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

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Abstract

This paper explores the transmission of idiosyncratic shocks through banking networks. We construct 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 granular-IV estimates suggest that a 1% increase in bank loan supply is associated with a 0.06-0.25 pp increase in economic growth. Lastly, this can potentially explain the Great Moderation.

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1 Introduction

Understanding how economic shocks propagate across borders and impact global economic activity is a fundamental question in economics. Cross-border linkages, particularly through banking and production networks, are widely recognized as critical conduits for these shocks. However, existing research offers conflicting perspectives. International real business cycle (IRBC) models suggest that banking linkages can reduce business cycle comovement by reallocating capital efficiently (Backus, Kehoe, and Kydland, 1992), while the trade literature posits that production networks amplify cross-border economic shocks, increasing comovement (Huo, Levchenko, and Pandalai-Nayar, 2024). This raises a fundamental question: how do global linkages, encompassing banking and production network connections, influence the transmission of economic shocks and comovement of economic growth? In other words, do banking linkages or trade linkages primarily drive shock transmission and growth comovement?

Despite its significance in the academic literature and the formulation of globalization policies, answering this question has proven challenging. The difficulty lies in identifying idiosyncratic demand shocks that are independent of both the financial system and trade linkages. Additionally, it requires exogenous variation in either trade or banking linkages to ensure that these shocks do not influence either domain.

This paper addresses this gap by exploiting the dissolution of regulatory barriers to geographic bank expansion in the United States between the 1980s and 1990s as an exogenous shock to the expansion of banking networks across state boundaries. We combine this natural experiment with state-level idiosyncratic demand shocks, constructed using labor productivity shocks to large firms à la Gabaix (2011) to examine the aggregate role of banking linkages in shock transmission and economic growth comovement. Our findings indicate that financial integration reduces business cycle comovement across states, highlighting the dominant role of financial linkages in shock transmission.

These findings have significant implications for understanding the effects of banking integration and financial globalization. First, we find that banking linkages dominate trade linkages in shock transmission, leading to a decrease in economic comovement following banking integration. Second, our results highlight the importance of financial integration in facilitating the movement of loanable funds towards productive investment. This result has important policy implications, particularly in the context of the European Union's financial integration initiatives, such as the European Banking Union and the European Capital Markets Union. Our results suggest that a robust banking union may lead to economic divergence among member states in response to idiosyncratic shocks. This consideration is also relevant to emerging markets transitioning to private banking systems and the recent backlash against financial globalization. Third, our research contributes to understanding the Great Moderation – a period of reduced macroeconomic volatility starting in the mid-1980s. We propose that banking integration tempered aggregate fluctuations through geographic diversification, leading to a reduction in business cycle comovement while synchronizing consumption patterns across states. This occurs as consumption becomes more closely tied to aggregate shocks following integration, providing empirical support for the canonical IRBC model presented in Backus, Kehoe, and Kydland (1992).

We begin by examining the impact of financial integration on business cycle comovement. To disentangle the relative importance of banking and trade linkages, we leverage the deregulation of the United States banking industry during the 1980s and 1990s as a natural experiment, providing a plausibly exogenous shock to banking networks. Importantly, prior research has established that pre-existing trade connections did not drive the formation of new banking linkages, and likewise, new banking linkages did not have an immediate impact on trade connections (Michalski and Ors, 2012). This short-term independence between trade and banking networks is essential, as it prevents the observed effects from being distorted by feedback loops between the two networks.

We construct state-level fluctuations 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 derived from labor productivity shocks to large firms for two key reasons. Firstly, these shocks are geographically isolated, lack temporal dynamics, and reflect firm-specific events, making them ideal for our analysis. Secondly, large firms are less reliant on banks for external financing (Gertler and Gilchrist, 1994; Kashyap, Lamont, and Stein, 1994), reducing the likelihood of contamination from bank-capital shocks. We verify this assumption by showing that the ratio of bank debt to total debt is lowest for the "shocked" firms in our sample. Furthermore, we find no significant relationships between these idiosyncratic shocks and bank constraints or bank deposits. Notably, idiosyncratic shocks predict future economic growth, influencing banks' expectations of future state-level economic growth. The geographic isolation, lack of temporal dynamics, orthogonality to contemporaneous bank capital, and predictive power for future economic growth make idiosyncratic shocks well-suited for measuring non-capital shocks.

Conceptually, idiosyncratic shocks impact future returns on capital without contemporaneously affecting bank capital. Distinguishing between bank capital shocks and idiosyncratic shocks is important. Bank capital shocks directly influence the *aggregate* amount of loanable funds, whereas idiosyncratic shocks affect the *relative* lending share across geographies, keeping the total fund stock fixed. In a banking network spanning two economies (domestic and foreign), foreign negative idiosyncratic shocks can increase domestic loan supply and subsequent economic growth through bank diversification. This mechanism has two key implications. Geographic diversification of banks can reduce business cycle fluctuation covariance across geographies in the presence of idiosyncratic shocks. On the other hand, banking networks can increase the vulnerability of the domestic (foreign) economy to foreign (domestic) idiosyncratic shocks, increasing the variance of business cycle fluctuations in both economies. Ultimately,the effect of banking integration on aggregate volatility depends on its relative impact on the covariance between the domestic and foreign economies and the variances of the economies.

Our analysis reveals 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 good (bad) news for state j was also 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 the 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 idiosyncratic 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 percentage points after the state pair (i, j) is integrated via banking linkages.

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 to the granular IV methodology presented in Gabaix and Koijen (2020). Using the idiosyncratic shock, $\Gamma_{j,t-1}$, in state j combined with banking integration as an instrument for bank lending in state i, we estimate that a 1% increase in a bank's loan supply in state i increases economic growth by 0.06-0.25 percentage points in state i. 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 states (i, j) does not change around the time of banking deregulation. Alternatively, the exclusion assumption holds if the covariance in loan demand is sticky relative to changes in the covariance in loan supply around banking integration. We note that even if this assumption is violated, it will bias our test towards a null result if the ex-ante covariance in loan demand is positive. The ex-ante covariance in loan demand is likely positive, as states behaved as complements before banking deregulation. We verify this assumption using a dynamic stochastic general equilibrium (DSGE) model.

Building on this framework, we empirically test a key prediction of Backus, Kehoe, and Kydland (1992) regarding the impact of banking integration on the comovement of economic growth and consumption across states. Specifically, we investigate how banking integration affects the correlation of GDP growth and food consumption across states. Our analysis reveals two striking findings: first, the correlation of GDP growth across states decreases after banking integration; and second, the correlation of food consumption increases over the same period. The coexistence of these two results is consistent with the shock transmission mechanism hypothesized in the standard international real business cycle model (Backus, Kehoe, and Kydland, 1992), which predicts that banking integration facilitates the insurance of region-specific risk and the efficient allocation of resources as markets become more complete.

We provide further evidence that the effect, indeed, operates through the banking channel.

Our analysis confirms that banks expanded across state lines following banking integration, and the heterogeneity in the baseline estimate across states can be attributed to the extent of out-of-state bank expansion in each state post-deregulation. Moreover, the effect develops gradually over time, consistent with the notion that while banking deregulation can be enacted swiftly, the development of actual banking infrastructure, acquisition of private information by banks, and formation of banking relationships takes time to mature.

Exploring the underlying mechanism, we dissect the anatomy of idiosyncratic shocks and find that the effect propagates through geographically isolated non-capital shocks. Our analysis reveals three key insights. First, consistent with the argument that geographic expansion provides diversification benefits to banks when shocks are uncorrelated across geographies, we show that the effect is driven by shocks with low spatial correlation. Second, banking integration increases banking competition, which alters the sensitivity of banks to different types of shocks. Pre-integration, persistent shocks matter more in monopolistic environments (Petersen and Rajan, 1994), whereas post-integration, banks become more sensitive to temporally isolated shocks in competitive environments (Diamond, 1984). Consistent with this view, we find that the effect is larger in magnitude for shocks with little temporal dynamics. Third, we examine the sign of the shock and find that our effect is smaller in magnitude for negative shocks. Negative shocks likely affect banks' total loanable funds by pushing them closer to their constraint, making it less likely for these shocks to be transmitted across state boundaries as hypothesized. To further support our conclusions, we replicate our baseline table using only positive firm-level shocks to construct state-level idiosyncratic shocks and find similar effects.

We further elucidate the underlying mechanism by investigating the role of bank constraints as a key friction driving our results. We argue that, unlike unconstrained banks that operate at the optimal investment level across regions, constrained banks face limited funding and cannot exhaust all investment opportunities. As a result, when hit by an idiosyncratic shock in a particular region, constrained banks may redirect funding to other regions. Our empirical analysis confirms this theoretical argument, showing that the transmission of idiosyncratic shocks across geographies is indeed more pronounced when banks face tighter capital constraints.

To further understand the transmission of idiosyncratic shocks across geographies, we examine the micro-level mechanisms underlying this phenomenon. Using a bank-firm matched dataset, we investigate how banks' reallocation of funds across firms contributes to the aggregate response in economic growth across states. We hypothesize that firms more dependent on banks as a source of external financing drive this response. Our analysis reveals that younger firms, which are more dependent on external finance, are more responsive to foreign idiosyncratic shocks after banking integration. Specifically, we find that younger firms exhibit greater sensitivity in debt growth, sales growth, market-to-book ratio, and work-in-progress inventory growth to foreign idiosyncratic shocks compared to older firms. We also find that idiosyncratic shocks to large, less-bank-dependent firms in state j transmit to small, bank-dependent firms in state i after banking integration.[1] This suggests that banks form expectations about future economic growth through shocks to firms that are less reliant on banks and transmit these shocks to bank-dependent firms across regions. Thus, our findings corroborate the hypothesis that firms which are more bank-dependent drive the aggregate response in economic growth.

To provide external validity to our mechanism, we employ a DSGE model that connects foreign idiosyncratic 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 experiences a negative idiosyncratic shock towards the unaffected economy, in a financially integrated system. We use this model to examine the transmission of idiosyncratic shocks. 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 idiosyncratic shocks. However, with increasing banking integration, the relation between domestic economic growth and shocks in foreign country becomes more positive when foreign shocks are bank capital shocks. We show that the empirical results obtained in the paper are more consistent with the model when the spatial correlation between idiosyncratic shocks is zero. Moreover, we show that the effect vanishes when the spatial correlation is one. This implies that banks benefit from geographic diversification if the shocks they face can be geographically diversified.

