controlling for aggregate annual shocks. Economically, the estimate implies that the share of gross domestic assets owned by out-of-state MBHCs grew by at least 7 pp post median deregulation year.

Table B.1: Geographic Expansion by out-of-state Banks and Deregulation Timing

| | (1) | (2) | (3) | (4) | (5) |
|--------------------|-----------------------|-----------------------|----------------------|----------------------|----------------------|
| Post (=1) | 0.1758*** (0.0443) | 0.1966*** (0.0324) | 0.0753** (0.0291) | 0.0708** (0.0304) | 0.0706** (0.0313) |
| State FE | | Yes | Yes | Yes | |
| Year FE | | | Yes | | |
| Region-Year FE | | | | Yes | Yes |
| State Linear Trend | | | | | Yes |
| # Obs | 816 | 816 | 816 | 816 | 816 |
| R^2 | 0.1049 | 0.7135 | 0.7861 | 0.8257 | 0.8263 |

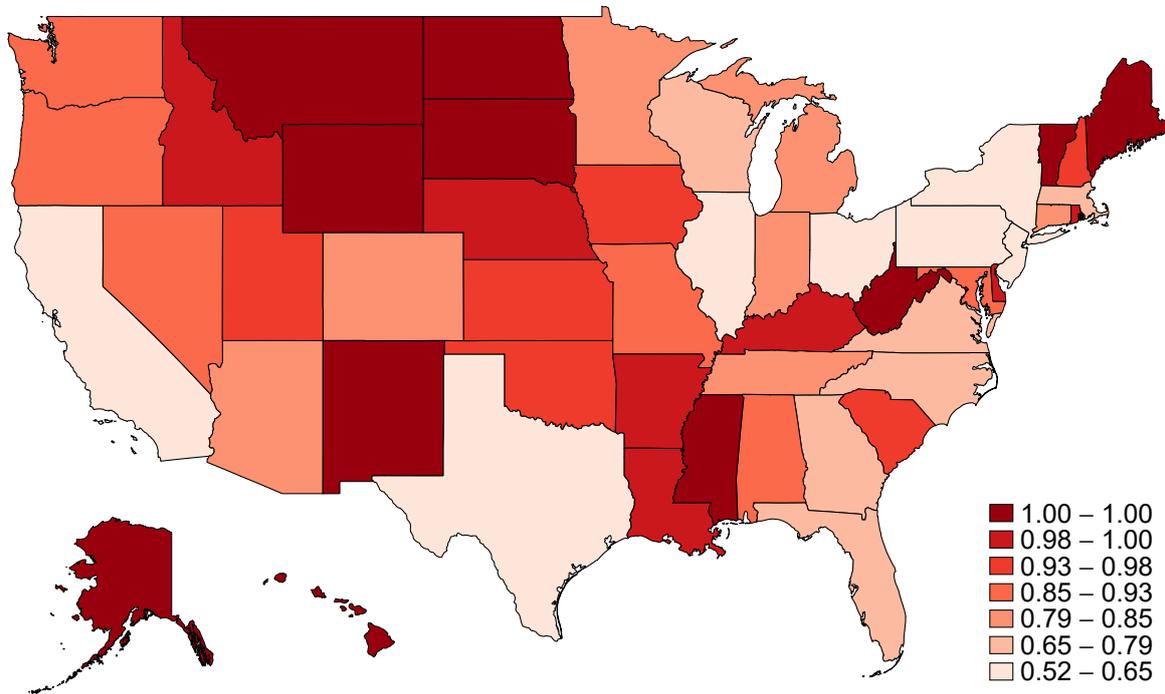
The table reports the regression of the share of gross domestic assets (GDA) owned by out-of-state (OOS) MBHCs on the Post (=1) variable. The variable Post (=1) takes a value of 1 after the median deregulation year. Median deregulation year is defined as the year by when that state deregulated with at least 50% of other states. The data on the share of GDA owned by OOS MBHCs comes from [Berger, Kashyap, and Scalise \(1995\)](#). Standard errors reported in parentheses are two-way clustered by state and year. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C Properties of Idiosyncratic Shocks

C.1 Presence of Fat Tails

We begin our analysis by verifying that each state is dominated by large firms. We examine the ratio of sales by top 10 firms by sales to the sales of all firms for each state and find strong evidence of dominance of state-level economies by large firms. Figure C.1 shows the average proportion of sales of top 10 firms by sales relative to the total sales by all firms head-quartered in that state. The minimum value of the ratio is 0.52 indicating that top 10 firms by sales account for at least 50% of sales by all firms in that state. This is prima-facie evidence of the existence of fat tails. There is some heterogeneity in the sales share of top 10 firms by state but on average top 10 firms account for 85% of total sales. Note that in some states, such as North Dakota, South Dakota, West Virginia etc., top 10 firms account for all the sales. This is primarily because the total number of firms head-quartered in that state are less or equal to 10. We supplement this analysis with a more formal description of the distribution of sales of all firms in each state. The distributions reported in figure C.2 provide strong evidence of the sales being fat tailed in each state.

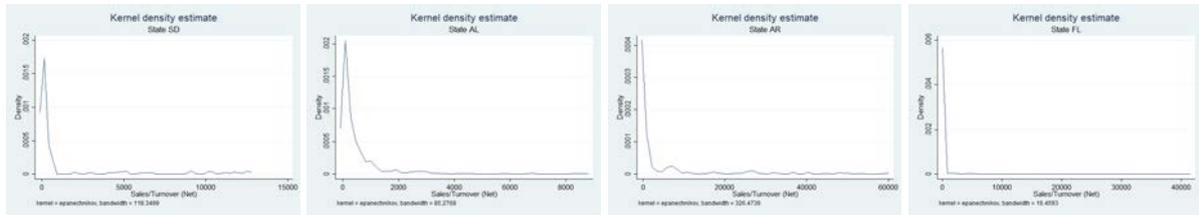
Figure C.1: Cross-sectional distribution of Sales Share of Top 10 Firms



The figure plots the cross-sectional distribution of sales of top 10 firms in the state to the sales of all firms in that state between 1978 to 1995. We report the time-series average of the sales ratio of top 10 firms for each state. The legend denotes the ratio of sales of top 10 firms in the state to the sales of all firms in that state.

Figure C.2: Sales distribution for firms headquartered in each state



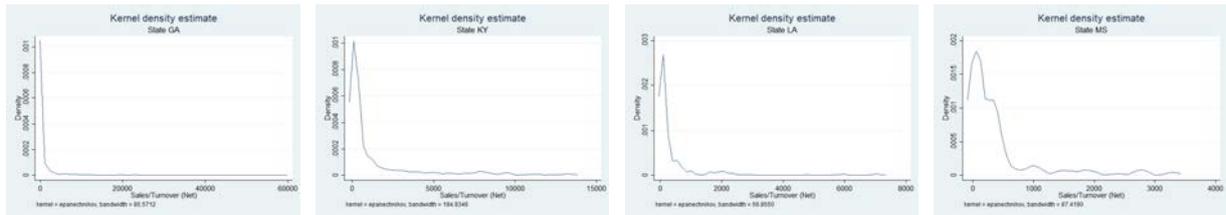


(a) South Dakota

(b) Alabama

(c) Arkansas

(d) Florida

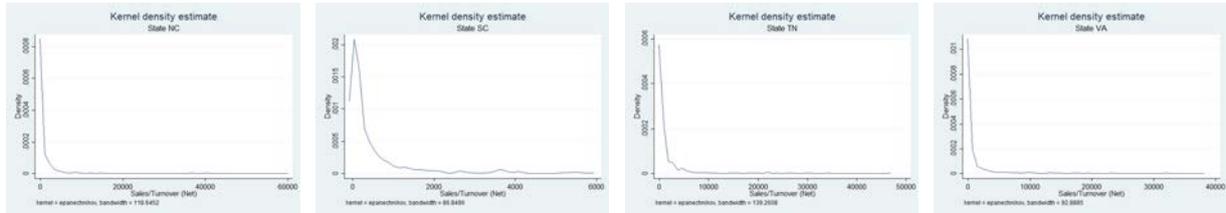


(e) Georgia

(f) Kentucky

(g) Louisiana

(h) Minnesota

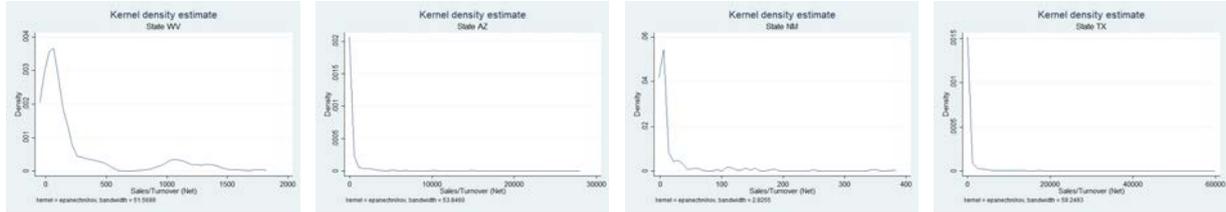


(i) North Carolina

(j) South Carolina

(k) Tennessee

(l) Virginia

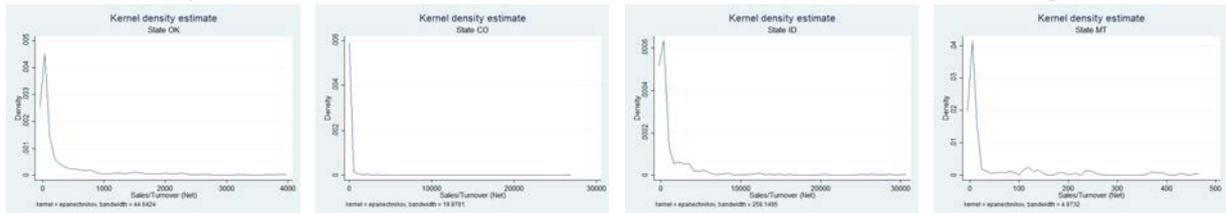


(m) West Virginia

(n) Arizona

(o) New Mexico

(p) Texas

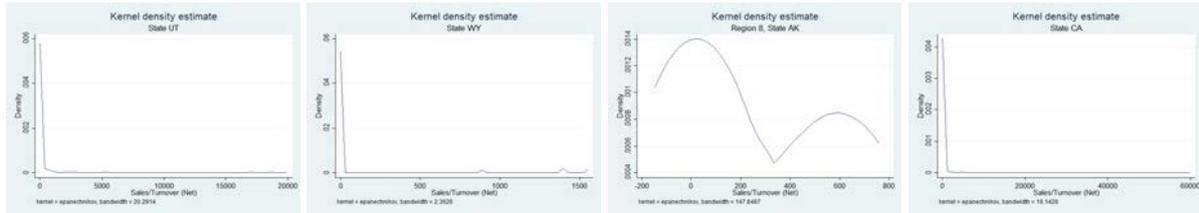


(q) Oklahoma

(r) Colorado

(s) Idaho

(t) Montana

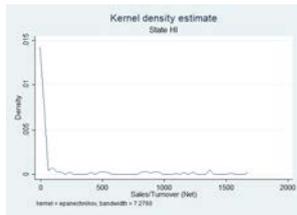


(u) Utah

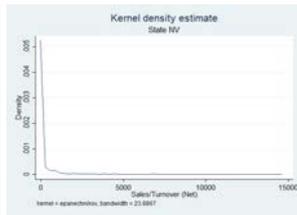
(v) Wyoming

(w) Alaska

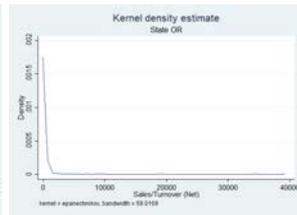
(x) California



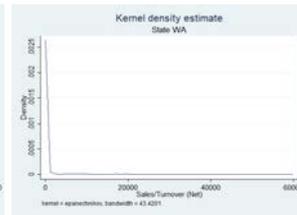
(a) Hawaii



(b) Nevada



(c) Oregon



(d) Washington

C.2 Idiosyncratic shocks can predict future economic growth

This section reports the graphical relation between idiosyncratic shocks and subsequent annual economic growth for certain states.