We argue that this phenomenon can help 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 tempered. Theoretically, the combined effect of banking integration and idiosyncratic shocks on aggregate volatility is ambiguous. The geographic diversification of banks in the presence of idiosyncratic 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, banking integration reduces the covariance of business cycle fluctuations across geographies. Second, this decline in covariance dominates the increase in individual variances, resulting in a decline in aggregate volatility. Our paper proposes an alternative theory explaining the Great Moderation, documenting how simultaneous changes in the banking system during the 1980s and 1990s increased banks' role in intermediating shocks between states. The presence of new cross-state intermediaries altered the transmission of shocks, allowing for greater diversification and reducing aggregate volatility. Banking

[1] As a falsification exercise, we show that the idiosyncratic shocks to large, less-bank-dependent firms in state j cannot explain the idiosyncratic shocks to large, less-bank-dependent firms in state i, post banking integration.

reforms provide a mechanism to explain why the overall US economy was less reactive to exogenous shocks during the Great Moderation than 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 results are 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 not driven by other confounding variables such as industry similarity, covariance of personal income growth, covariance of GDP growth, exports, imports, and migration across state-pairs.

The key contribution of this work is identifying how economic shocks propagate across borders and impact global economic activity. IRBC models suggest that banking linkages reduce the comovement of business cycles by efficiently reallocating capital (Backus, Kehoe, and Kydland, 1992; Kalemli-Ozcan, Papaioannou, and Peydró, 2013; Kalemli-Ozcan, Papaioannou, and Perri, 2013), while the trade literature posits that production networks amplify cross-border economic shocks, increasing comovement (Huo, Levchenko, and Pandalai-Nayar, 2024). We contribute to this literature by documenting that financial integration reduces business cycle comovement across states. Notably, our results indicate that financial linkages dominate trade channels in shock transmission, contrary to standard theories in which trade channels are the primary drivers of economic comovement. Therefore, this paper provides one of the first well-identified pieces of evidence documenting the benefits of financial integration via banks when loanable funds move towards productive investment opportunities as predicted by classical macroeconomic models since Backus, Kehoe, and Kydland (1992). Our findings also speak directly to the first-order diversification function of banks in an economy as posited in Diamond (1984).

In this regard, our work is closest to Kalemli-Ozcan, Papaioannou, and Peydró (2013). 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. To the best of our knowledge, Kalemli-Ozcan, Papaioannou, and Peydró (2013) is the only other paper that also documents the negative effect of finance on co-movement. We contribute to this work in several ways. First, by focusing on within-country variation across states and leveraging the exogenous shock of banking deregulation, we provide a more precise identification strategy. Second, we *empirically* identify the underlying mechanism by which banking integration leads to negative output synchronization.

Another key contribution of this work is documenting the transmission of idiosyncratic shocks through banking linkages. Understanding how shocks that materialize inside and outside of the banking sector transmit across geographies is critical for deepening our understanding of how the typology of shocks is a key determinant of macroeconomic consequences. Perri and Quadrini (2018) show that with banking integration, endogenous banking sector shocks may result in the synchronization of business cycles, whereas exogenous country-specific shocks outside the banking sector may desynchronize them.[2] While a large body of empirical work has studied the transmission of bank capital shocks through banking networks, it has yet to address how idiosyncratic shocks propagate through banking networks.[3] We address this gap in two key ways. First, we overcome a major challenge of identifying idosyncratic shocks – real shocks – that are orthogonal to bank capital, and studying their transmission through banks within an economy. Second, we provide empirical evidence that geographically diversified banks divert funds away from economies experiencing negative idiosyncratic or non-capital shocks, towards other unaffected economies, contrary to expectations if bank capital shocks were transmitted through banking linkages. Lastly, our distinction between shock types also reconciles our findings with Morgan, Rime, and Strahan (2004) which finds that the volatility of a state's economic growth declines as banks in that state become more integrated with banks in other states. This is attributed to shocks to bank capital as the dominant source of aggregate fluctuations. We complement Morgan, Rime, and Strahan (2004) by distinguishing non-capital shocks from bank 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.

Our paper provides a critical link in the discussion on the Great Moderation by proposing an alternative explanation.[4] 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, following 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 idiosyncratic 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 idiosyncratic 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 Great Moderation.

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

[2] Holmstrom and Tirole (1997) also highlight these two competing mechanisms.

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

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

2 Institutional Details

This section examines the natural experiment of state pairwise banking deregulation, which removed regulatory barriers and enabled cross-border banking expansion from the 1980s to the 1990s. This experiment has been utilized in previous studies (Morgan, Rime, and Strahan, 2004; Michalski and Ors, 2012; Landier, Sraer, and Thesmar, 2017) to analyze the effects of deregulation.

The McFadden Act of 1927 prohibited interstate branching, restricting national banks to operate within their home state. However, the banking sector underwent significant changes in the 1980s, leading to deregulation in a staggered manner across states until 1994. During this period, three main types of reforms occurred based on reciprocity: national non-reciprocal, national reciprocal, and bilateral reciprocal. National non-reciprocal reforms allowed banks from all other states to enter a state's banking market, accounting for 33.8% of state-pairs. National reciprocal reforms permitted interstate banking deregulation between states with similar reforms, involving 21.6% of state-pairs. Bilateral reciprocal agreements between individual state-pairs resulted in deregulation for 8.8% of state-pairs. For further details on banking deregulation, see (Amel, 1993; Morgan, Rime, and Strahan, 2004; Michalski and Ors, 2012). The era of banking deregulation concluded with the enactment of the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) in 1994, allowing banks to branch across all state lines.

State pairwise banking deregulation provides an exogenous source of variation in banking linkages across states in equation A.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 banks. However, there is limited evidence whether these agents are responsible for the expansion in credit supply post deregulation.[5]

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 to 17 percentage points increase

[5] Mian, Sufi, and Verner (2020) document that the credit supply expansion following banking deregulation primarily affected real economic activity through the household demand channel. Moreover, large banks were responsible for the credit supply expansion post banking deregulation (Demsetz and Strahan, 1997; Stiroh and Strahan, 2003).

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

3 Data

The data set used in this analysis is a 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, total loan supply and total commercial loan supply issued in state i, 1977 state pairwise commodity flow data, and food consumption in state i. We use five 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), idiosyncratic shocks constructed using Compustat data, and food consumption data from the Survey of Buying Power published by the Sales and Marketing Management magazine from 1978 through 1995.

3.1 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.

3.2 Food Consumption Data

We compile novel state-level food consumption data by hand-collecting and digitizing food sales figures from the Survey of Buying Power reports published by the Sales and Marketing Management magazine from 1978 through 1995. Note that we were unable to retrieve data for 1989 and 1990 because the reports for these years are not available in the archives. This data is used to test whether consumption patterns are more synchronized after states following banking integration, shedding light on the Backus, Kehoe, and Kydland (1992) puzzle. We focus on food sales as it aligns more closely to consumption in classical macroeconomic models than measures of total spending.

3.3 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.[6] [7] 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.

3.3.1 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^s_{kt}) 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.[8] We define labor productivity shock to firm k in state i as $g^{(i)}_{kt}$ where $g^{(i)}_{kt} = z^{(i)}_{kt} - z^{(i)}_{k,t-1}$.

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^i_{kt}) 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 K largest 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

[6] Compustat 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.

[7] As 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 G.6).

[8] This assumption may result in a geography-based measurement error problem. We refer the readers to Section 6.5 for a detailed discussion on this issue.

idiosyncratic shocks as, Γ_{it}, computed as follows:

$$g_{kt}^{(i)} = \theta_{mt} + \varepsilon_{kt}^{(i)} \tag{1}$$

$$\Gamma_{it} \equiv \sum_{\substack{k=1 \\ k \in i}}^{K} \frac{S_{k,t-1}^{(i)}}{Y_{t-1}} \varepsilon_{kt}^{(i)} \tag{2}$$

Γ_{it} is used as our main measure of the idiosyncratic shock at the state-level, referred to as Γ_{it}^{ind}. We construct state-level shocks, Γ, using the top 10 firms in each state.[9]

3.3.2 Properties of Idiosyncratic Shocks

We begin by examining the cross-sectional distribution of idiosyncratic shocks, denoted as Γ. Figure 1a illustrates the distribution of Γ from 1978 to 2000 across states, revealing significant heterogeneity in both the magnitude and sign of these shocks. Notably, certain states, such as Texas, North Carolina, South Carolina, Florida, and New York, experienced predominantly negative shocks during the sample period. In contrast, states like California, Washington, Illinois, and Michigan encountered mostly 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 the top 10 firms by sales in a state account for at least 50% of sales by all firms in that state.[10] 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%).[11] Hence, these shocks exhibit predictability of future economic growth at the state level.[12]

Next, we analyze the idiosyncratic shocks further by examining their persistence over time and their spatial correlation across states. Figure 1c reports the kernel density of the coefficients of a state-wise AR(1) process for Γ. While the AR(1) estimate exhibits heterogeneity, the majority of the mass is bunched around zero. The average AR(1) estimate for a pooled regression has a value of -0.092. This indicates on

[9] In Section 6.3 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.

[10] A 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.

[11] We 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.

[12] Shocks 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.

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 (see Appendix C.3). 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 the 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 cannot explain idiosyncratic shocks in other states.

Lastly, we investigate the impact of idiosyncratic shocks on banks' capital constraints. The underlying intuition is that if idiosyncratic shocks influence bank capital, a significant negative correlation should exist between bank constraints and idiosyncratic shocks. Appendix Table C.2, Panel A, examines the effect of state-level idiosyncratic shocks on state-level bank constraints. The state-level bank constraint measure is constructed by weighting each bank's constraint level in a state by its lending share in that state.[13] The point estimate reported in Appendix Table C.2 is economically small, precisely estimated with a small standard error, and statistically insignificant. Panel B of Appendix Table C.2 yields similar results using bank deposits as the dependent variable. This suggests a weak economic relationship between idiosyncratic shocks and bank constraints and deposits, consistent with the assumption that idiosyncratic shocks derived from large firms are unlikely to affect bank health.

3.3.3 Why use these Shocks?

The idiosyncratic shocks constructed in Section 3.3.1 enable us to identify the impact of geographically isolated non-capital shocks. We focus on these shocks for three key reasons. Firstly, they are geographically isolated and do not exhibit long-run temporal dependence, making them ideal for analyzing localized economic effects. Secondly, the shocks predict future economic growth, which may influence 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.

3.3.4 Narrative Analysis of Idiosyncratic Shocks

In this section, we employ a narrative-driven approach to investigate how firm-level labor productivity shocks, used to construct state-level shocks, can be attributed to firm-specific events. We identify the top three firms per state-year with the largest magnitude of temporally adjusted labor productivity as

[13] Bank constraint is measured as the ratio of liabilities to assets.

significant observations. For each significant firm-year observation, we conduct a thorough event study, gathering historical events from (www.fundinguniverse.com),[14] supplemented by additional sources, including Businessweek Archives, ABI/INFORM Collection, and 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 1 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.

3.4 Data Description

Table 2 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 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles for GDP growth are 1.4% and 5.3% respectively. The granular residual has a median of 0.000. The 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles are -0.053 and 0.059. The idiosyncratic shock is centered ~0 on average, and the distribution is symmetric. In addition, the table 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. Lastly, the table reports the log of food sales. The average value for this is 15.024, with a standard deviation of 1.054.

4 Results

This section examines the aggregate trend in the comovement of economic growth in state i and idiosyncratic shocks in state j, revealing that banking integration between state-pairs drives this comovement. Through an instrumental variable strategy, we demonstrate that the effect is mediated by shocks to loan supply, providing evidence of a causal link between banking integration and the comovement of economic growth and idiosyncratic shocks.

4.1 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 βs from five-year forward rolling regressions of $\Delta gdp_{i,t}$ on $\Gamma^{Avg}_{j,t-1}$, i.e., $\Delta gdp_{i,t} = \alpha + \beta\Gamma^{Avg}_{j,t-1} + \varepsilon_{i,t}$ from 1978 through 1995, where $\Gamma^{Avg}_{j,t-1}$ is the average of $\Gamma^{ind}_{j,t-1}$ for all other states. The magnitude of β exhibits a monotonically declining trend from 1978 until 1991.

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

The estimated value decreases from a value of ~+1 in 1978 to a value of ~-1 in 1991.[15] The average β coefficient exhibits a notable shift between the two sub-periods. Specifically, it is positive, 0.28, for the 1978-1986 period, but turns negative, -0.39, for the 1986-1994 period. [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 quantiles of ΔGDP (see Appendix E.1). Next, we move to a more robust specification to formally attribute the shift in the relationship between economic growth in state i and idiosyncratic shocks in state j to geographic banking integration.

4.2 Baseline Result

Motivated by the observed aggregate trend in the comovement of economic growth in state i and idiosyncratic shocks in state j, and its coincidental timing with banking deregulation in the US, we investigate whether this trend can be attributed to increased banking integration across state-pairs. To this end, we estimate a difference-in-difference specification as in equation 3. 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.

$$\Delta GDP_{it} = \beta_0 Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} + \beta_1 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{i,j,t}, \quad i \neq j \tag{3}$$

[15] The 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.

[16] The 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.

where ΔGDP_{it} denotes real GDP growth for state i, $\Gamma^{ind}_{j,t-1}$ 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 $\Gamma^{ind}_{j,t-1}$ as it is absorbed within θ_{jt}. We also control for $\theta_i \times t$ denoting linear trend specific to state i.[17] $\varepsilon_{i,j,t}$ denotes the idiosyncratic term in the baseline specification.

The baseline specification, 3, is estimated at the state-pair level, building on the conceptual framework outlined in Section A.1. Importantly, each state (state i) appears in the regression sample N-1 times per year, with the residual of each other state (state j) serving as a regressor in turn ($i \neq j$), where N is the total number of states. This system of equations can be equivalently represented by the collapsed specification in Equation 4. The econometric equivalence between these two specifications is provided in Appendix A.3.

$$\Delta GDP_{it} = \beta_0^* \sum_{j,j\neq i} \left(Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}\right) + \beta_1^* \sum_{j,j\neq i} Post_{i,j,t} + \beta_2 * \sum_{j,j\neq i} \Gamma^{ind}_{j,t-1} + \alpha_i^* \times t + \theta_t^* + \varepsilon_{i,t}^* \tag{4}$$

However, estimating specification 3 offers several advantages over the collapsed specification 4. First, it allows us to exploit heterogeneity in deregulation at the state-pair level. Second, by including state-pair fixed effects, we effectively control for all time-invariant state-pair heterogeneity. Third, time-varying fixed effects for state j encompass a broad array of observed and unobserved factors that contribute to idiosyncratic shocks specific to state j. This includes state-specific economic conditions, policy changes, and other unique circumstances that may impact state j over time. Importantly, specification 3 implicitly controls for idiosyncratic shocks in other states and their interactions with the timing of deregulation. Nonetheless, to assess robustness, we estimate the collapsed specification in Appendix Table G.1 and find consistent results. Given the potential for correlation in the error term at the state-pair level, standard errors for specification 3 are two-way clustered by state i and state j.

Table 3 reports the estimates of the state-level impact of idiosyncratic shocks on GDP growth 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), resulting in a decrease in the point estimate of the interaction term and its associated standard error. The estimate remains negative and statistically significant at 1% level.

[17] Our results are robust to the exclusion of $\theta_i \times t$.

The addition of further fixed effects in Columns (3) to (6) does not alter the significance of the negative interaction term, indicating a robust relationship. Column (6) estimates the specification in equation 3. Economically, the baseline estimate of column (6) indicates that a one standard deviation (0.3) negative $\Gamma^{ind}_{j,t-1}$ increases economic growth in state i by 0.05 percentage points post banking integration.[18]

To assess the robustness of our results to domestic idiosyncratic shocks, we augment the baseline specification by incorporating state-level idiosyncratic shocks for state i, denoted as $\Gamma^{ind}_{i,t-1}$, and its interaction with $Post_{i,j,t}$. This interaction term allows us to control for domestic idiosyncratic shocks that could influence bank capital reallocation across states after banking integration. Results from the augmented specification, presented in Table 4, show that the coefficient on the interaction between Post and foreign idiosyncratic shocks remains negative, statistically significant, and comparable to the baseline estimate in Table 3. This suggests our findings are robust to domestic idiosyncratic shocks.

Another concern with our baseline model may be that the estimation repeats the outcome variable for each state 49 times. This could lead to a misspecification error, possibly biasing our estimates. To address this, we conduct a robustness test using a state$_i$-year level of observation, rather than a state$_i$-state$_j$-year level. We create a time-varying deregulation index for each state$_i$ based on the fraction of other states with which state$_i$ has deregulated, ranging from 0 to 1. Idiosyncratic shocks are computed as the average of all other state-level idiosyncratic shocks. Appendix Table E.1 presents the relationship between economic growth in state$_i$ on the interaction term of the deregulation index and average foreign idiosyncratic shocks. The estimate of the interaction term is negative, statistically significant and similar to the baseline estimate presented in Table 3.

4.2.1 Effect on State Pairwise GDP Growth Correlation

As noted earlier there are several advantages of preserving the bilateral structure of the data. Alternatively, we can calculate the rolling GDP growth correlation for all state pairs and regress this correlation on $Post_{i,j,t}$. This specification has the key advantage of being insensitive to the methodology used to construct foreign idiosyncratic shocks and can capture time-varying heterogeneity for both states in the pair by including state$_i\times$ year and state$_j\times$ year fixed effects. Appendix Table E.2 presents the results, showing a negative and statistically significant coefficient on $Post_{i,j,t}$, supporting our hypothesis. Although this alternative specification provides a useful robustness check, we retain our original baseline specification as the primary one due to its greater transparency in revealing the underlying mechanisms driving our results. Overall, this finding suggests that banking integration led to reduced co-movement of GDP across states.

[18] All 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 $\Gamma = \beta_o \times \sigma_{\Delta GDP} = 0.0164 \times 3.254 = 0.0534$

4.2.2 Effect on State Pairwise Consumption Correlation

Classical models predict that increased banking integration should facilitate the pooling of state-specific output risks, thereby decoupling domestic consumption growth from state-specific income shocks (Backus, Kehoe, and Kydland (1992)). Consequently, consumption patterns across states should become more synchronized following banking integration, as they respond primarily to aggregate shocks rather than state-specific factors. This leads to the prediction that consumption correlations across states should increase significantly post-integration.

To test this conjecture, we compile novel state-level food consumption data by hand-collecting and digitizing food sales figures from the Survey of Buying Power reports published by the Sales and Marketing Management magazine from 1978 through 1995.[19] Table 5 reports the results from regressing the rolling consumption correlation across all state pairs on $Post_{i,j,t}$. Our preferred specification includes state pair fixed effects as well as state$_i\times$ year and state$_j\times$ year fixed effects, to control for time-varying heterogeneity. The coefficient of interest is consistently positive and statistically significant across all specifications, indicating a significant increase in consumption correlation across states following banking integration.

Overall, our findings shed light on the Backus, Kehoe, and Kydland (1992) puzzle. Specifically, we demonstrate that consumption correlation across state pairs increases following banking integration, aligning with predictions from canonical macroeconomic models.

4.2.3 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. Appendix Table E.3 reports the results from the weighted estimation. Results show that a one standard deviation $\Gamma_{j,t-1}$ shock increases economic growth in state i by 0.13-0.19 percentage points post banking integration. 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.

[19]Note that we focus on food sales as it aligns more closely to consumption in classical macroeconomic models than measures of total spending.

4.3 Staggered Nature of Treatment

Recent advances in the differences-in-differences literature have highlighted that the standard DID estimator may not yield a valid estimand in staggered treatment designs with heterogeneous treatment effects. Specifically, Sun and Abraham (2021) point out that the conventional staggered DID estimator can be biased due to the "bad comparisons" problem, which arises when different treated cohorts experience distinct treatment effect trajectories. To address this issue, we adopt the "stacked regression" approach of Gormley and Matsa (2011), as implemented by Vats (2020).[20]

Table 6 presents the results from the stacked regression. There are several treatment cohorts (state pairs) in the stacked regression that underwent treatment until 1993. We use state-pairs that underwent treatment in 1994 as the set of controls. We restrict the sample until 1993 to ensure that our control group of state-pairs are never treated in the data. This method of creating a control group is similar to the strategies adopted in the new DID estimator literature when all units get treated eventually. The data is structured at the cohort-state-pair level. Specifically, all state pairs that deregulated in year t are compared to the state pairs that deregulated in 1994. Together, these groups form the treatment and control groups for cohort t. Column 1 presents the results with the set of fixed effects identical to the baseline specification. Column 3 presents the results from the estimation of our preferred specification which interacts all the fixed effects with the cohort indicator variable. This inclusion ensures that our estimates represent weighted averages of differences between treatment and control groups within each cohort, mitigating the potential issue of "bad comparisons." The results indicate that our baseline finding is robust to heterogeneous treatment effects across cohorts.