Figure C.5: Relation between Γ_t and Δgdp_{t+1} for selected states

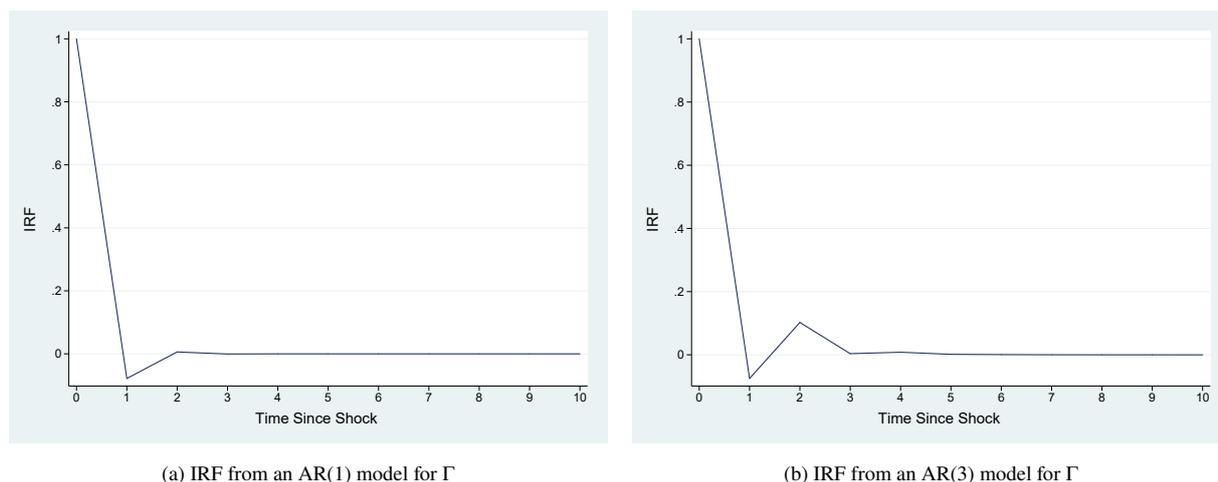


The figure plots the relation between idiosyncratic shocks Γ_t and subsequent annual economic growth Δgdp_{t+1} for some selected states. All variables are standardized to mean 0 and variance 1. The sample period spans from 1977 to 2000.

C.3 Persistence of Idiosyncratic shocks

This section reports the impulse response functions for idiosyncratic shocks obtained from a pooled AR(1) and an AR(2) model.

Figure C.6: Impulse Response Functions (IRF) for Γ from AR(p) models



The figure plots the impulse response functions from an AR(1) and an AR(3) model for Γ_t^{ind} . We estimate a panel VAR AR(p) model to estimate the impulse response functions.

C.4 Bank Debt and Sample Firms

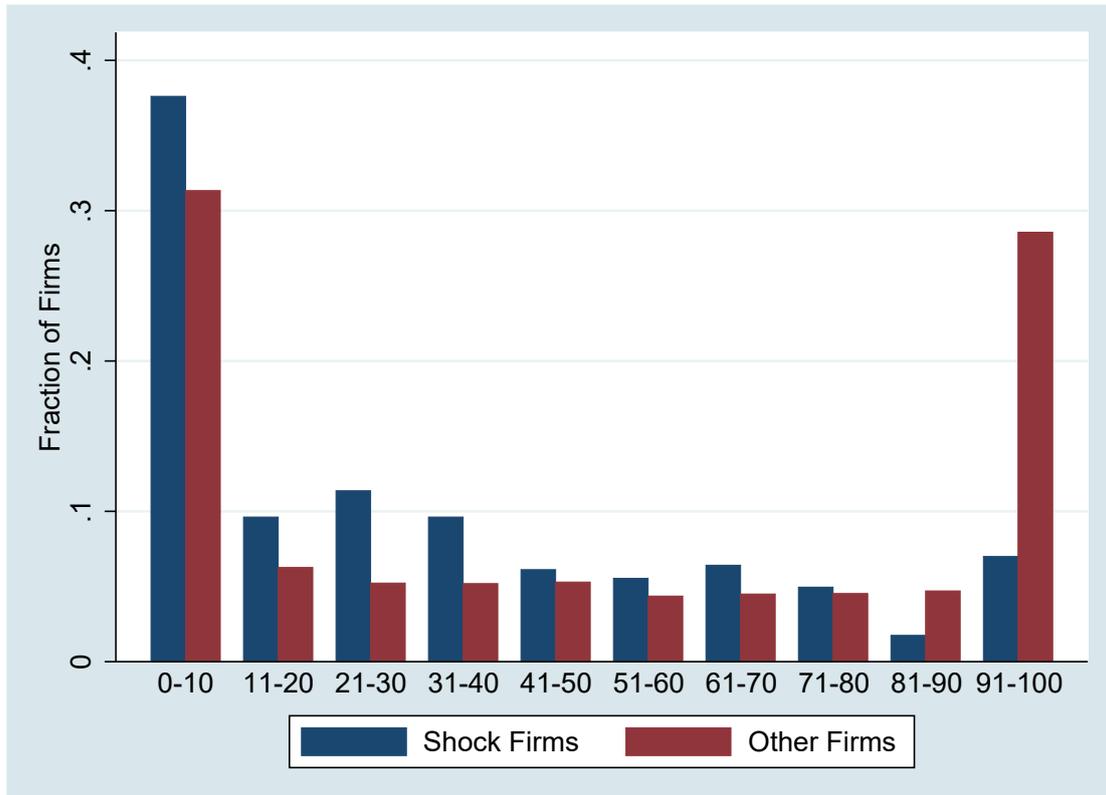
This section compares the ratio of bank debt to total debt for firms used to construct state level idiosyncratic shocks (shock firms) to all other firms in the S&P Capital IQ database. The data on bank debt and total debt comes from Capital IQ database. Due to data limitations we can only compare the bank debt to total debt ratio from 1989 onwards. Total debt is constructed by adding secured and unsecured debt for each firm. Table C.1 compares the mean and the median bank debt to total debt ratio for the shock firms and other firms. The median (mean) bank debt to total debt ratio for shock firms is 23.63% (30.35%), compared to a value of 44.63% (48.03%) for other firms. The mean and the median of bank debt to total debt ratio is lower for shocks firms by ≈ 20 pp relative to other firms. The t-statistic for the difference in the mean (median) bank debt to total debt for the two groups is 8.17 (4.17). This indicates that the shock firms are substantially less reliant on bank debt as source of external financing. We further validate this by examining the distribution of bank debt to total debt ratio across the two group of firms in figure C.7.

Table C.1: Bank Debt to Total Debt - Shock Firms and Other Firms

| | Mean | Median | St Dev |
|----------------------------|-----------|-----------|--------|
| Shock Firms | 30.35 | 23.63 | 29.94 |
| Other Firms | 48.03 | 44.63 | 40.09 |
| Difference | -17.68*** | -20.99*** | |
| t-Statistic for Difference | 8.17 | 4.17 | |

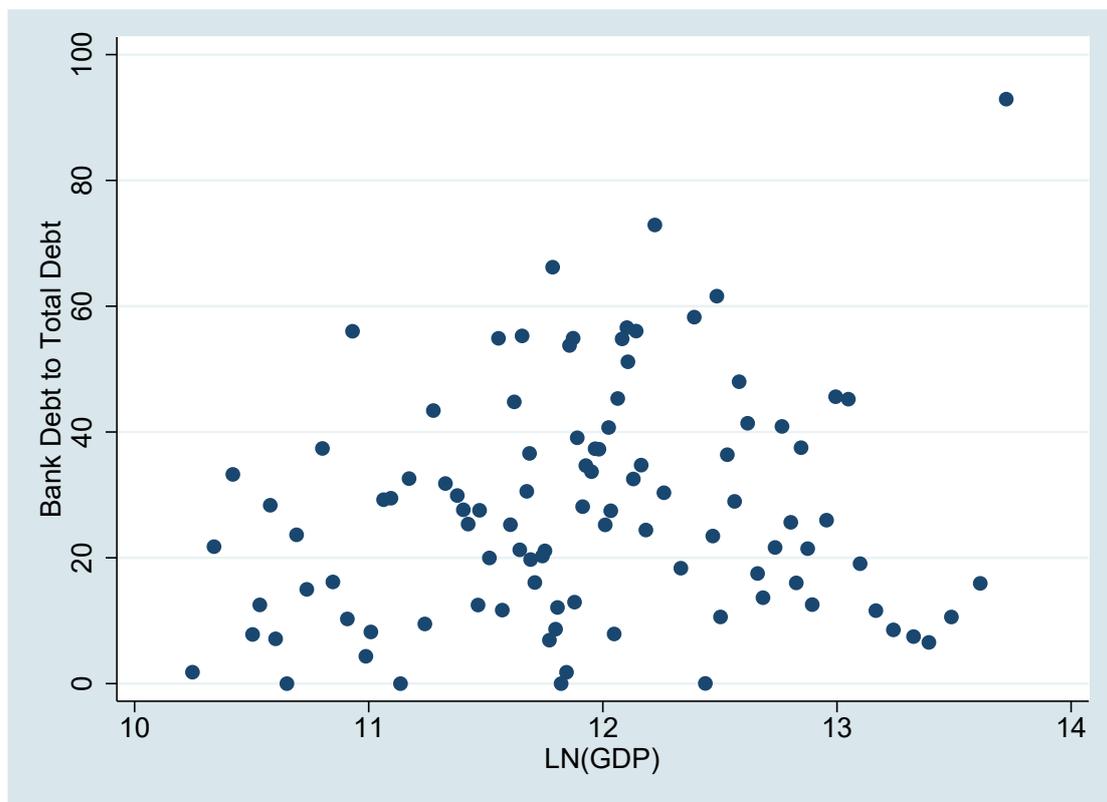
This table reports mean, median and the standard deviation for the bank debt to total debt ratio in percentage. Shock firms refer to the top 10 firms in each state used to construct state-level idiosyncratic shocks. All other firms not used to construct state-level idiosyncratic shocks are classified as other firms. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.7: Bank Debt to Total Debt - Shock Firms and Other Firms



The figure plots fraction for firms in each bin of bank debt to total debt ratio across the shock firms and other firms. The x-axis plots the bin for the total bank debt to total debt ratio. There are 10 bins, representing deciles of the ratio of bank debt to total debt. *Shock firms* refer to the top 10 firms in each state used to construct state-level idiosyncratic shocks. All other firms not used to construct state-level idiosyncratic shocks are classified as *other firms*.