4.3.1 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 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

[20] Note that alternative estimators, such as those discussed in (De Chaisemartin and d'Haultfoeuille, 2020; Borusyak, Jaravel, and Spiess, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021), are not directly applicable to our setting due to its unique features. Our primary interest lies in the interaction term between the treatment and foreign idiosyncratic shocks, rather than the treatment coefficient itself. Extending these estimators to accommodate the interaction term is non-trivial and beyond the scope of this paper.

statistically significant at the 90% level of confidence.[21] 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 10$^{\text{th}}$ percentile of the estimates is -0.1073 and the 90$^{\text{th}}$ percentile is 0.0327. For illustration, California, Maine, Maryland and South Carolina exhibit β values in the 10$^{\text{th}}$ percentile range, while Indiana, Washington and Vermont exhibit β values below the 10$^{\text{th}}$ percentile value. The estimates for all of these states are statistically significant at the 90% level. Conversely, Wyoming, Idaho, New Mexico, Connecticut, Utah and Alaska exhibit estimates above the 90$^{\text{th}}$ percentile value. Apart from Idaho and Utah, the majority of these estimates are statistically insignificant at the 90% level. Massachusetts and Louisiana exhibit estimates numerically very close to zero.[22] In Appendix E.4 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.

4.3.2 Assessment of Pre-Trends

A key identifying assumption is that, in the absence of treatment, treated and control groups would have followed similar trends. To assess this parallel trends assumption, we examine whether the response of GDP growth in state i to idiosyncratic shocks in state j exhibits common trends for treated and control state pairs before banking integration. Following Baker, Larcker, and Wang (2022), we employ a dynamic version of the stacked regression discussed in Section 4.3. Our control group comprises state pairs that were treated in 1994. We restrict the sample to pre-1994 data to ensure the control group remains untreated throughout the sample period. Figure 3 presents these trends. We find no substantial differences in the response of domestic GDP growth to foreign idiosyncratic shocks between treated and control state pairs in the pre-deregulation period.

4.4 Instrumental Variable Strategy

Thus far, we have established that banking integration alters the relationship between economic growth in state i and idiosyncratic shocks in state j. To provide stronger evidence that this effect operates through changes in loan supply, we employ an instrumental variable (IV) strategy similar in spirit to the "granular" IV of Gabaix and Koijen (2020). This section presents the results and discusses the validity of the exclusion restrictions. A detailed framework for our IV design is provided in Appendix D.

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

[22] We direct readers to Appendix E.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 E.4b.

4.4.1 Identifying Assumptions

Our identification relies on two key assumptions: relevance and exclusion. The relevance of the instrument stems from the assumption that geographically diversified banks allocate funds away from states experiencing negative idiosyncratic shocks, increasing loan supply in other states. This assumption is verified in the first stage, which shows substitution of lending away from affected states 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. While assuming shocks in state j do not effect loan demand in state i would ensure exclusion, this assumption may be implausible as the state-pair is likely to have non-zero covariance in loan demand via non-banking channels such as trade, input-output linkages, etc. To address this, we rely on two alternative identification assumptions. First, the *weak identification assumption* posits that the covariance in loan demand between states is stable in magnitude around the timing of banking integration. This allows loan demand in state i to respond to idiosyncratic shocks in state j, while ensuring identification of the pure loan supply effect in the difference-in-differences setup of the first stage. Additionally, if the covariance in loan demand is assumed to be time-invariant, state-pair fixed effects control for fluctuations in loan demand. Second, a relatively *weaker identification assumption* posits that the covariance in loan demand between two states is sticky relative to loan supply around the deregulation event.[23] This allows the covariance in loan demand to change post-deregulation but assumes that changes in loan supply covariance between states are more immediate than changes in loan demand covariance.[24] These assumptions enable us to control for fluctuations in loan demand and isolate the loan supply effect. We discuss potential violations of the exclusion restriction in Appendix E.5 and argue that such violations would likely bias estimates towards a null effect, as states behave as complements on aggregate in the absence of banking linkages.

4.4.2 2SLS Estimation Results

Table 7 presents the first and second-stage IV estimates. The results indicate that following banking integration, a negative idiosyncratic shock in state j is associated with increased bank lending in state i, which in turn increases economic growth in state i.

The first stage estimation regresses loan supply in state i on idiosyncratic shocks in state j, and an indicator for a banking linkage between state i and j. The coefficient of interest, β_2, represents the interaction term of $\Gamma_{j,t-1} \times Post_{i,j,t}$. The negative and statistically significant estimate reported in column (1) indicates that a negative idiosyncratic shock in state j increases loan supply in state i after banking integration. In column (3), we augment the specification by controlling for time-varying regional

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

[24] The extant literature is 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.

demands and state-pair level time-invariant heterogeneity through state-pair fixed effects. This estimator aligns with our weak identification assumption, allowing us to isolate the pure effect of the loan supply channel. By controlling for all time-varying heterogeneity at the $state_j$ level, we obtain a more precise estimate of the interaction term. Notably, the point estimate in column (3) is smaller than the estimate in column (1), which captures the combined effects of both loan demand and loan supply channels. In column (5), we control for the interaction of $Post_{i,j,t}$ and the lag of idiosyncratic shock in state j. 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 1% level. The estimates from columns (1), (3), (5) and (7) indicate that after banking integration, a negative idiosyncratic shock in state j leads to an increase in bank lending in state i through the loan supply channel.

Despite strong second-stage results, the first-stage F-statistic, as indicated by the Kleibergen-Paap (KP) rk Wald F statistic, particularly in Columns 1 and 3, raises concerns about weak instruments. While Columns 5 and 6 exhibit F-statistics above the conventional threshold of 10, we employ the robust inference approach suggested by Andrews, Stock, and Sun (2019), reporting identification-robust Anderson-Rubin confidence intervals, which remain statistically significant across all specifications.[25]

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 associated with the predicted $log(C\&I - Loan_{it})$ denoted by $log(C\&I \hat{-} Loan_{i,j,t})$. The point estimate is positive and statistically significant at the 5% level across columns (2), (4), (6), and (8).This coefficient estimate represents the loan supply effect on economic growth, revealing a positive relationship between economic growth and lending. A notable observation is the increase in magnitude of the second-stage estimates from columns (4), (6), and (8) compared to column (2). While this might initially suggest a weakening instrument due to additional controls, the substantial increase in the first-stage F-statistic from 3.9 in Column (1) to values exceeding the conventional threshold of 10 in Columns (5) and (7) suggests that this is unlikely the primary explanation. Instead, the higher second-stage estimates from the 2SLS specifications may be attributed to the fact that 2SLS estimators help alleviate classical measurement error issues, which can downward bias the estimate in a simple OLS regression (Reiersøl, 1941; Geary, 1943; Aldrich, 1993). Pancost and Schaller (2022) argue that classical measurement error can explain why IV estimates are generally larger than OLS estimates, even when omitted variable bias is expected to lead to the opposite result. This phenomenon, where 2SLS estimators tend to be higher in magnitude than OLS estimators, has been observed in the

[25] Andrews, Stock, and Sun (2019) suggests that when researchers are confident in the validity of their instruments but suspect they may be weak, relying solely on F statistic screening may be undesirable, as it may lead to the exclusion of economically meaningful specifications.

returns to education literature Card (2001) and the finance literature by Jiang (2017). For comparison, we report the OLS coefficients associated with the 2SLS specification in Appendix Table D.1.

4.4.3 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 0.06-0.25 percentage points.[26] 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.

Our estimate of the impact of loan supply on economic growth is notably lower than previous literature. This discrepancy may be attributed to several factors. First, our sample period (1978-2000) encompasses multiple business cycles, potentially diluting the estimated effect. Second, unlike prior studies that primarily rely on negative bank shocks, our analysis includes both positive and negative shocks. This suggests a possible asymmetry in bank responses, with more pronounced reactions to negative shocks. Such behavior is consistent with loss aversion, i.e., banks prefer avoiding losses to experiencing equivalent gains.[27]

5 Mechanism

In this section, we explore how idiosyncratic shocks are transmitted through banks. We find that the effect of deregulation develops slowly over time, consistent with the notion that banking linkages and relationships develop over time. Regarding 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 idiosyncratic shocks following banking integration.

5.1 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

[26] direct readers to Appendix D.1 for a detailed discussion on calculating the economic magnitude of the effect.

[27] While 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.

over time by constructing time windows of varying length around the event. Figure 5 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 3, 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 a lack of pre-trends, discussed in Section 4.3.2.

5.2 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 idiosyncratic shocks via banking integration.

How do idiosyncratic 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 8 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 R^2 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, we find our effect is smaller in magnitude when shocks are negative, see column (3) Table 8. Further, we replicate our baseline table, constructing state-level idiosyncratic shocks using only positive firm-level shocks, shown in Appendix Table G.4.

5.3 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 9. 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 standard deviations increase in debt growth, 0.47 standard deviations increase in sales growth, 0.46 standard deviations increase in market-to-book ratio, and 0.89 standard deviations 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.

5.4 Domestic Small Firms, Banking Integration & Shocks to Large Foreign Firms

This section complements the analysis in Section 5.3 by documenting that idiosyncratic shocks to large firms in foreign states affect the idiosyncratic shocks to small firms in the home state. Specifically, we document that negative shocks to large firms in state j result in positive shocks to small firms in state i after the two states are financially integrated. We construct shocks to small firms in a state by aggregating the Domar weighted labor productivity shocks experienced by firms below the top 10 firms by sales, after adjusting for industry $\times$ year fixed effects. Column (1) of Table 10 reports the results of regressing idiosyncratic shocks to small firms in state i on the interaction term of idiosyncratic shocks to large firms in state j and an indicator for the post deregulation period. The estimate of interest is negative and statistically significant. The estimate indicates that negative shocks to large, less-bank-dependent firms in the foreign state are transmitted as positive shocks to small bank-dependent firms in the home state, following banking integration. As a falsification test, we present the regression of idiosyncratic shocks to large firms in state i on the interaction term of idiosyncratic shocks to large firms in state j and an indicator for the post deregulation period. The underlying intuition of this test is that larger firms are less reliant on bank financing, and therefore, are unlikely to be directly impacted by the reallocation of bank funds across borders. Consistent with this expectation, the estimate of interest is economically small and statistically insignificant, suggesting no discernible effect on large firms. Overall, the results presented in Table 10 provide valuable insights into the specific channel through which banks intermediate shocks via their networks.

5.5 Bank Constraint and Transmission of Idiosyncratic Shocks

Bank constraints are an important friction that plays a crucial role in the transmission of idiosyncratic shocks through banking networks. Geographically diversified, unconstrained banks are likely to operate at the first-best investment level across regions, and hence, have little scope to divert funding to other geographies when a particular geography is hit by an idiosyncratic shock. However, constrained banks cannot exhaust the set of available investment opportunities due to their limited supply of funds. Hence, constrained banks are more likely to transmit idiosyncratic shocks across geographies. This section documents the role of constrained banking sector in the transmission of non-capital shocks across geographies.

Table 11 reports the results. We measure the average constraint of banks in a state by weighting a bank's constraint in each state by the bank's share of lending in that state. Bank constraint is measured as the ratio of liabilities to assets. Our coefficient of interest, the triple interaction of idiosyncratic shocks to large firms in state j, average constraint of banks in state j in the pre-deregulation period, and the indicator for the post deregulation period, is negative, economically large, and statistically significant. Moreover, our estimate of the interaction term of idiosyncratic shocks to large firms in state j and the indicator for the post deregulation period decreases in magnitude. Together, these results indicate that bank capital constraint plays a crucial role in driving the transmission of idiosyncratic shocks across geographies.

5.6 Model

In this section, we provide an overview of the theoretical model presented in Kalemli-Ozcan, Papaioannou, and Perri (2013) and leverage this framework to demonstrate that financial integration is the primary mechanism linking shocks to economic growth. The model enables us to conduct a counterfactual analysis, which allows us to examine how the relationship between economic growth in state i and idiosyncratic shocks in state j changes based on the ex-ante correlation of idiosyncratic shocks. This counterfactual exercise helps us assess the validity of the exclusion restriction discussed in Section 4.4.1.

5.6.1 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).[28]. 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 idiosyncratic 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 F for in depth discussion on model details such as setup, solution, calibration etc.

5.6.2 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 distinct scenarios: productivity shocks only, 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 6a presents this result. The key result is that the relation between economic growth in state i and idiosyncratic shocks in state j changes with the degree of banking integration, λ. For foreign idiosyncratic 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. As noted earlier, the distinction between the two shocks is that bank capital shocks alter the total supply of capital available for lending whereas idiosyncratic 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 -

[28]This figure is reproduced in Appendix Figure F.1

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 6b 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, this result aligns with our identification strategy, which posits that when states exhibit complementary behavior with positive demand correlation, our estimation strategy is biased towards finding a null effect due to the presence of non-banking channels.

6 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 banking integration.

6.1 How Well do our Shocks Capture Idiosyncratic Shocks?

Our interpretation of the findings hinges critically on the assumption that idiosyncratic shocks accurately capture non-capital shocks. However, our construction of idiosyncratic shocks may not exclusively capture non-capital shocks due to various factors. Large local economic shocks may simultaneously impact both large and small firms, while shocks to large firms may have spillover effects on smaller firms. In both cases, our idiosyncratic shocks may inadvertently capture shocks that contemporaneously affect bank capital, potentially confounding our results. In this section, we argue that these concerns are unlikely to threaten our core hypothesis for five reasons.

First, contamination of idiosyncratic shocks by capital shocks will underbias our results, as the latter will result in amplification rather than the substitution effect that we argue. Second, we present a narrative analysis of our constructed shocks in Section 3.3.4 to show that we are indeed capturing idiosyncratic shocks specific to large firms.

Third, our shock construction methodology orthogonalizes industry × year fixed effects in an attempt to measure shocks that are devoid of industry-specific macroeconomic cycles that can affect both large and small firms, and hence, bank capital. However, our shocks may still capture some degree of state-specific macroeconomic cycles. We address this concern by modifying our shock construction methodology to orthogonalize state × year fixed effects, in addition to the industry × year fixed effects. Appendix Table G.2 reports the results from our baseline estimation, using shocks that are orthogonalized to state × year fixed effects, in addition to the baseline industry × year fixed effects. Qualitatively, the results reported in Table G.2 are similar to the results reported in our baseline Table 3. Quantitatively, the magnitude of the estimate presented using our modified shock construction approach is larger than the magnitude of the estimate in Table 3. This indicates that our results are not only robust to partialling out all state-specific shocks, but strengthens our first argument that the estimate under our hypothesis is likely to be understated if our shocks are contaminated by bank capital shocks.

Fourth, we examine whether idiosyncratic shocks to small firms predict those of large firms.[29] This could be a concern if a state-level banking shock helps small firms, which in turn benefits their large firm customers. Appendix Table G.3 presents the results, showing that shocks to small firms have limited predictive power for shocks to large firms. Quantitatively, shocks to small firms explain only 1.22% of the variation in shocks to large firms.

We extend our baseline specification by incorporating interaction terms between the post-deregulation indicator and aggregated shocks to small firms in both the home state and foreign state. The results, presented in Table 1, show that our key finding remains unchanged. The interaction between idiosyncratic shocks to large firms and the post-deregulation indicator is negative, statistically significant, and consistent with our baseline estimate. This suggests that our baseline estimate is robust to controlling for shocks to small firms in both the home state and foreign state. Notably, the interaction term between idiosyncratic shocks to small firms and the post-deregulation indicator is positive. This supports the idea that shocks to small firms affecting bank capital are transmitted across states after banking integration, similar to a bank capital shock.

Fifth, we re-run our baseline specification, after explicitly controlling for bank capital shocks measured through loan loss provisions of banks in the foreign state. Specifically, we control for the interaction term of aggregate loan loss provisions of banks in state j and the indicator for the post deregulation period. We calculate aggregate loan loss provisions at the state level by aggregating the loan loss provisions of individual banks, weighted by their lending share within the state. Specifically, for each state, we sum the product of each bank's lending share within that state and its loan loss provision, across all banks. Table 13 presents the results from this exercise. Our coefficient of interest – the interaction of idiosyncratic shocks and the indicator for the post deregulation period – is negative, statistically significant, and qualitatively similar to our baseline estimate. This evidence strengthens our confidence that the shocks are not contaminated by other factors affecting bank capital.

6.2 Alternative Transmission Mechanisms

Another concern of our identification strategy is that pre-existing non-banking relationships between two states may drive our findings. This may be due to the endogeneity of banking deregulation, the transmission of shocks through non-banking channels, or the interaction of the newly formed banking

[29] *Small* firms are those that are not among the top ten firms in terms of sales in the state in which they are headquartered. *Large* firms are defined as those that *are* among the top ten firms in terms of sales in the state in which they are headquartered.

channel with these pre-existing non-banking channels that can result in the transmission of shocks between two states, following banking deregulation.[30]

We account for these concerns by controlling for the trade relationship, personal income comovement, GDP comovement, and state-pair proximity in industry composition. First, we measure the trade relationship between two states, using the share of goods exported from state i to j and imports into state i from state j. The data on bilateral trade flows is from 1977 and comes from Michalski and Ors (2012). Second, we construct the covariance in personal income growth and GDP growth between two states, using data from the pre-deregulation period to account for the comovement in personal income growth or business cycles between two states. Third, we construct the state-pair proximity by industry composition, measured by the Euclidean distance of the share of employment in 77 industries between the two states. This number is large when the two states have very different industrial specializations. Additionally, we also control for the pre-period average of income per capita in the foreign state.

Table 14 presents the baseline specification augmented with interaction terms between foreign idiosyncratic shocks and several control variables: share of exports and imports, foreign state income per capita, income covariance, industry similarity, and GDP growth covariance. These interactions account for potential pre-existing non-banking channels of shock transmission. We further include triple interaction terms involving these covariates, foreign idiosyncratic shocks, and the post-deregulation indicator to address the possibility that our findings are driven by interactions between the new banking channel and existing non-banking channels. Finally, we control for interactions between these covariates and the post-deregulation indicator. Our core estimate, the interaction of idiosyncratic shocks and the post-deregulation indicator, remains negative, statistically significant, and qualitatively similar to the baseline, suggesting our results are unlikely driven by pre-existing non-banking channels.

6.3 Alternative Measures of Idiosyncratic Shocks

We conduct several robustness checks to verify the sensitivity of our results to the methodology used in constructing idiosyncratic shocks. First, we alter the construction methodology by using the top 20 and top 30 firms instead of the top 10 firms. Second, we employ 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. Our results remain robust across these alternative measures (see Appendix Table G.5). Fourth, we test the sensitivity of our results to states where top 10 firms' share of sales is high. We repeat our baseline analysis with alternative samples, excluding states where the top 10 firms account for more than 95%, 90%, 80%, and 70% of all sales. The point estimate remains insensitive to these alternative samples (see Appendix Table G.6). Fifth, we reconstruct state-level idiosyncratic shocks by partialling out the idiosyncratic shocks to small firms from

[30] The analysis in this section controls for covariates based on their pre-deregulation values. However, for completeness, we also present our results with time-varying characteristics. Appendix Table E.4 reports the results with time-varying covariates and finds similar results to ones reported in Table 14.

those to large firms using three methods: (1) directly controlling for idiosyncratic shocks to small firms in state j, (2) subtracting idiosyncratic shocks to small firms from those to large firms, and (3) regressing idiosyncratic shocks to large firms on those to small firms and using the residuals as the measure of idiosyncratic shocks. Our baseline results remain robust across these methods (see Appendix Table G.7). Furthermore, we reconstruct idiosyncratic shocks assuming heterogeneous, but time-invariant exposure to aggregate macroeconomic shocks. Under this factor structure assumption, we find that the point estimate for shocks constructed using this framework is quantitatively similar to our baseline estimates (see Appendix Table G.10). For further discussion on methodology, properties, and baseline results using shocks constructed under the factor structure methodology, we refer readers to Appendix G.2.