Figure C.8: Bank Debt to Total Debt and Size of the State



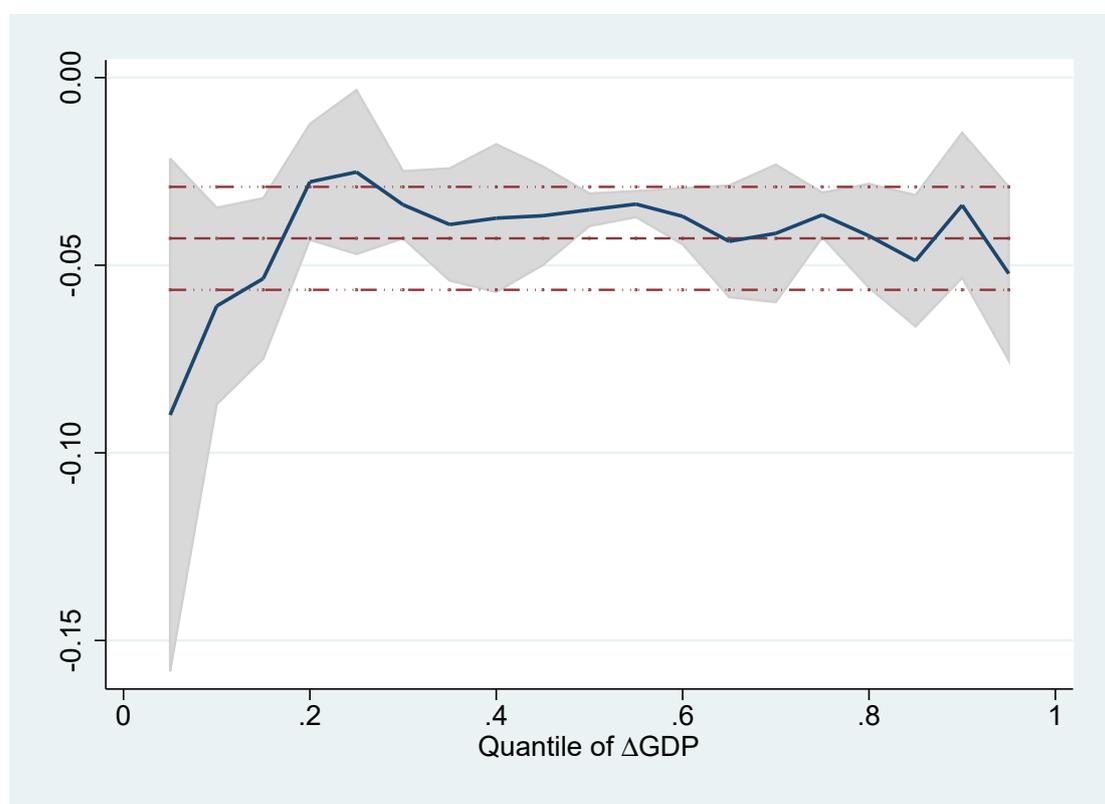
The figure presents the scatter plot of bank debt to total ratio (y-axis) and the size of the economy (x-axis) for the shock firms. *Shock firms* refer to the top 10 firms in each state used to construct state-level idiosyncratic shocks. The size of the economy is measured using the natural logarithm of the nominal GDP of the state. The bank debt to total ratio on the X-axis is the average value of the bank debt to total ratio for the shock firms in the state.

Appendix D Additional Results & Discussion

This section reports additional results and discussion that either support or add credibility to the main results in the paper. We refer the readers to these results in the paper wherein required. The additional results do not substantially add to the results reported in the paper but as outlined, add credibility to the results.

D.1 Baseline Results

Figure D.1: Point Estimate Difference between Pre & Post Period in Figure 2b: OLS & Quantile Regression Estimates



The figure plots the point estimate for the difference in the relation between GDP growth in state i and idiosyncratic shocks in state j where $i \neq j$ in the pre and post deregulation period. *Pre* refers to a sample of all state-pairs before banking integration. *Post* refers to a sample of all state-pairs after banking integration as in figure 2b. The dashed red line reports the OLS estimate with 95% confidence interval and the blue line reports the estimate obtained from the quantile regression for different quantile of ΔGDP along with the 95% confidence interval in grey.

D.2 Violation of the Exclusion Restriction

Here, we discuss violations of the exclusion restriction in identifying the relation between bank lending and economic growth, and consider two counterfactual cases to assess how our point estimates may change. Our analysis suggests that the violation of the even weak identifying assumption biases our empirical strategy to estimate a magnitude of zero.

The Pre estimate reported in 2b indicates that, in aggregate, the relation between GDP growth in state i and idiosyncratic shocks in state j is weakly positive. Hence, the counterfactual cases capture incidents in which states behave as complements in the absence of banking linkages. The strong and weak forms of the exclusion restriction are as follows. The strong form of the exclusion restriction is that idiosyncratic productivity shocks in state j impact bank lending in state i strictly through loan supply, not loan demand. Even if the strong form does not hold, we can still identify the relation between bank lending and economic growth, as long as the covariance in loan demand between the two states is fixed around the deregulation shock, or that the covariance in loan demand between the two states is sticky relative to loan supply around the deregulation shock.

Counterfactual #1:

Consider the case where states are linked by cross-state sales. If a firm in Virginia sells largely to consumers in Maryland and the state of Maryland experiences a large negative shock in a given year, consumption will fall in Maryland in that year. This means that the demand for the Virginian firm's goods will fall, which in turn, decreases total sales for that year. The decline in quantity suggests that the magnitude of our point estimates in Table 5 are downward biased.

Counterfactual #2:

Consider the case where states are linked by input-output linkages. For illustration, suppose there is corporate law firm based in Connecticut and a corrupt firm in New York. The corrupt firm in New York requires attorneys from the law firm in Connecticut to continue operating. If the law firm in Connecticut experiences a large negative shock, the corrupt firm in New York will suffer. In this case, the demand for the corrupt firm's goods will fall. Similar to the case above, the reduction in demand suggests that the magnitude of our point estimates in Table 5 are downward biased.

In light of these considerations, how reasonable is the exclusion restriction? We have shown that even if the strong identifying assumption is violated, the magnitude of our estimates is downward biased, not upward biased.

D.3 Heterogeneous Treatment Effects

Furthermore, to ensure that the estimates are not driven by extreme values, Figure D.2a plots the state-level median estimate obtained from state-pairwise regression. We run the baseline regression at state-pair level and estimate the coefficient of the interaction term. The mean (median) value of the median estimate is -0.025 (-0.033) with ~69% of state-level estimates being strictly negative.

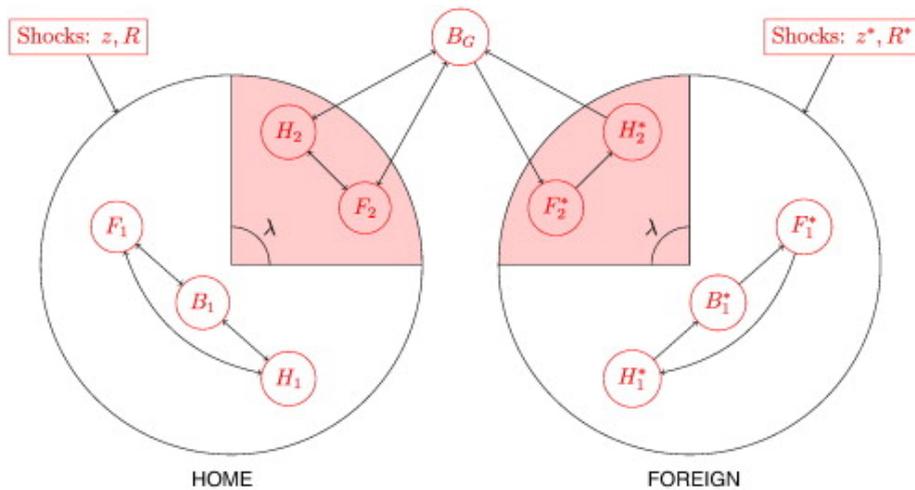
Appendix E Theoretical Model

In this section, we outline the model of [Kalemli-Ozcan, Papaioannou, and Perri \(2013\)](#), and replicate their key theoretical finding.

E.1 Setup

This is a model of international business cycles with banks. There are two countries, e.g., *home* and *foreign* (distinguished by superscript *), each with two segments with size λ and $1 - \lambda$ respectively. The λ segments (segment 2) of each country are financially integrated, while the $1 - \lambda$ segments are financially separate (segment 1), i.e., a $1 - \lambda$ share of the domestic and foreign economies operate in autarky so that banks intermediate only between households and firms in that $1 - \lambda$ segment, respectively. In each segment of each country, there are households which supply labor to firms and save with banks. Firms pay dividends and wages to the households, and make investment decisions. In addition, firms borrow from banks. Banks in segments 2 of each country are *global banks* as λ share of each economy is financially integrated. For illustration of the schema of the economy in the model, we reproduce below the figure 1 from [Kalemli-Ozcan, Papaioannou, and Perri \(2013\)](#). The model focuses on two types of shocks that drive economic fluctuations: a standard productivity

Figure E.1: The structure of the economy



Source: This figure is taken from [Kalemli-Ozcan, Papaioannou, and Perri \(2013\)](#)

shock, and banking shocks that affect the value of risky assets held by banks. In particular, we use the model to study how exogenous changes to financial integration affect output correlation, cross-border transmission of shocks, and synchronization of the business cycle.

E.1.1 Households

In each segment i of each country, there is a continuum of identical, infinitely-lived household with preferences:

$$E_0 \sum_{t=0}^{\infty} \beta^t U(c_{it}, l_{it})$$

where c_{it} denotes consumption and l_{it} denotes labor, $\beta \in (0, 1)$ is the discount factor, E_0 denotes expectation at date 0 across time and possible states of the world. Utility is subject to the following budget constraint:

$$c_{it} + \frac{D_{it+1}}{R_{it}} = w_{it}l_{it} + d_{it} + D_{it}$$

where D_{it} denotes the amount of bank deposits that are carried over, w_{it} is the wage rate, d_{it} are firms' dividends, and R_{it} is the gross rate of return of bank deposits. The consumers' problem is to choose c_{it} , l_{it} and D_{it} . Consumers in segment 2 can shop for banks in both countries, so by arbitrage deposit rate is the same in segment 2 of both the countries:

$$R_{2t} = R_{2t}^* \forall t$$

E.1.2 Firms

Firms operate a technology F that uses capital, k_{it} and labor l_{it} to produce a good. Production is subject to stochastic, country specific, productivity shocks z_t and z_t^* . It is assumed that firms need to pay workers before they realize sales, hence, firms must borrow from the bank working capital that is equal to the wage bill. Firms in segment i pay gross lending rate R_{it}^e on bank loans

$$\begin{aligned} d_{it} &= e^{z_t} F(k_{it}, l_{it}) - R_{it}^e w_{it} l_{it} - x_{it} \\ k_{it+1} &= (1 - \delta)k_{it} + x_{it} - \phi k_{it} \left[\frac{x_{it}}{k_{it}} - \delta \right]^2 \\ \begin{bmatrix} z_t \\ z_t^* \end{bmatrix} &= A_z \begin{bmatrix} z_{t-1} \\ z_{t-1}^* \end{bmatrix} + \begin{bmatrix} \epsilon_t^z \\ \epsilon_t^{z*} \end{bmatrix} \end{aligned}$$

where R_{it}^e is a gross lending rate on bank loans, x_{it} is the investment in physical capital, δ is the depreciation rate, ϕ represents capital adjustment costs. In terms of the shock process, A_z is a 2×2 matrix and $[\epsilon_t^z, \epsilon_t^{z*}]$ is a vector of iid innovations with mean 0, standard deviation σ_ϵ^z and correlation

ρ_ϵ^z . The firms' problem in each country and segment i

$$\max_{l_{it}, k_{it}, x_{it}} E \sum_{t=0}^{\infty} d_{it} Q_{it}$$

where $Q_{it} = \beta_t U_c(c_{it}, l_{it})$ – the MRS of domestic consumers (owners of firm) which is the stochastic discount factor. Moreover, in the financially integrated segment, firms can shop for banks, therefore:

$$R_{2t}^e = R_{2t}^{e*}$$

E.2 Banks

Banks operating in segmented areas raise deposits $\frac{D_{1t+1}}{R_{1t}}$ and $\frac{D_{1t+1}^*}{R_{1t}^*}$ respectively from consumers in home and foreign areas. Global banks' deposits are given by $\frac{D_{2t+1} + D_{2t+1}^*}{R_{2t}}$. Further, it is assumed that deposit-raising is costly, therefore banks need to pay ι of deposits that represents a gamut of forces (intermediation cost/term spread/net interest margin).

In this economy, banks have the option of extending loans to firms, which are considered to be *risk-free* loans, or investing in *risky* technology. Banks in segment 1 only lend to firms in that segment/country and only invest in risky tech of that country. Banks in segment 2 can lend to firms in both countries and invest in a diversified international fund with equal shares of risky tech of both countries

In addition, banks experience stochastic gross returns on risky tech in the two countries (equal mean in each country), R_t^m and R_t^{m*} .