6.4 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. Appendix Figure G.3 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 variables is identical across state-pairs.[31]

6.5 Addressing Geography-based Measurement Error

In the construction of Γ in Section 3.3.1,we assume that a firm's sales and employment are located in the same state as its headquarters. This assumption may introduce measurement error, but we argue that its impact is likely minimal for two reasons. Firstly, measurement error is expected to be small, as headquarters and production facilities tend to be clustered in the same state (Chaney, Sraer, and Thesmar (2012)). Moreover, headquarters represent a significant fraction of corporate real estate assets, and, on average, firms have a substantial proportion of their employees at their headquarters (Barrot and Sauvagnat (2016)). Specifically, the average (median) Compustat firm in their sample has 60% (67%) of

[31] In 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 G.3.2).

its employees at its headquarters. Secondly, even if measurement error is significant, it is likely to bias our estimates against finding the proposed effect. Therefore, our results are likely to be conservative, and the true effect may be even more pronounced than what we estimate.[32]

Nevertheless, we compute two alternative measures of state-level shocks to circumvent the measurement issue and find qualitatively similar results (see Appendix G.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 limited 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.[33]

6.6 Addressing Concerns Related to Migration

This section addresses concerns of whether the results presented in the paper are driven by interstate 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 region$_i$×region$_j$×year fixed effects, and region$_i$×state$_j$×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 random-region$_i$×random-region$_j$×year fixed effects, and random-region$_i$×state$_j$×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 Post$_{i,j,t}$ and $\Gamma^{ind}_{j,t-1}$. The second test, in contrast to the first test, assumes that the choice set of within-US migration is coarsely distributed across space. Appendix G.5 discusses these results and finds that the coefficient of interest is qualitatively and statistically similar to the baseline results. Hence, our findings are unlikely to be driven by contemporaneous migration.

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[32] Assume 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.

[33] We direct the readers to Appendix G.4.1 and G.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 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 were 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.

Our simulations show that as. However, the decrease in covariance is substantial enough to offset the increase in variance, resulting in a decrease in aggregate economic volatility.

We exploit the two-country model presented in Section 5.6 to demonstrate how banking integration can lead to a decrease in aggregate volatility. Banking integration influences the variance and covariance of economic growth between two geographies.[34] The data simulated from the model shows that banking integration increases, the covariance in economic growth between the two geographies decreases, while the variance in economic growth in each geography increases. The decrease in covariance is sufficiently large to compensate for the increase in variance, resulting in a net decrease in aggregate economic volatility for the entire system as banking integration increases. Figure 7 provides a visual depiction of

[34] We find similar conclusions on the effect of banking integration on variance and covariance in the extension of simple framework of Section A.1 presented in Appendix A.2.

this result. Specifically, when increases from 0 to 1, the variance in each geography increases by 22%, while the covariance decreases by 240%. Consequently, aggregate volatility decreases by 2%, with a 25% contribution from increased variance and a -27% contribution from decreased covariance. Notably, the decline in aggregate volatility is likely to be more pronounced in a multi-country setup, as shocks are distributed across a larger geographic area, amplifying the decrease in covariance while dampening the increase in individual geographic variance.

8 Conclusion

In this paper, we identify the effect of banking networks on the cross-border transmission of idiosyncratic shocks. We introduce new empirical findings on how idiosyncratic shocks transmit through the economy via banks. Specifically, we provide evidence that geographically diversified banks divert funds away from states that experience negative shocks, 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 idiosyncratic shocks through banking networks. Our results suggest that the transmission of idiosyncratic 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 idiosyncratic 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 0.06-0.25 percentage points 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 idiosyncratic 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 idiosyncratic 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 microeconomies 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 idiosyncratic 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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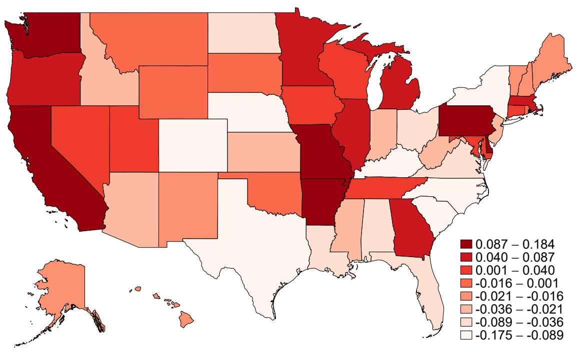
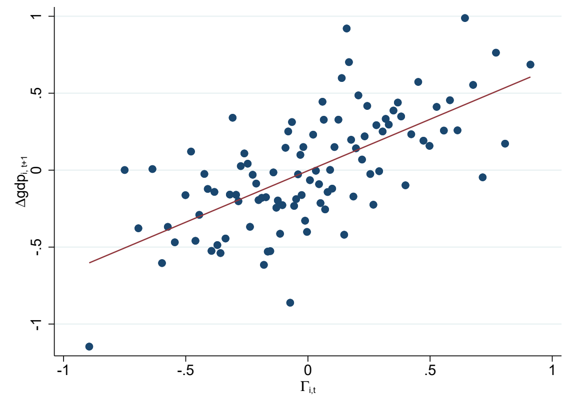
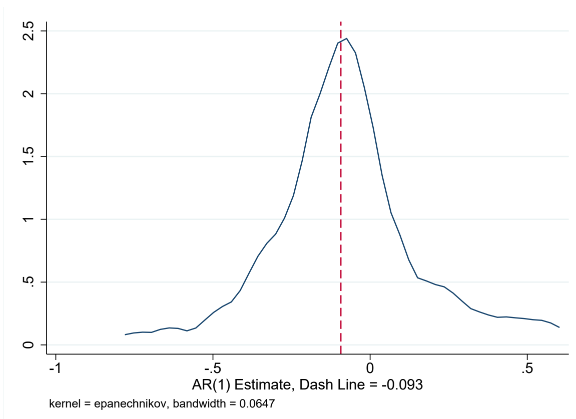
Figure 1: Properties of Idiosyncratic Shocks, Γ



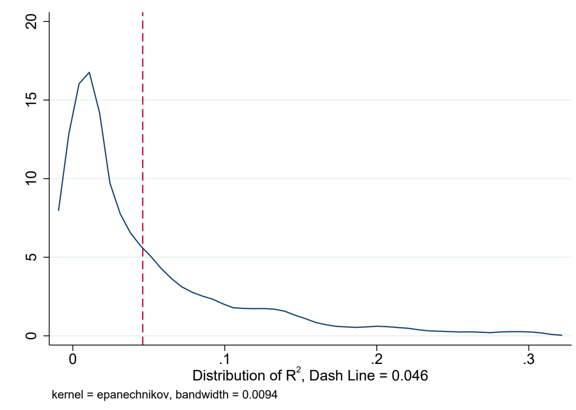
(a) Spatial distribution of Γ



(b) Γ predict subsequent Δgdp



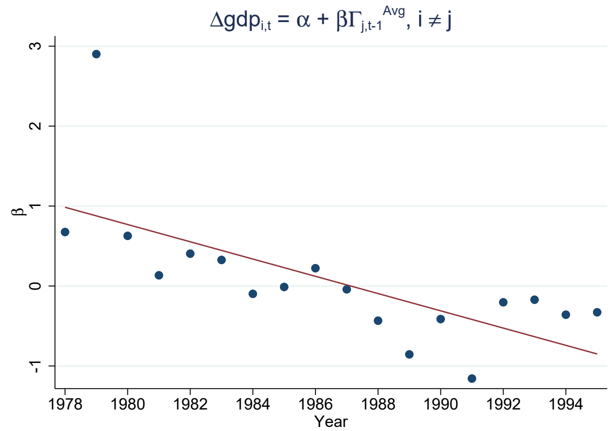
(c) Distribution of state-wise AR(1) estimate for Γ



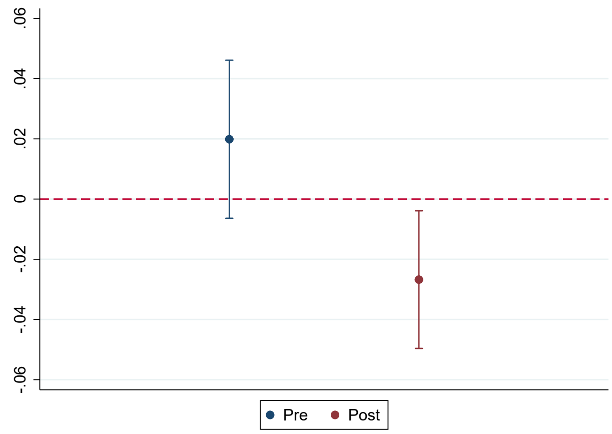
(d) Distribution of state-pairwise R^2 of Γ

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 $\Gamma^{ind}_{j,t-1}$ 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



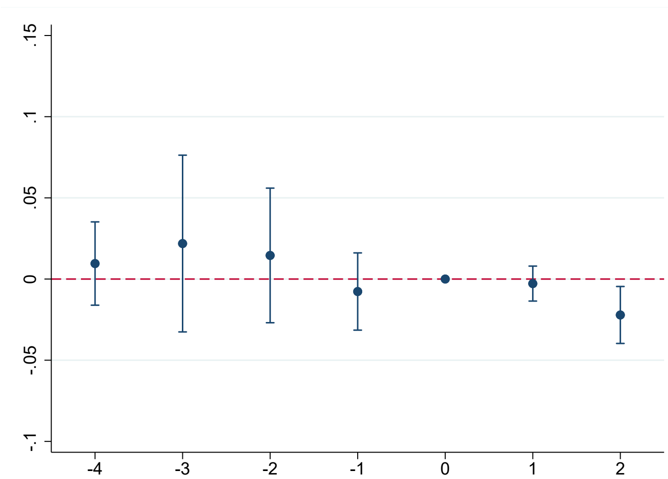
(a) Relation Over Time



(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 $\Gamma^{Avg}_{j,t-1}$ 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