- Credit shocks follow a bivariate auto-regressive process

$$\begin{bmatrix} R_t^m \\ R_t^{m*} \end{bmatrix} = \begin{bmatrix} \bar{R}^m \\ \bar{R}^{m*} \end{bmatrix} + A_R \begin{bmatrix} R_{t-1}^m \\ R_{t-1}^{m*} \end{bmatrix} + \begin{bmatrix} \epsilon_t^R \\ \epsilon_t^{R*} \end{bmatrix}$$

where A_R is a 2×2 matrix and $[\epsilon_t^R, \epsilon_t^{R*}]$ is a vector of iid innovations with mean 0, standard deviation σ_ϵ^R and correlation ρ_ϵ^R .

First, banks decide how much to invest in the risky asset without knowing the realization of returns R_t^m and R_t^{m*} . It is assumed in the model that the expected return on risky asset is high enough, so each bank invests maximum share of deposits allowed by regulation, i.e., $0 < \bar{m} < 1$. After returns R_t^m and R_t^{m*} are observed but not cashed, banks offer competing loans to firms. Because firms borrow enough working capital to finance their wage bill, the equilibrium

amount of loans in the economy is given by:

$$\begin{aligned} L_{1t} &= w_{1t}l_{1t}; & L_{1t}^* &= w_{1t}^*l_{1t}^* \\ L_{2t} &= w_{2t}l_{2t}; & L_{2t}^* &= w_{2t}^*l_{2t}^* \end{aligned}$$

At the end of period, banks receive proceeds from lending and risky investments, and pay back deposit and interest to consumers, as well as margin costs, ι .

E.2.1 Solving the model

The equilibrium conditions from solving the model are as follows:

Equilibrium: Consumers and firms

Consumers and firms solve problems given prices and shocks. Banks invest a share \bar{m} in risky portfolio and make zero profits in each segment $\forall t$:

$$\begin{aligned} \bar{m}R_{1t}^m + (1 - \bar{m})R_{1t}^e &= R_{1t} + \iota \\ \bar{m}R_{1t}^{m*} + (1 - \bar{m})R_{1t}^{e*} &= R_{1t}^* + \iota \\ \bar{m}\left(\frac{1}{2}R_{2t}^m + \frac{1}{2}R_{2t}^{m*}\right) + (1 - \bar{m})R_{2t}^e &= R_{2t} + \iota \end{aligned}$$

Revenues per unit of deposit from risky capital and lending = Cost for bank

Equilibrium: Goods market clearing

Investment in banking deposits, physical capital, and consumption are equal to production and resources generated by risky tech, net of margin costs $\forall t$

$$\begin{aligned} c_{1t} + x_{1t} + (D_{1t+1} - D_{1t}) &= e^{z_t}F(k_{1t}, l_{1t}) + \frac{D_{1t+1}}{R_{1t}}(\bar{m}(R_t^m - 1) - \iota) \\ c_{1t}^* + x_{1t}^* + (D_{1t+1}^* - D_{1t}^*) &= e^{z_t^*}F(k_{1t}^*, l_{1t}^*) + \frac{D_{1t+1}^*}{R_{1t}}(\bar{m}(R_t^{m*} - 1) - \iota) \\ c_{2t} + c_{2t}^* + x_{2t} + x_{2t}^* + (D_{2t+1} - D_{2t})(D_{2t+1}^* - D_{2t}^*) &= \\ = e^{z_t}F(k_{2t}, l_{2t}) + e^{z_t^*}F(k_{2t}^*, l_{2t}^*) + \frac{D_{2t+1}^* + D_{2t+1}}{R_{2t}}\left(\frac{\bar{m}}{2}(R_t^m + R_t^{m*} - 2) - \iota\right) \end{aligned}$$

Equilibrium: Financial intermediation market clearing

Demand for working capital from firms in the segment equals supply of loans in that segment

(fraction invested in risk-free \times total deposits) $\forall t$.

$$L_{1t} = (1 - \bar{m}) \left(\frac{D_{1t+1}}{R_{1t}} \right)$$

$$L_{1t}^* = (1 - \bar{m}) \left(\frac{D_{1t+1}^*}{R_{1t}} \right)$$

$$L_{2t} + L_{2t}^* = (1 - \bar{m}) \frac{(D_{2t} + D_{2t}^*)}{R_{2t}}$$

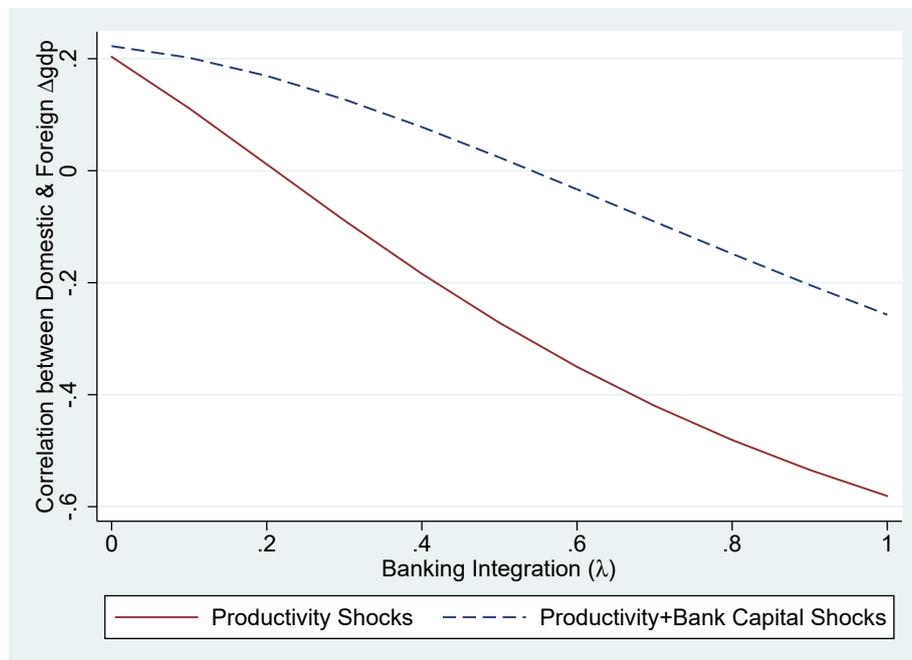
E.3 Parameterization and Theoretical Findings

Functional forms and baseline parameter values

- **Utility:** $U(c, l) = \log(c) - \alpha l$
- **Production:** $F(k, l) = k^\alpha l^{1-\alpha}$
- **Capital share:** $\alpha = 0.36$
- **Depreciation rate:** $\delta = 0.075$
- **Productivity process:** $A_Z = \begin{bmatrix} 0.95 & 0 \\ 0 & 0.95 \end{bmatrix}$; $\rho_\epsilon^z = 0.2$, $\sigma_\epsilon^z = 0.70\%$ (productivity only);
 $\sigma_\epsilon^z = 0.48\%$ (productivity and credit)
- **Adjustment cost:** $\phi = 0.43$
- **Degree of integration:** $\lambda = [0, 1]\%$
- **Share of risky assets in banks portfolio:** $\bar{m} = 0.18$
- **Credit shocks process:** $A_R = \begin{bmatrix} 0.95 & 0 \\ 0 & 0.95 \end{bmatrix}$; $\rho_\epsilon^R = 0.2$, $\sigma_\epsilon^R = 3\%$; $\bar{R}^m = 1.06$
- **Intermediation cost** $\iota = 4\%$

In figure E.2, we consider how the output correlation between home and foreign economies varies as a function of the degree of financial integration under two parameterizations: productivity shocks only, and productivity and banking shocks. The blue line represents an economy with only productivity shocks. This line indicates that a higher level of banking integration is associated with less correlated output cycles, and greater negative comovement in the output cycles. The red line represents an economy with both bank capital shocks and productivity shocks. The difference between these two lines increases with the degree of banking integration. This suggests that there is a positive marginal effect of banking integration on the comovement in output cycles between two economies in “crisis” periods with both capital and non-capital shocks (Kalemli-Ozcan, Papaioannou, and Perri (2013)).

Figure E.2: Financial Integration and Output Correlation



The figures plot the output correlation between the home and foreign areas using synthetic data produced from the model for varying levels of financial integration. The red line represents an economy with both bank capital shocks and productivity shocks. The blue line represents an economy with only productivity shocks.

Appendix F Robustness

Table F.1: Robustness - Alternative Specification

| Δgdp_{it} | (1) | (2) | (3) |
|--|------------------------|----------------------|-----------------------|
| $\sum_{j \neq i} Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0196*** (0.0037) | -0.0095* (0.0056) | -0.0125** (0.0052) |
| $\sum_{j \neq i} \Gamma_{j,t-1}^{ind}$ | 0.0070*** (0.0021) | -0.0070 (0.0168) | -0.0023 (0.0174) |
| $\sum_{j \neq i} Post_{i,j,t}$ | 0.0063*** (0.0016) | 0.0039 (0.0032) | 0.0041 (0.0025) |
| Region _{<i>i</i>} × Year FE | | Yes | Yes |
| State _{<i>i</i>} FE | | | Yes |
| # Obs | 1,173 | 1,173 | 1,173 |
| R^2 | 0.0285 | 0.5171 | 0.6122 |

This table presents the estimates for an alternative specification, in which we aggregate the idiosyncratic shocks across state j . The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\sum_{j \neq i} Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ which denotes the aggregated value of idiosyncratic productivity shocks to top 10 firms in state i interacted with $Post_{i,j,t}$ which takes a value of 1 if state i and j deregulated interstate banking by year t . The unit of observation in each regression is a state_{*i*}-year. Standard errors reported in parentheses are clustered by state_{*i*}. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F.1 Alternative Measures of Idiosyncratic Shocks

We begin by constructing state-level idiosyncratic shocks using only positive firm-level productivity shocks. These results are ported in table F.2. The point estimates of the interaction term of interest are qualitatively similar to baseline results. Further, we test that our results are not driven by exceptional features in our specification of $\Gamma_{j,t-1}$, checking that our results are robust to alternative measures of Γ . These results are presented in Table F.3. $\Gamma_{j,t-1}$ is defined as the idiosyncratic productivity shock computed using top 20 firms in state j (column 1), and top 30 firms in state j (column 2), a time-series average of idiosyncratic productivity shocks (column 3), and non-industry adjusted value (column 4).

Table F.2: Robustness - Constructing $\Gamma_{j,t-1}^{ind}$ using only positive firm-level shocks

| Δgdp_{it} | (1) | (2) | (3) | (4) | (5) | (6) |
|---|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{ind-pos}$ | -0.0825*** (0.0157) | -0.0031*** (0.0008) | -0.0052*** (0.0017) | -0.0076*** (0.0002) | -0.0168*** (0.0053) | -0.0148*** (0.0047) |
| $\Gamma_{j,t-1}^{ind-pos}$ | 0.0618*** (0.0166) | 0.0012*** (0.0003) | 0.0026*** (0.0004) | 0.0037*** (0.0001) | | |
| $Post_{i,j,t}$ | 0.2535*** (0.0643) | 0.0086 (0.0789) | 0.0766 (0.0604) | 0.0771 (0.0471) | 0.0860 (0.0526) | 0.0785 (0.0492) |
| Year FE | | Yes | | | | |
| Region _{<i>i</i>} -Year FE | | | Yes | Yes | Yes | Yes |
| Region _{<i>j</i>} -Year FE | | | Yes | Yes | | |
| State _{<i>i</i>} -State _{<i>j</i>} FE | | | | Yes | Yes | Yes |
| State _{<i>j</i>} -Year FE | | | | | Yes | Yes |
| State _{<i>i</i>} -Linear Trend | | | | | | Yes |
| N | 57,700 | 57,700 | 57,700 | 57,700 | 57,700 | 57,700 |
| R^2 | 0.0181 | 0.3094 | 0.5168 | 0.6113 | 0.6114 | 0.6583 |

This table reports the results from the estimation of baseline specification with state-level idiosyncratic shocks constructed using only positive firm-level labor productivity shocks. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10, by sales, firms in state j . The unit of observation in each regression is a state_{*i*}-state_{*j*}-year pair. All non-binary variables used in the regression are standardized to mean zero and variance 1. Standard errors reported in parentheses are two-way clustered by state_{*i*} and state_{*j*}. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table F.3: Robustness - Alternative Construction of Γ

| | (1) | (2) | (3) | (4) |
|---|---------------------------|---------------------------|----------------------------|-------------------------|
| Δgdp_{it} | $\Gamma_{j,t-1}^{ind-20}$ | $\Gamma_{j,t-1}^{ind-30}$ | $\Gamma_{j,t-1}^{ind-avg}$ | $\Gamma_{j,t-1}^{norm}$ |
| $Post_{i,j,t} \times \Gamma_{j,t-1}^*$ | -0.0159*** (0.0011) | -0.0162*** (0.0009) | -0.1178* (0.0636) | -0.0037* (0.0019) |
| $Post_{i,j,t}$ | 0.0782 (0.0491) | 0.0782 (0.0491) | 0.0777 (0.0491) | 0.0778 (0.0492) |
| Region _i -Year FE | Yes | Yes | Yes | Yes |
| State _i -State _j FE | Yes | Yes | Yes | Yes |
| State _j -Year FE | Yes | Yes | Yes | Yes |
| State _i -Linear Trend | Yes | Yes | Yes | Yes |
| N | 57,700 | 57,700 | 57,700 | 57,700 |
| R ² | 0.6583 | 0.6583 | 0.6583 | 0.6583 |

This table presents the estimates for baseline specification with alternative construction of Γ . The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^*$ which denotes the idiosyncratic production shocks to top 20 firms ($\Gamma_{j,t-1}^{ind-20}$) in other states in column (1), to top 30 firms ($\Gamma_{j,t-1}^{ind-30}$) in column (2), the a time-series average of idiosyncratic production shocks to top 10 firms ($\Gamma_{j,t-1}^{ind-avg}$) in each state in column (3) and using non-industry adjusted value of $\Gamma_{j,t-1}^*$ in column (4). The unit of observation in each regression is a state_i-state_j-year pair. Standard errors reported in parentheses are two-way clustered by state_i and state_j. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The point estimates of the interaction term in columns 1 and 2 of table F.3 are similar to the baseline result. The estimate is larger in column 3 and smaller in column 4. The estimate is larger in column 3 because the measure Γ by construction incorporates future information biasing the estimate upwards. The estimate in column 4 is smaller because the local shocks are only adjusted for aggregate temporal shocks making these shocks less geographically isolated. In all specifications, the relation between idiosyncratic shocks in other states and the state-level impact on GDP growth after banking integration is statistically significant. Hence, we rule out concerns that the relation is attributable to the ad-hoc calculation of idiosyncratic shocks using top 10 firms.

Furthermore, we check whether our results are driven by oversized productivity shocks experienced by states where top 10 firms share of sales is high. We test whether our results change under alternative samples. These results are presented in Table F.4. Column (1) reports the baseline specification under complete sample, columns (2)-(5) only include a state_i – state_j pair if the average ratio of sales of top 10 firms to all firms between 1978 and 2000 in state *j* is less than 95%, 90%, 80%, and 70% respectively. The point estimate remains stable even after restricting the sample to varying degrees. Moreover, the relation remains statistically significant. The precision of the estimate decreases from column (1) to (3) due to the reduction in the sample size. The precision

of the estimate stabilizes thereafter. Hence, the result is not driven by monopolistic states.

Table F.4: Robustness - Alternative Samples

| | (1) | (2) | (3) | (4) | (5) |
|--|------------------------|------------------------|------------------------|-----------------------|-----------------------|
| Δgdp_{it} | All | >95% | >90% | >80% | >70% |
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0164*** (0.0007) | -0.0195*** (0.0026) | -0.0154*** (0.0054) | -0.0145** (0.0054) | -0.0176** (0.0058) |
| $Post_{i,j,t}$ | 0.0783 (0.0491) | 0.0870 (0.0547) | 0.1028* (0.0522) | 0.0987* (0.0503) | 0.1284* (0.0604) |
| Region _i -Year FE | Yes | Yes | Yes | Yes | Yes |
| State _i -State _j FE | Yes | Yes | Yes | Yes | Yes |
| State _j -Year FE | Yes | Yes | Yes | Yes | Yes |
| State _i -Linear Trend | Yes | Yes | Yes | Yes | Yes |
| N | 57,700 | 29,900 | 25,300 | 17,250 | 8,050 |
| R^2 | 0.6583 | 0.6567 | 0.6564 | 0.6561 | 0.6569 |

This table presents the estimates for baseline specification with alternative samples. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ which denotes the idiosyncratic production shocks to top 10 firms. The unit of observation in each regression is a state_i-state_j-year pair. Column (1) includes the entire sample, column (2), (3), (4) and (5) only includes a state_i-state_j-year pair if the average ratio of sales of top 10 firms to all firms between 1978 and 2000 in state_j is less than 95%, 90%, 80% and 70% respectively. Standard errors reported in parentheses are two-way clustered by state_i and state_j. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F.2 Factor Structure with Heterogeneous Exposures

In this section, we assume that firm-level productivity shocks are heterogeneous, but have time-invariant exposure to macroeconomic shocks. We do this to investigate the claim if our measurement of idiosyncratic shocks is corrupted by the presence of a factor structure in such shocks making these shocks capture some degree of aggregate shocks and not local shocks. Under the heterogeneous but time-invariant factor structure assumption, the residuals obtained from running a firm-level regression of labor productivity shocks adjusted for industry shocks on macroeconomic variables are taken to be idiosyncratic. We define $g_{it}^{(i)}$ as in equation 4. For each firm, we run the following regression of $g_{it}^{(i)}$ on macroeconomic shocks for each year.

$$g_{it}^{(i)} = \alpha_i + \beta_i \Delta \Omega_t + \varepsilon_{it} \quad (\text{F.1})$$

$\Delta \Omega_t$ refers to the vector of macroeconomic shocks observed for each year. Macroeconomic shocks include change in effective Fed Funds rate, GDP growth rate, change in unemployment rate, change in inflation rate, Hamilton oil price shocks, and market risk premium. F.5 and F.6 provide a brief summary of the macroeconomic shocks employed here.

Table F.5: Summary of Data Sources for Macroeconomic Variables

| Description | Sources | Measure |
|---|--|-------------------------------------|
| Change in Effective Federal Funds Rates | FRED St. Louis Fed | ΔEFR_t |
| Real Gross Domestic Product Growth | FRED St. Louis Fed | $\frac{\Delta GDP_t}{GDP_{t-1}}$ |
| Consumer Price Index Growth | FRED St. Louis | Annual average |
| Change in Unemployment Rate | FRED St. Louis Fed | $\Delta \text{Unemployment Rate}_t$ |
| Hamilton Structural Oil Supply Shocks | Christiane Baumeister Research Website | Annual average |
| Market Risk Premium | Kenneth French Data Library | Annual average |

This table presents a summary of the data sources and construction methodology for the macroeconomic variables.

Table F.6: Summary Statistics of Macroeconomic Variables Across Years (Raw)

| | N | p25 | Median | p75 | Mean | Std. Dev. |
|--|----|--------|--------|-------|--------|-----------|
| Change in Effective Federal Funds Rate | 24 | -1.209 | 0.025 | 1.447 | 0.050 | 1.941 |
| GDP Growth | 24 | 2.719 | 3.723 | 4.464 | 3.371 | 1.927 |
| CPI Growth | 24 | 0.666 | 0.857 | 1.326 | 1.154 | 0.759 |
| Change in Unemployment Rate | 24 | -0.617 | -0.267 | 0.125 | -0.156 | 0.855 |
| Hamilton Structural Oil Supply Shock | 24 | -0.237 | -0.054 | 0.269 | -0.057 | 0.415 |
| Market Risk Premium | 24 | -0.105 | 0.909 | 1.619 | 0.706 | 1.090 |

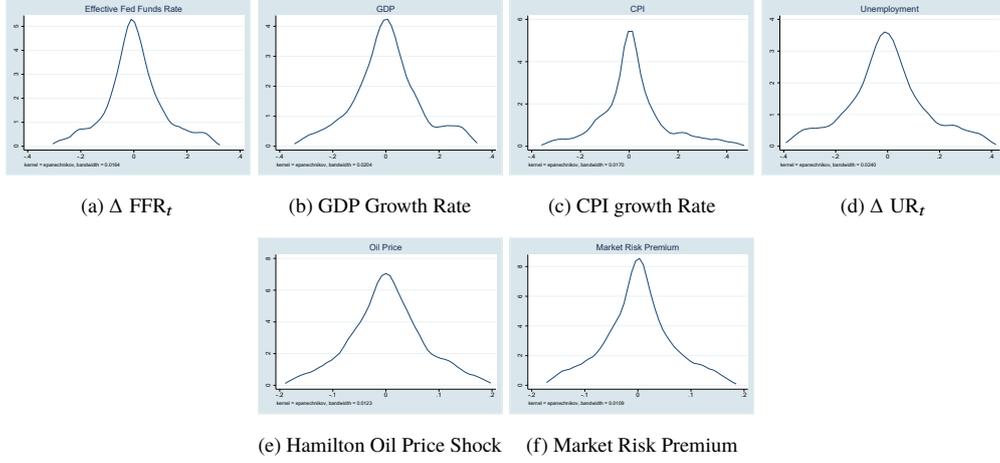
This table presents the summary statistics for the macroeconomic variables of interest from 1977-2000.

The firm-level regression allows the firms to have heterogeneous exposure to macroeconomic shocks. Figure F.1 reports the kernel density of the sensitivity of $g_{it}^{(i)}$ to macroeconomic shocks. These sensitivities are computed at firm-level using the data between 1977 and 2000. Across all macroeconomic variables, the densities are centered around zero. This indicates that for the macroeconomic shocks considered, the average response is zero. The median and the mean estimate for sensitivity related to the monetary policy rate and unemployment rate are negative, as expected, but small in magnitude. However, the sensitivities to the monetary policy rate and unemployment rate have large variance, suggesting that firms have varied responses to these macroeconomic shocks. Sensitivities related to change in unemployment rate, inflation, GDP growth and monetary policy rate have the largest variation. Variation attributed to Hamilton shocks is rather small, as oil supply shocks have a more concentrated effect in specific industries.

The ε_{it} for the top 10 firms in each state are extracted from equation F.1, and aggregated at the state-level using Domar weights as in equation 5. Figure F.2 presents a binscatter plot of our standard measure of state-level idiosyncratic shock, $\Gamma_{j,t}^{industry}$ and the idiosyncratic shock generated from the factor model, $\Gamma_{j,t}^{factor}$. The correlation between $\Gamma_{j,t}^{industry}$ and $\Gamma_{j,t}^{factor}$, is 69.08%. Moreover, regressing $\Gamma_{j,t}^{factor}$ on $\Gamma_{j,t}^{industry}$ reveals that the R^2 value is 47.71%, with a β of ~ 0.7 . This indicates that the two measures of idiosyncratic shocks are highly correlated.

Table F.7 reports the results of the baseline estimation using the shock generated from the factor model, $\Gamma_{j,t}^{factor}$ as the measure of state-level idiosyncratic shocks. Column (6) reports the result by constructing $\Gamma_{j,t}^{factor}$ using all macroeconomic shocks, namely, change in effective federal funds rate, national GDP growth, oil supply shock, inflation, unemployment change, and the market risk premium. $\Gamma_{j,t}^{factor}$ are constructed by step-wise inclusion of factors as we move from column (1) to (6). Column (1) uses a single factor, the change in the effective federal funds rate. $\Gamma_{j,t}^{factor}$ used in columns (2)-(6) are constructed by step-wise inclusion of factors. The results in all columns are quantitatively and qualitatively similar to each other and to the estimate obtained in column (6) of Table 3. The point estimates in all columns are negative, stable across different construction of $\Gamma_{j,t}^{factor}$ and statistically significant at 1% level.