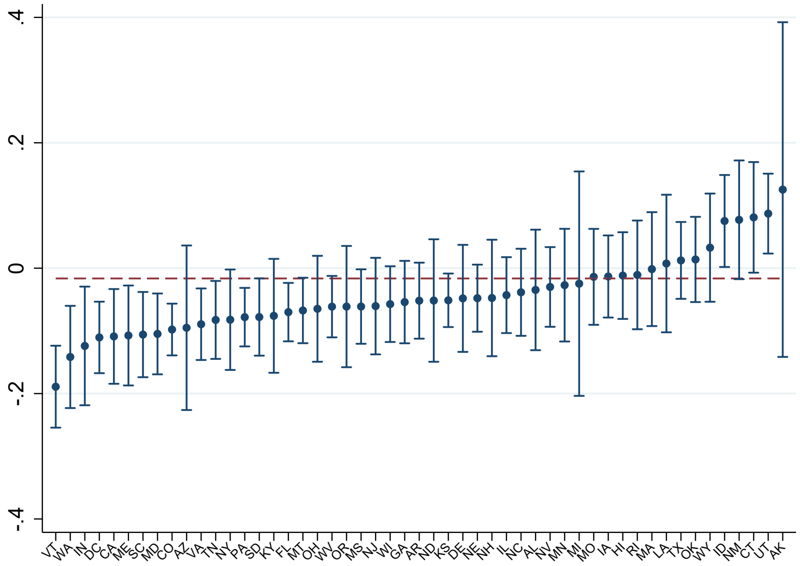


The figure plots the estimated coefficients β_k and the 90% confidence interval from the following equation:

$$\Delta GDP_{i.c,t} = \sum_{k=-4,k\neq-1}^{k=+2} \beta_k Treatment_{i,j,c} \times Time_{i,j,c,t}(t=k) \times \Gamma^{ind}_{j,t-1} + \sum_{k=-4,k\neq-1}^{k=+2} \lambda^1_k Treatment_{i,j,c} \times Time_{i,j,c,t}(=k)$$
$$+ \sum_{k=-4,k\neq-1}^{k=+2} \lambda^2_k Treatment_{i,j,c} \times \Gamma^{ind}_{j,t-1} + \alpha_{i,j,c} + \theta_{i,c} \times t + \theta_{j,c,t} + \varepsilon_{i,j,ct}, i \neq j$$

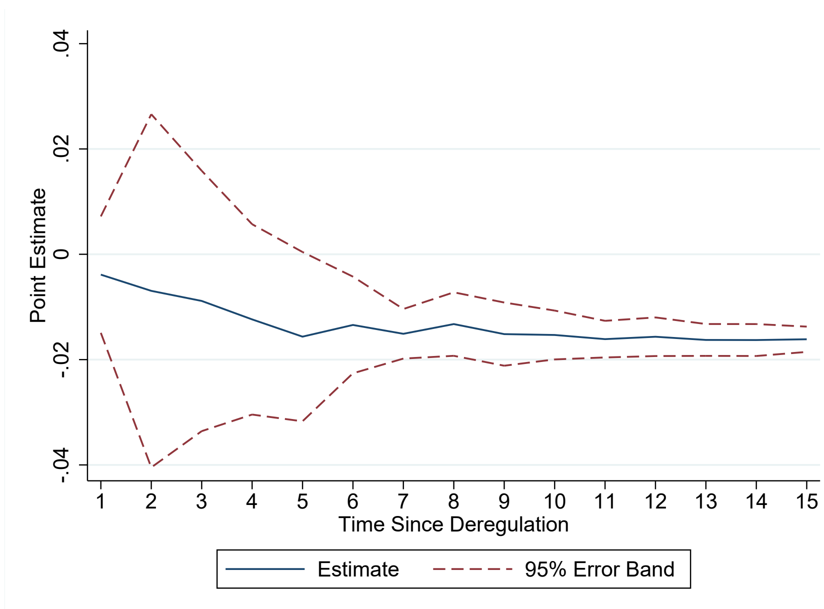
which includes a set of leads and lags of the deregulation between states i and j interacted with state-level idiosyncratic shocks in state j. The excluded category is one year before the deregulation. There are several treatment cohorts (state pairs) in the stacked regression that underwent treatment until 1993. We use state-pairs that underwent treatment in 1994 as the set of controls. We restrict the sample until 1993 to ensure that our control group of state-pairs are never treated in the data. The data is structured at the cohort-state-pair level. Specifically, all state pairs that deregulated in year c are compared to the state pairs that deregulated in 1994. Together, these groups form the treatment and control groups for cohort c. All variables are standardized to mean zero and standard deviation of one. The 90% error bands are estimated using standard errors two-way clustered at the state$_i$ and state$_j$ level.

Figure 4: Heterogeneous Treatment Effects



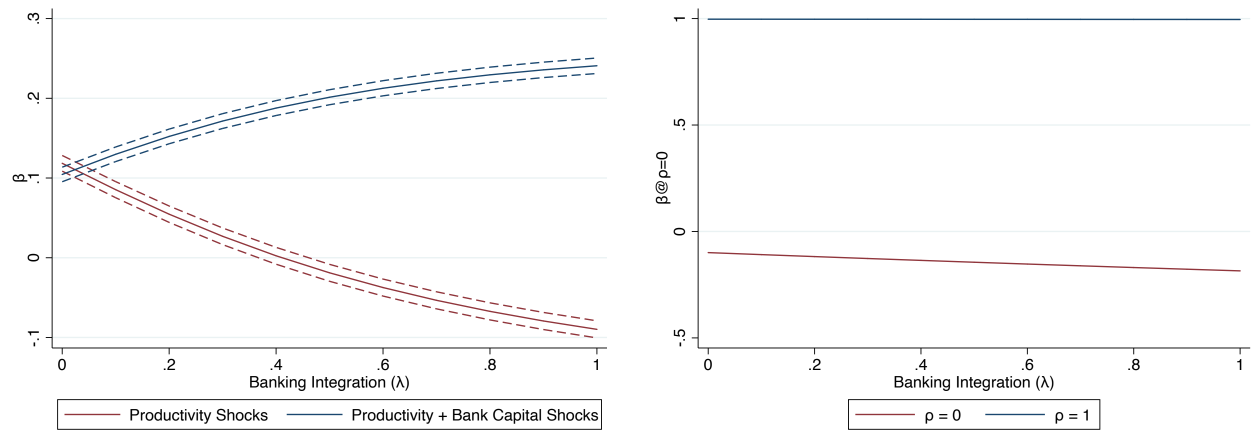
The figure plots the point estimates of the interaction term of post and Γ in the baseline specification for each state, i.e., we run the baseline specification as in Table 3 for each state i and estimate the coefficient of the interaction term of post and Γ. The graph also reports the 90% CI associated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

Figure 5: Long-Run Effect



The figure plots the effect of impact of 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 90% error bands are estimated using standard errors two-way clustered at the state$_i$ and state$_j$ level.

Figure 6: Domestic Growth, Foreign Shocks & Banking Integration

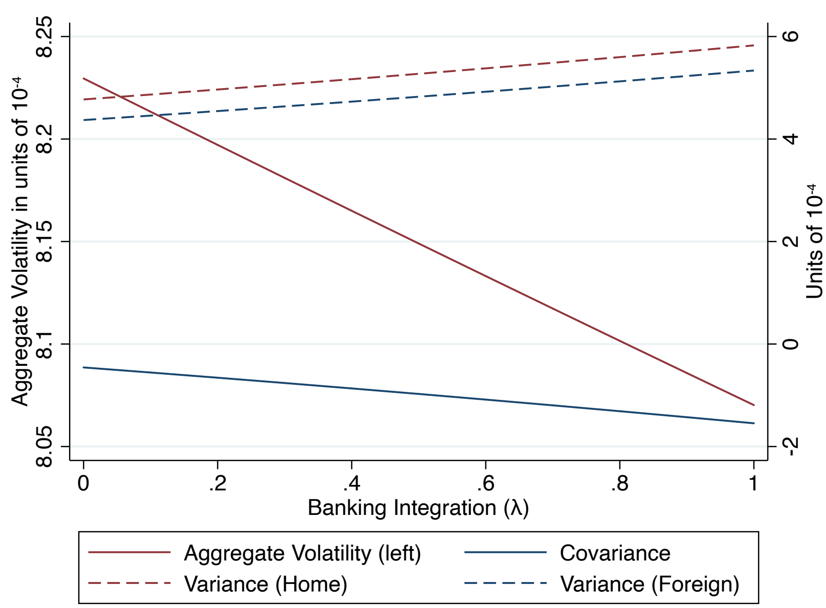


(a) Types of Shocks

(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 6a plots the relationship for different types of shocks - productivity shocks or idiosyncratic shocks and productivity shocks along with bank capital shocks. Figure 6b 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 6b are productivity shocks.

Figure 7: 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 shows 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: 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 Coomunications 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%	Aramco 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 2: Summary Statistics

	N	p25	Median	p75	Mean	Std. Dev.
ΔGDP	1,173	1.400	3.300	5.300	3.247	3.254
Γ^{ind}	1,157	-0.053	0.000	0.059	0.005	0.331
log (C&I Loans)	1,173	15.668	16.526	17.388	16.651	1.334
log(Total Loans)	1,173	17.295	18.036	18.923	18.132	1.262
log(Food Sales)	805	14.228	15.092	15.754	15.024	1.054

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 3: Baseline Specification

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

Δgdp_{it}	(1)	(2)	(3)	(4)	(5)	(6)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0428	-0.0026	-0.0058	-0.0079	-0.0177	-0.0164
	(0.0178)	(0.0005)	(0.0012)	(0.0001)	(0.0021)	(0.0007)
$\Gamma^{ind}_{j,t-1}$	0.0184	0.0010	0.0023	0.0031		
	(0.0155)	(0.0002)	(0.0005)	(0.0000)		
$Post_{i,j,t}$	0.2550	0.0085	0.0764	0.0769	0.0857	0.0783
	(0.0641)	(0.0789)	(0.0605)	(0.0470)	(0.0526)	(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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. 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$_j$.

Table 4: Augmented Specification

$$\Delta gdp_{it} = \beta_0 Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} + \beta_1 Post_{i,j,t} + \beta_3 Post_{i,j,t} \times \Gamma^{ind}_{i,t-1} + \beta_4 \Gamma^{ind}_{i,t-1} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{ijt},$$
$$i \neq j$$

Δgdp_{it}	(1)	(2)	(3)	(4)	(5)	(6)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0436	-0.0028	-0.0051	-0.0071	-0.0159	-0.0141
	(0.0178)	(0.0006)	(0.0014)	(0.0008)	(0.0019)	(0.0015)
$Post_{i,j,t} \times \Gamma^{ind}_{i,t-1}$	-0.0547	0.0017	0.0130	0.0057	0.0057	0.0033
	(0.0351)	(0.0260)	(0.0242)	(0.0213)	(0.0213)	(0.0225)
$\Gamma^{ind}_{j,t-1}$	0.0217	0.0011	0.0021	0.0029		
	(0.0154)	(0.0003)	(0.0005)	(0.0003)		
$\Gamma^{ind}_{i,t-1}$	0.0294	0.0013	-0.0002	0.0011	0.0012	-0.0010
	(0.0294)	(0.0212)	(0.0167)	(0.0169)	(0.0169)	(0.0166)
$Post_{i,j,t}$	0.2519	-0.0081	0.0665	0.0693	0.0776	0.0665
	(0.0669)	(0.0776)	(0.0601)	(0.0467)	(0.0524)	(0.0502)
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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. $\Gamma^{ind}_{i,t-1}$ denotes the idiosyncratic shocks in state i constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state i after accounting for industry-year fixed effects. 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$_j$.