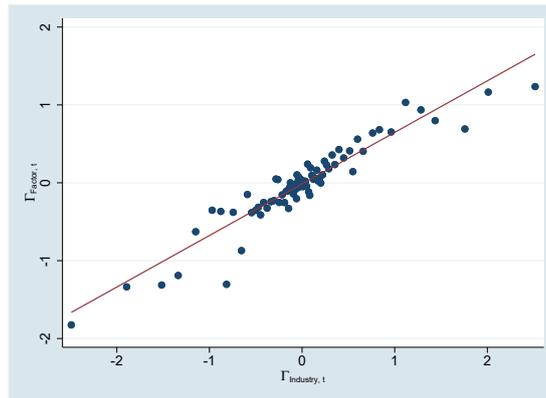
Figure F.1: Kernel Densities of Heterogeneous Exposures of firm-level shocks to Macroeconomic Variables



| | p25 | Median | p75 | Mean | Std. Dev. |
|--------------------|--------|--------|-------|--------|-----------|
| β_{FF} | -0.059 | -0.006 | 0.045 | -0.007 | 0.104 |
| β_{GDP} | -0.061 | 0.001 | 0.072 | 0.006 | 0.122 |
| β_{CPI} | -0.053 | 0.003 | 0.060 | 0.007 | 0.130 |
| β_{Unemp} | -0.081 | -0.001 | 0.081 | -0.000 | 0.150 |
| $\beta_{Hamilton}$ | -0.039 | 0.001 | 0.043 | 0.001 | 0.067 |
| β_{Market} | -0.033 | 0.000 | 0.038 | 0.002 | 0.063 |

This figure plots the kernel density of the heterogeneous exposure of industry-year adjusted firm level labor productivity shocks to macroeconomic variables. The kernel density is plotted after trimming the variables at the 10th and 90th percentiles. Panel a, b, c, d, e and f report the kernel density for change in effective federal funds rate, GDP growth rate, CPI growth rate, change in unemployment rate, Hamilton Oil price Shocks and the market risk premium respectively. Table F.5 provides details on data sources and calculation of the macroeconomic variables employed. The table reports the summary statistics for the firm β values associated with the macro variables of interest.

Figure F.2: Relation between $\Gamma_{j,t}^{factor}$ and $\Gamma_{j,t}^{industry}$



The plot presents a binscatter plot of our standard measure of state-level idiosyncratic shock, $\Gamma_{j,t}^{industry}$ and the idiosyncratic shock generated from the factor model, $\Gamma_{j,t}^{factor}$. The correlation between $\Gamma_{j,t}^{industry}$ and $\Gamma_{j,t}^{factor}$, is 69.08%. Moreover, regressing $\Gamma_{j,t}^{factor}$ on $\Gamma_{j,t}^{industry}$ reveals that the R^2 value is 47.71% between the two. The β value of the regression is 0.69.

Table F.7: Baseline Results with Factor Structure of Shocks

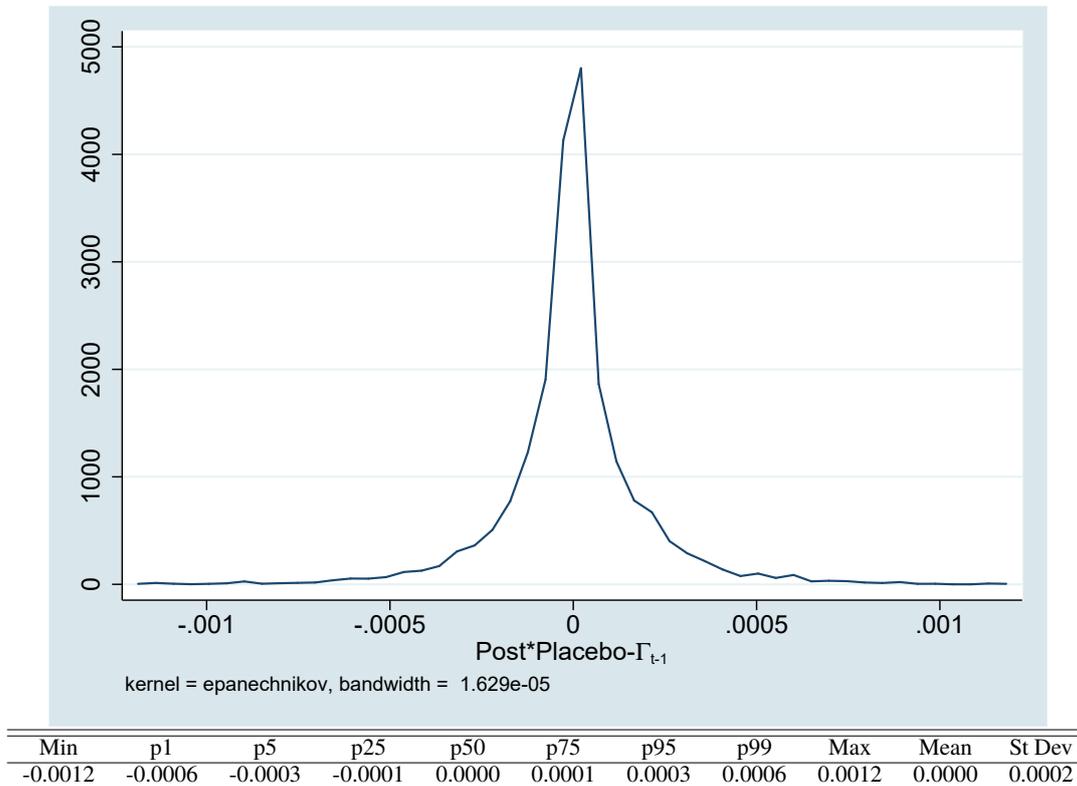
| Δgdp_{it} | (1) | (2) | (3) | (4) | (5) | (6) |
|---|------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{factor}$ | -0.0177*** (0.0015) | -0.0141*** (0.0033) | -0.0142*** (0.0043) | -0.0150*** (0.0047) | -0.0155*** (0.0046) | -0.0160*** (0.0054) |
| $Post_{i,j,t}$ | 0.0782 (0.0491) | 0.0783 (0.0491) | 0.0783 (0.0491) | 0.0781 (0.0492) | 0.0782 (0.0492) | 0.0780 (0.0492) |
| Region _i -Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State _i -State _j FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State _j -Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State _i -Linear Trend | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 57,700 | 57,700 | 57,700 | 57,700 | 57,700 | 57,700 |
| R^2 | 0.6583 | 0.6583 | 0.6583 | 0.6583 | 0.6583 | 0.6583 |

This table presents the estimates for baseline specification with alternative construction of Γ where the shocks are constructed using a factor structure. Column (6) reports the result, after controlling for all factors we consider, namely, change in effective federal funds rate, GDP growth, oil supply shock, inflation, unemployment change, and the market risk premium. We start in column (1) with a single factor under consideration: the change in the effective federal funds rate. As we move from column (1) to column (6), we introduce an additional factor in the model in a step-wise fashion. In column (1), the idiosyncratic shock is estimated after controlling for the change in effective federal funds rate. In column (2), the idiosyncratic shock is estimated after controlling for the change in effective federal funds rate and the GDP growth. In column (3), the shock is estimated after controlling for the change in effective federal funds rate, GDP growth, and oil supply shock. In column (4), the factors are the change in effective federal funds rate, GDP growth, oil supply shock, and inflation. In column (5), the factors are the change in effective federal funds rate, GDP growth, oil supply shock, inflation, and change in unemployment. In column (6), the factors are the change in effective federal funds rate, GDP growth, oil supply shock, inflation, change in unemployment, and market risk premium. Standard errors in parentheses are double clustered at $state_i$ and $state_j$ level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

F.3 Placebo Test

We randomize the state-level idiosyncratic shocks. We generate a series of idiosyncratic shocks by randomly drawing from a Cauchy distribution with location parameter -0.0173 , and scaling parameter 0.1539 .³⁶ We re-run the baseline specification with the randomly generated $Placebo - \Gamma_{j,t-1}$ and estimate the coefficient of the interaction term of $Post_{i,j,t} \times Placebo - \Gamma_{j,t-1}$. Figure F.3 plots the kernel density of the point estimates of $Post_{i,j,t} \times Placebo - \Gamma_{j,t-1}$ obtained from 3,500 such Monte-Carlo simulations. The distribution of the point estimates is centred around zero with a standard deviation of 0.0002 . The minimum point estimate obtained from the exercise is -0.0012 which is lower than any of the point estimates presented in Table 3. Hence, we can rule out the claim that the results are spurious in nature.

Figure F.3: Placebo Test: Randomization of $\Gamma_{j,t-1}^{ind}$



The figure plots the kernel density of the point estimates of $Post_{i,j,t} \times Placebo - \Gamma_{j,t-1}^{ind}$ obtained from the 3,500 Monte-Carlo simulations. We generate a random data for $Placebo - \Gamma_{j,t-1}^{ind}$ using a Cauchy distribution with a location parameter of -0.0173 and scaling parameter of 0.1539 . These parameters are obtained by fitting the empirical CDF to Cauchy CDF using maximum likelihood estimator (MLE). We run our baseline specification with $Placebo - \Gamma_{j,t-1}^{ind}$. The table underneath the figure gives the numbers associated with the distribution of the estimates plotted in figure.

³⁶The parameters are estimated by fitting the empirical CDF of true idiosyncratic shocks to a Cauchy CDF using maximum likelihood estimator (MLE). We consider Cauchy distribution because inspection of state-level idiosyncratic shocks indicates presence of fat-tails

F.4 Geography-based Measurement Error

F.4.1 State Level Value Added Shocks

To validate our results, we redo our empirical exercise using value-added shocks,. These shocks are constructed as follows:

$$\Gamma_{it}^{ind} = \sum_{d \in I} \frac{VA_{d,t-1}^{(i)}}{Y_{i,t-1}} (\Delta \text{Ln}(VA_{d,t}^{(i)}) - \overline{\Delta \text{Ln}(VA_{d,t})})$$

$$\Gamma_{it}^{norm} = \sum_{d \in D} \frac{VA_{d,t-1}^{(i)}}{Y_{i,t-1}} (\Delta \text{Ln}(VA_{d,t}^{(i)}) - \overline{\Delta \text{Ln}(VA_t)})$$

where, I is the set of all industries, $VA_{d,t}^{(i)}$ denotes the value added for a given industry, d , in a state, i at time t . $\overline{VA_{d,t}}$ and $\overline{VA_t}$ denote the mean growth rate in d 's industry in year t and across all industries in year t respectively. The shocks constructed using the value-added measures exhibit properties similar to our main measure of idiosyncratic productivity shocks constructed using Compustat data. Γ_{it}^{ind} has a median value -0.0006 and the 25th and 75th percentiles are -0.0171 and 0.0160 respectively. Γ_{it}^{norm} has a median value -0.0005 and the 25th and 75th percentiles are -0.0179 and 0.01564 respectively.

The results of the baseline regression are reported in table F.8. The estimates from both regressions are statistically significant, and the point estimates are stable and within range of the previous estimates. The point estimate of the interaction term computed using this alternative measure is smaller than the baseline specification. This reduction in the point estimate can be attributed to the fact that the idiosyncratic shocks computed using value added data includes shocks to bank-dependent firms. The shocks to the bank-dependent firms can be caused by shocks to the banking sector or could result in shocks to the banking sector. Hence, these shocks are not as purely exogenous as our baseline measure of idiosyncratic shocks, hence, explains why the point estimate is smaller in magnitude.

Table F.8: Robustness - Value Added Measure of Γ

| Δgdp_{it} | (1) | (2) |
|---|------------------------|------------------------|
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0044*** (0.0013) | |
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{norm}$ | | -0.0061*** (0.0012) |
| $Post_{i,j,t}$ | 0.0885* (0.0490) | 0.0884* (0.0490) |
| Region _i -Year FE | Yes | Yes |
| State _i -State _j FE | Yes | Yes |
| State _j -Year FE | Yes | Yes |
| State _i -Linear Trend | Yes | Yes |
| N | 51,000 | 51,000 |
| R ² | 0.6719 | 0.6719 |

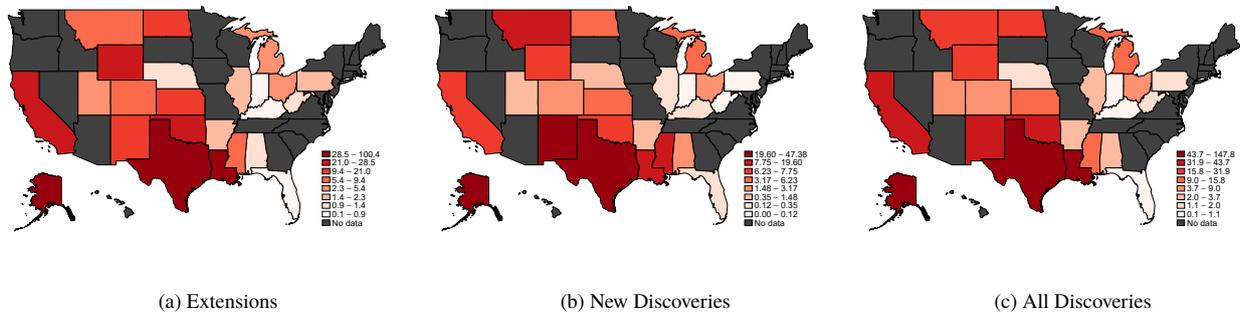
This table presents the estimates for baseline specification with alternative construction of Γ using the value-added measure. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ and $\Gamma_{j,t-1}^{norm}$ which denote the value-added shocks after adjusting for the mean growth rate of each industry in a given year, and for a given year, respectively. The unit of observation in each regression is a state_i-state_j-year pair. All non-binary variables are standardized to mean 0 and variance 1. Standard errors reported in parentheses are two-way clustered by state_i and state_j. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F.4.2 Oil Discoveries as State Level Idiosyncratic Shocks

We construct another measure of state-level shocks using the discovery of new oil reserves. We construct three different measures of oil discovery. The first measure, *extensions*, measures the enlargement of reserves in existing reservoirs. The second measure, *new discoveries*, refers to the discovery of new reservoirs in old and new fields. The third measure, *all discoveries*, is the aggregate of the two measures – *extensions* and *new discoveries* in a state. These discoveries combine both onshore and offshore discoveries. We use the natural logarithm of one plus the magnitude of these discoveries as our measure of state-level shocks.

The magnitude of oil extensions and discoveries is measured using the number of barrels in millions. The majority of the oil discoveries occurred via *extensions* with an average discovery of 15 million barrels a year between 1978 and 2000, as compared with 8 million barrels a year of *new discoveries* during the same period. The *new discoveries* are a rare event relative to *extensions*. In terms of the geographic dispersion of these discoveries, Texas, Louisiana and New Mexico in the Southern region, experienced the largest oil discoveries during the period. The states of Illinois, Indiana, Ohio, and Michigan in the Midwest region experienced a modest degree of oil discoveries. California was the only western Pacific state to experience new oil reserves discovery during the period. See, figure F.4 for the geographic distribution of these discoveries, and figure F.5 for detailed summary statistics, the time series variation of oil discoveries.

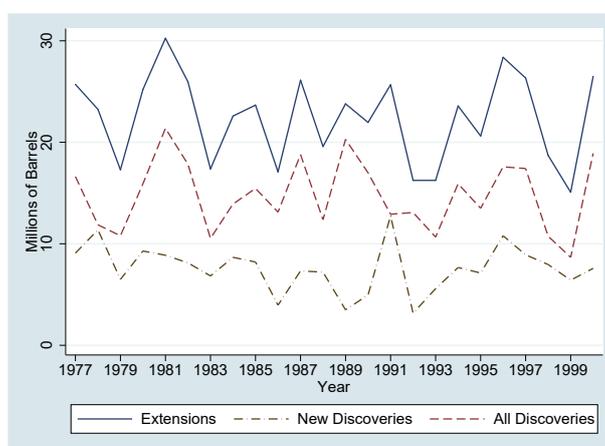
Figure F.4: Geographic Dispersion of Oil Discoveries (1977-2000)



The figure plots the geographic distribution of the average oil discoveries between 1977 and 2000 for all states that experienced at least one discovery or extension during the period. The first measure, *extensions*, measures the reserves enlargement in existing reservoirs. The second measure, *new discoveries*, refers to the discovery of new reservoirs in old and new fields. The third measure, *all discoveries*, is the aggregate of the two measures - *extensions* and *new discoveries* in a state. These measures combine both onshore and offshore discoveries. Each discovery is measured in million barrels.

Relative to our baseline shocks, oil discovery shocks are immune to geographic measurement error, and are relatively straightforward to comprehend. However, there are three limitations of these shocks. First, due to geological reasons, these shocks can be constructed for only a limited number of states. Second, these shocks are left-censored at zero and are always positive in nature. Third, the oil discovery shocks become more predictable towards the second half of the sample. We

Figure F.5: Oil Discovery: Summary Statistics & Average Over Time



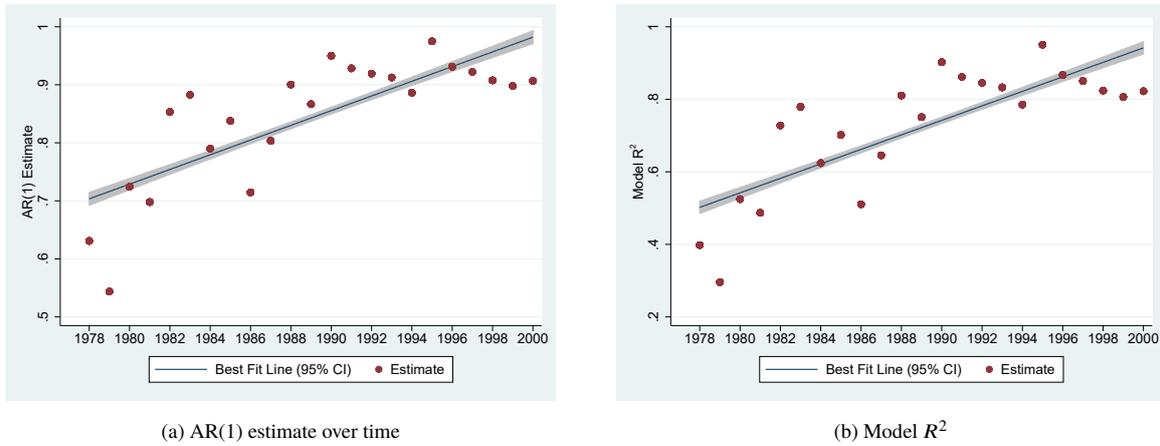
| | N | % Zeros | p25 | Median | p75 | Mean | Std. Dev. |
|-----------------|-----|---------|-----|--------|-----|-------|-----------|
| Extensions | 576 | 23.6% | 1 | 4 | 14 | 14.81 | 31.24 |
| New Discoveries | 576 | 40.6% | 0 | 1 | 8 | 7.58 | 17.95 |
| All Discoveries | 576 | 21.4% | 1 | 6 | 26 | 22.38 | 43.69 |

The figure plots the average oil discovery for each year between 1978 and 2000 for all states that experienced at least one discovery or extension during the period. The table reports the summary statistics - number of observations, percentage of data-points with no discoveries, first quartile, median, third quartile, mean, and standard deviation of observations for oil discoveries for the identical sample. We use three measures of oil discovery. The first measure, *extensions*, measures the reserves enlargement in existing reservoirs. The second measure, *new discoveries*, refers to the discovery of new reservoirs in old and new fields. The third measure, *all discoveries*, is the aggregate of the two measures - *extensions* and *new discoveries* in a state. These measures combine both onshore and offshore discoveries. Each discovery is measured in million barrels.

analyze the predictability of oil shocks and find that the predictability of oil shocks increases over time. We estimate the cross-sectional regression of oil discovery shock on its one period lag for each year between 1978 and 2000 and find that both the the model R^2 and the AR(1) coefficient increase over time, see figure F.6. Past oil discovery shocks provide insight into the oil endowment in that geography and facilitates learning about the geology of that area, making future discoveries more likely (Hamilton and Atkinson (2013)). However, under rational expectations, the predictability of the oil shocks only pushes the point estimate towards zero. Additionally, we control for previous period oil discoveries to account for the predictability of these shocks as in Arezki, Ramey, and Sheng (2017).

Table F.9 replicates the baseline specification using oil discovery shocks. The oil discovery shocks measure banks' expectations of future economic growth in that state. The sample size is reduced as oil discovery shocks can be constructed for a selected sample of states due to natural geological reasons. Column (1), (2), (3) and (4) measure shocks in state j using our baseline idiosyncratic shocks, *extensions*, *new discoveries*, and *all discoveries*, respectively. The point estimate of the coefficient of the interaction term of oil discovery shocks and the *Post* variable is negative in all columns and comparable in magnitude to one another, as well as the baseline estimate. However, the point estimate is statistically insignificant for columns (2)-(4). The statistical

Figure F.6: Predictability of Oil Shocks



The figure plots AR(1) estimates and the corresponding model R^2 obtained from the cross-sectional regression of oil discovery shock on its one period lag. The cross-sectional regression is estimated for each period for a balanced sample between 1978 and 2000. The oil shock in state i at time t is defined as the natural logarithm of all discoveries plus one in state i at time t . All states that experienced at least one discovery or extension during the period 1977 and 2000 is included in the sample.

insignificance of the estimates in column (2)-(4) is attributable to the loss in the power of the test due to the reduced sample size and small variation in the oil discovery shocks as there are a large number of zeros in the data. We provide a detailed power analysis in figure F.7. The power analysis indicates that a sample size of $\approx 30,000$ observations is required to have a 90% probability that we reject the null at 1% significance level when the magnitude of the effect is 0.016. By contrast, table F.9 has $\approx 22,000$ observations indicating a lack of power in the test given the sample size.

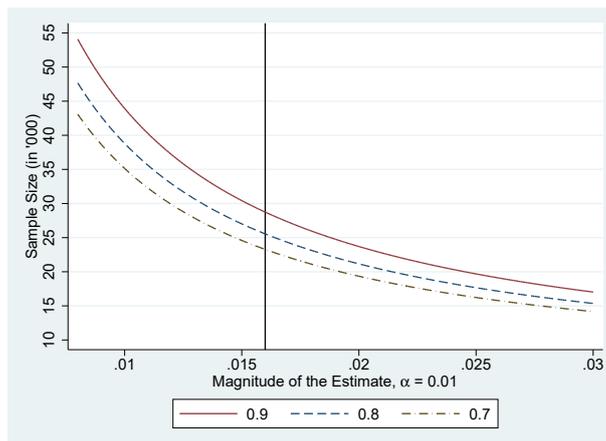
Despite the lack of power, the point estimates in column (2)-(6) are comparable to our baseline estimate of -0.016 and larger than the estimate of -0.010, estimated using baseline shocks for an identical sample. The larger magnitude of the point estimates using oil shocks relative to the baseline point estimates indicates that the geography-based measurement error attenuates the estimate in our baseline table 3. This lends support to our argument that the geography-based measurement error is likely to bias our estimate towards finding an effect of lower magnitude.

Table F.9: Robustness - Measuring Γ Using Oil Discovery Shocks

| | (1) | (2) | (3) | (4) |
|---|------------------------|---------------------|---------------------|---------------------|
| Δgdp_{it} | Baseline | Extensions | New Disc. | All Disc. |
| $Post_{i,j,t} \times \Gamma_{j,t-1}$ | -0.0103*** (0.0018) | -0.0132 (0.0212) | -0.0157 (0.0373) | -0.0364 (0.0382) |
| Post | 0.0739 (0.0574) | 0.1207 (0.0812) | 0.0990 (0.0637) | 0.0953 (0.0802) |
| Past Exploration Control | No | Yes | Yes | Yes |
| Region _i -Year FE | Yes | Yes | Yes | Yes |
| State _i -State _j FE | Yes | Yes | Yes | Yes |
| State _j -Year FE | Yes | Yes | Yes | Yes |
| State _i -Linear Trend | Yes | Yes | Yes | Yes |
| N | 21,850 | 21,850 | 21,850 | 21,850 |
| R^2 | 0.6688 | 0.6688 | 0.6688 | 0.6689 |

This table presents the estimates for baseline specification with alternative construction of Γ constructed using oil exploration shocks. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variables are $\Gamma_{j,t-1}^*$ which denotes the oil extension shocks in column (2), all discoveries including new field discoveries and new reservoirs in old fields in column (3), and, all extensions and discoveries in column (4). The baseline specification is reported in column (1) for comparison. Specifications (2-4) include a *Past Exploration Control* to control for all previous shocks in state j . This is used to control for possible serial correlation in oil discoveries (Arezki, Ramey, and Sheng (2017)). The unit of observation in each regression is a state_i-state_j-year pair. All non-binary variables are standardized to mean 0 and variance 1. Standard errors reported in parentheses are two-way clustered by state_i and state_j. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure F.7: Oil Discovery: Power Analysis



The figure plots the iso-power curves with the required size of the sample on the Y axis and the magnitude of the effect of the X-axis. The iso-power curve gives the sample size, the required numbers of observations (in thousands), that would be required for adequately powered inference to not reject the null when the null is indeed false give the magnitude of the effect at a significance level. The iso-power curves are plotted for a significance level of 1% for power of 0.7, 0.8 and 0.9. The black line denotes the magnitude of the effect estimated from the baseline table.

F.5 Addressing Concerns Related to Migration

This section presents two tests addressing the concern that the baseline result is not driven by inter-state migration contemporaneous with the state pairwise banking deregulation. This section presents two tests to argue that the results discussed thus far are unlikely to be driven by within US migration.

In the first test we augment the baseline specification, equation 6, to include the $\text{region}_i \times \text{region}_j \times \text{year}$ fixed effects, and $\text{region}_i \times \text{state}_j \times \text{year}$, where region refers to the BEA economic region of the state.³⁷ This test assumes that within US migration is likely to be smoothly distributed across space, i.e., the tendency to move between state i and state j are likely to be similar across other states in the same economic regions as state i and state j . Table F.10 reports these results. Column (1) estimate the baseline specification, equation 6, for reference. Column (2) and (3) augment the baseline specification with $\text{region}_i \times \text{region}_j \times \text{year}$ fixed effects, and $\text{region}_i \times \text{state}_j \times \text{year}$ respectively. The point estimate of the interaction term of $\text{Post}_{i,j,t}$ and $\Gamma_{j,t-1}^{\text{ind}}$ is negative and statistically significant at 1% level across all three columns indicating addition of these fixed effects have little impact on the magnitude and the significance of the estimate.

The second test, in contrast to the first test, assumes that choice set of within US migration is coarsely distributed across space. Under this setup, we randomly assign states into groups of different sizes and call these random groups as random regions and re-estimate the baseline specification with $\text{random-region}_i \times \text{random-region}_j \times \text{year}$ fixed effects, and $\text{random-region}_i \times \text{state}_j \times \text{year}$ fixed effects. We repeat this process of randomization of states into groups 3,500 times and estimate the distribution of the interaction term of the $\text{Post}_{i,j,t}$ and $\Gamma_{j,t-1}^{\text{ind}}$ while including the $\text{random-region}_i \times \text{random-region}_j \times \text{year}$ fixed effects, and $\text{random-region}_i \times \text{state}_j \times \text{year}$ fixed effects. Table F.12 reports the mean, median, standard deviation and t-statistic of the distribution of estimates. The mean and the median values reported in table F.12 are negative with a small standard deviation. Moreover, a t-test of the estimates indicate that average of the distribution is less than zero. Hence, combining the results from these two tests we can rule out the results discussed in this paper are driven by within-US cross-state migration.

³⁷We refer the readers to table F.11 for the delineation of states into eight different economic regions by the Bureau of Economic Analysis.

Table F.10: Robustness - Addressing Migration Concerns Using Region Interaction Fixed Effects

| $\Delta gdp_{i,t}$ | (1) | (2) | (3) |
|---|------------------------|------------------------|------------------------|
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0164*** (0.0007) | -0.0170*** (0.0025) | -0.0208*** (0.0060) |
| $Post_{i,j,t}$ | 0.0783 (0.0491) | 0.0793 (0.0503) | 0.0834 (0.0529) |
| Region _i -Year FE | Yes | | |
| State _i -State _j FE | Yes | Yes | Yes |
| State _j -Year FE | Yes | Yes | |
| State _i -Linear Trend | Yes | Yes | Yes |
| Region _i -Region _j -Year FE | | Yes | |
| State _j -Region _i -Year FE | | | Yes |
| N | 57,700 | 57,700 | 57,700 |
| R^2 | 0.6583 | 0.6583 | 0.6594 |

This table reports the results from the estimation of baseline specification, in column (1), augmented to include Region_i×Region_j×Year fixed effects in column (2), and Region_i×State_j×Year fixed effects in column (3). The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10, by sales, firms in state j . The unit of observation in each regression is a state_i-state_j-year pair. All non-binary variables used in the regression are standardized to mean zero and variance 1. Standard errors reported in parentheses are two-way clustered by state_i and state_j. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table F.11: BEA Regions and their Constituents

| BEA Region | States |
|----------------|--|
| New England | CT, MA, ME, NH, RI, VT |
| Mideast | NY, PA, MD, DC, DE, NJ |
| Great Lakes | WI, IL, IN, OH, MI |
| Plains | ND, SD, NE, KS, MO, IA, MN |
| Southeast | VA, WV, KY, TN, AR, LA, MS, AL, GA, FL, SC, NC |
| Southwest | OK, TX, NM, AZ |
| Rocky Mountain | MT, ID, UT, WY, CO |

Table F.12: Robustness - Addressing Migration Concerns Using Random-Region Interaction Fixed Effects

| Panel A: Random-Region _i ×Random-Region _j ×Year FE | | | | | |
|--|---------|---------|---------|---------|---------|
| # Groups | 6 | 7 | 8 | 9 | 10 |
| # Simulation | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 |
| Median | -0.0121 | -0.0119 | -0.0118 | -0.0117 | -0.0115 |
| Mean | -0.0120 | -0.0118 | -0.0118 | -0.0116 | -0.0115 |
| St Dev | 0.0037 | 0.0040 | 0.0043 | 0.0046 | 0.0049 |
| t-statistic | 190.00 | 170.00 | 160.00 | 150.00 | 140.00 |

| Panel B: Random-Region _i ×State _j ×Year FE | | | | | |
|--|---------|---------|---------|---------|---------|
| # Groups | 6 | 7 | 8 | 9 | 10 |
| # Simulation | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 |
| Median | -0.0132 | -0.0131 | -0.0130 | -0.0132 | -0.0131 |
| Mean | -0.0131 | -0.0132 | -0.0131 | -0.0131 | -0.0131 |
| St Dev | 0.0042 | 0.0046 | 0.0050 | 0.0054 | 0.0058 |
| t-statistic | 190.00 | 170.00 | 150.00 | 140.00 | 130.00 |

This table reports the mean, median, standard deviation and t-statistic for the distribution of the interaction term of $Post_{i,j,t}$ and $\Gamma_{j,t-1}^{ind}$ from the estimation of baseline specification augmented to include Random-Region_i×Random-Region_j×Year fixed effects in panel a, and Random-Region_i×State_j×Year fixed effects in panel b. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10, by sales, firms in state j . The unit of observation in each regression is a state_i-state_j-year pair. All non-binary variables used in the regression are standardized to mean zero and variance 1. We randomly allocate states into groups and run the baseline specification with Random-Region_i×Random-Region_j×Year and Random-Region_i×State_j×Year fixed effects. We repeat this randomization 3,500 times and estimate the coefficient of the interaction term of $Post_{i,j,t}$ and $\Gamma_{j,t-1}^{ind}$ in each simulation. Panel a and b report the mean, median, standard deviation and t-statistic of the 3,500 values of these estimates. The columns report the number of groups into which the 50 states and DC have been grouped into.

F.6 Dropping the states of South Dakota and Delaware

This section reports the estimation results of the baseline specification, equation 6 after dropping the states of South Dakota and Delaware from the sample. We drop these states as they had an explicit focus on attracting the credit card companies during the sample period. Table F.13 reports the results from the alternative sample. Column (1) reports the baseline regression with full sample for reference. Column (2) drops the states of South Dakota and Delaware from the set of state i while column (3) drops these states from the set of $state_j$. Lastly, column (4) drops the two states from both state i or state j . The results indicate the stability of the magnitude and the statistical significance of the estimate of interest across the four columns indicating the results are unlikely to be driven by the inclusion of the states of South Dakota and Delaware.

Table F.13: Robustness - Removing South Dakota & Delaware from the Sample

| $\Delta gdp_{i,t}$ | (1) | (2) | (3) | (4) |
|--|------------------------|------------------------------|------------------------------|---------------------------------|
| $Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$ | -0.0164*** (0.0007) | -0.0153*** (0.0034) | -0.0180*** (0.0003) | -0.0167*** (0.0019) |
| $Post_{i,j,t}$ | 0.0783 (0.0491) | 0.0685 (0.0493) | 0.0750 (0.0487) | 0.0652 (0.0489) |
| Region $_i$ -Year FE | Yes | Yes | Yes | Yes |
| State $_i$ -State $_j$ FE | Yes | Yes | Yes | Yes |
| State $_j$ -Year FE | Yes | Yes | Yes | Yes |
| State $_i$ -Linear Trend | Yes | Yes | Yes | Yes |
| N | 57,700 | 55,438 | 55,400 | 53,184 |
| Sample | Full Sample | -{SD & DE} from state i | -{SD & DE} from state j | -{SD & DE} from state i, j |
| R^2 | 0.6583 | 0.6618 | 0.6583 | 0.6618 |

This table reports the results from the estimation of baseline specification after dropping the states of South Dakota and Delaware from the sample. Column (1) uses the full sample, column (2), and (3) drop the states of South Dakota (SD) and Delaware (DE) from state i and j respectively, and column (4) drops the two states from both state i and j . The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma_{j,t-1}^{ind}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10, by sales, firms in state j . The unit of observation in each regression is a state $_i$ -state $_j$ -year pair. All non-binary variables used in the regression are standardized to mean zero and variance 1. Standard errors reported in parentheses are two-way clustered by state $_i$ and state $_j$. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Imprint and acknowledgements

We thank Steven Davis, Douglas Diamond, João Granja, Lars Peter Hansen, Zhiguo He, John Heaton, Kilian Huber, Matthew Jaremski, Sebnem Kalemli-Ozcan, Anil Kashyap, Ralph Koijen, Andrei A. Levchenko, Yueran Ma, Stefan Nagel, Nagpurnanand Prabhala, Elias Papaioannou, Raghuram Rajan, Amir Sufi, Chad Syverson, Pietro Veronesi, Michael Weber, Thomas Winberry, Luigi Zingales, and Eric Zwick for helpful comments and suggestions. We thank Evren Örs for sharing data and Fabrizio Perri for sharing the MATLAB code. We are also thankful to the seminar participants at the 16th Macro Finance Society Workshop 2020, OFR Ph.D. Symposium on Financial Stability 2020, 5th Empirics and Methods in Economics Conference (EMCON) 2020, Young Economist Symposium 2020, CEPR's 3rd Endless Summer Conference on Financial Intermediation and Corporate Finance, Chicago Finance Brownbag Seminar, Midwestern Finance Association Meeting 2021, and Chicago Economic Dynamics and Financial Markets Working Group. Nishant Vats thanks Liew Fama-Miller Fellowship for financial support.

We do not have any conflicts of interest to disclose. We take responsibility for all errors.

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ISSN 2467-0677 (pdf)
ISBN 978-92-9472-235-5 (pdf)
DOI 10.2849/203552 (pdf)
EU catalogue No DT-AD-21-015-EN-N (pdf)