Table 5: Rolling Consumption Correlation and Banking Deregulation

$Corr(cons_{it}, cons_{jt})$	(1)	(2)	(3)	(4)	(5)	(6)
$Post_{i,j,t}$	0.0441	0.0376	0.0384	0.0595	0.0392	0.0234
	(0.0212)	(0.0207)	(0.0199)	(0.0259)	(0.0203)	(0.0097)
State$_i$-State$_j$ FE			Yes	Yes	Yes	Yes
State$_j$-Year FE						Yes
Year FE				Yes		
Region$_i$-Year FE	Yes	Yes	Yes			
Region$_j$-Year FE		Yes	Yes		Yes	
State$_i$-Year FE					Yes	Yes
N	36,346	36,346	36,346	36,346	36,346	36,346
R^2	0.2605	0.3302	0.4309	0.3088	0.6038	0.7884

This table reports the results from the estimation of the following regression specification:

$$\text{Corr}(\text{cons}_{it}, \text{cons}_{jt}) = \beta_0 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{ijt}, i \neq j$$

The dependent variable is the rolling consumption correlation between states i and j, computed over a 5-year window from t-4 until t. State-level consumption is measured as the natural logarigm of the total value of food sales in state i during year t. The unit of observation in each regression is at the state$_i$-state$_j$-year level. Standard errors reported in parentheses are two-way clustered by state$_i$ and state$_j$.

Table 6: Stacked Regression

Δgdp_{it}	(1)	(2)	(3)
Treatment$_{i,j}\times$ Post$_{i,j,t}$ $\times\, \Gamma^{ind}_{j,t-1}$	-0.0204	-0.0203	-0.0185
	(0.0098)	(0.0095)	(0.0091)
Treatment$_{i,j}\times$ Post$_{i,j,t}$	0.0335	0.0299	0.0318
	(0.0516)	(0.0500)	(0.0473)
Treatment$_{i,j}$ $\times\, \Gamma^{ind}_{j,t-1}$	0.0033	0.0028	0.0032
	(0.0089)	(0.0087)	(0.0079)
Post$_{i,j,t}$ $\times\, \Gamma^{ind}_{j,t-1}$	-0.0007	0.0005	
	(0.0011)	(0.0011)	
Post$_{i,j,t}$	0.0015		
	(0.0030)		
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	
Cohort-Year FE		Yes	
Cohort-Treatment FE		Yes	Yes
Region$_i$-Year-Cohort FE			Yes
State$_j$-Year-Cohort FE			Yes
State$_i$-State$_j$-Cohort FE			Yes
State$_i$-Linear Trend-Cohort			Yes
N	218,128	218,128	218,128
R^2	0.6704	0.6707	0.6743

This table reports the results from the estimation of baseline specification using the stacked regression framework. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. There are several treatment cohorts (state pairs) in the stacked regression that underwent treatment until 1993. We use state-pairs that underwent treatment in 1994 as the set of controls. We restrict the sample until 1993 to ensure that our control group of state-pairs are never treated in the data. The data is structured at the cohort-state-pair level. Specifically, all state pairs that deregulated in year c are compared to the state pairs that deregulated in 1994. Together, these groups form the treatment and control groups for cohort c. The results indicate that our baseline finding is robust to issues arising due to treatment effect heterogeneity across treated cohorts. 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$_j$.

Table 7: Instrumental Variables Regression

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

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

	(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		7.5966		5.3601		4.1422
		(0.5844)		(2.8664)		(0.5940)		(1.5187)
Post$_{i,j,t}$	0.4169	-0.5600	-0.0300	0.2729	-0.0272	0.2023	-0.0240	0.1596
	(0.0877)	(0.2641)	(0.0553)	(0.4208)	(0.0545)	(0.2668)	(0.0539)	(0.2070)
Post$_{i,j,t}\times\Gamma^{ind}_{j,t-1}$	-0.0492		-0.0077		-0.0092		-0.0067	
	(0.0211)		(0.0040)		(0.0039)		(0.0031)	
$\Gamma^{ind}_{j,t-1}$	0.0200							
	(0.0129)							
Post$_{i,j,t}\times\Gamma^{ind}_{j,t-2}$					-0.0091		-0.0082	
					(0.0019)		(0.0020)	
$\Gamma^{ind}_{i,t-1}$							-0.0110	0.0469
							(0.0102)	(0.0432)
$\Gamma^{ind}_{i,t-2}$							-0.0206	0.0783
							(0.0085)	(0.0445)
Constant	16.4706	-30.9787						
	(0.1786)	(9.5737)						
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	50,838	50,838	50,838	50,838	50,561	50,561	50,180	50,180
Hansen χ^2 p-value	0.5569		1.0000		0.4076		0.9206	
Anderson-Rubin χ^2	10.27		5.84		20.80		12.09	
Anderson-Rubin χ^2 p-value	0.0059		0.0157		0.0000		0.0024	
KP LM statistic	3.908		2.201		4.762		7.596	
KP χ^2 p-value	0.1417		0.1380		0.0925		0.0224	
KP F-Statistic	2.997		3.750		12.421		10.868	
Sanderson-Windmeijer F statistic	3.00		3.75		12.42		10.87	
Sanderson-Windmeijer F statistic p-value	0.0592		0.0586		0.0000		0.0001	

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. The unit of observation in each regression is a state$_i$-state$_j$-year pair. Observations are weighted by the share of exports from state i to state j, using the 1977 Commodity Flow Survey Data. All non-binary variables used in the regression are standardized to mean zero and variance 1 except $log(C\&I - Loan_{i,t})$. Standard errors reported in parentheses are two-way clustered by state$_i$ and state$_j$.

Table 8: Asymmetric Effect by Properties of Shock

Δgdp_{it}	(1)	(2)	(3)
$Low-R^2 \times Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0111		
	(0.0006)		
$Low-R^2 \times Post_{i,j,t}$	-0.0023		
	(0.0012)		
$Low-AR(1) \times Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$		-0.0073	
		(0.0033)	
$Low-AR(1) \times Post_{i,j,t}$		-0.0057	
		(0.0019)	
$(Neg=1) \times Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$			-0.0101
			(0.0100)
$(Neg=1) \times Post_{i,j,t}$			-0.0387
			(0.0151)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0074	-0.0121	-0.0205
	(0.0011)	(0.0033)	(0.0045)
$Post_{i,j,t}$	0.0815	0.0812	0.0992
	(0.0501)	(0.0484)	(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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. 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$_i$. $\mathbb{N}\mathrm{eg} = \mathbb{1}$ 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$_j$.

Table 9: Reallocation of Funds to Bank-Dependent Firms

	(1)	(2)	(3)	(4)
	$\Delta Ln(Debt)_{f,t}$	$\Delta Ln(Sales)_{f,t}$	$\frac{M_{f,t}}{B_{f,t}}$	$\Delta Ln(Inventory)_{f,t}$
$Young_f \times Post_{i,t} \times \Gamma^{avg}_{j,t-1}$	-0.7539	-0.4722	-0.4601	-0.8924
	(0.3690)	(0.2515)	(0.1206)	(0.4345)
$Post_{i,t} \times \Gamma^{avg}_{j,t-1}$	0.5137	0.0857	-0.0265	0.4141
	(0.1841)	(0.1753)	(0.1038)	(0.2160)
$Young_f \times \Gamma^{avg}_{j,t-1}$	0.9111	0.1695	0.0531	0.7623
	(0.2076)	(0.1651)	(0.0683)	(0.3241)
$Young_f \times Post_{i,t}$	0.0126	0.2986	0.4332	-0.0564
	(0.1220)	(0.0974)	(0.1725)	(0.1281)
$Post_{i,t}$	0.1461	-0.0572	0.0170	0.1403
	(0.0824)	(0.0702)	(0.0657)	(0.0718)
$\Gamma^{avg}_{j,t-1}$	-0.4733	0.0341	0.3585	-0.0446
	(0.4289)	(0.2809)	(0.3468)	(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 $Young_f \times Post_{i,t} \times \Gamma^{avg}_{j,t-1}$. 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. $\Gamma^{avg}_{j,t-1}$ 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.

Table 10: Domestic Small Firms, Banking Integration & Shocks to Large Foreign Firms

$\Gamma_{i,t}^{ind}$	(1) Small Firms	(2) Large Firms
$Post_{i,j,t} \times \Gamma_{j,t-1}^{ind}$	-0.0134	0.0021
	(0.0032)	(0.0222)
$Post_{i,j,t}$	0.0021	-0.2470
	(0.0393)	(0.1502)
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	38,454	40,376
R^2	0.4511	0.2924

This table reports the results from regressing the idiosyncratic shock experienced by small and large firms in the home state on lagged foreign idiosyncratic shocks. The dependent variable is the idiosyncratic shock experienced in the home state by small (large) firms in column 1 (2). 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 firms, by sales 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 one. Standard errors reported in parentheses are two-way clustered by state$_i$ and state$_j$.

Table 11: Bank Constraint and Transmission of Idiosyncratic Shocks

Δgdp_{it}	(1)	(2)	(3)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0164	-0.0148	0.0630
	(0.0007)	(0.0011)	(0.0339)
$Post_{i,j,t}$	0.0783	0.5134	0.5066
	(0.0491)	(0.1768)	(0.1755)
$Post_{i,j,t} \times Constrained_j$		-0.8572	-0.8431
		(0.3360)	(0.3325)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times Constrained_j$			-0.1481
			(0.0657)
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	57,700	57,700	57,700
R^2	0.6583	0.6583	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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j. The unit of observation in each regression is a state$_i$-state$_j$-year pair. We account for the degree of bank constraint for each state by weighting a bank's level of constraint in each state by the bank's share of lending in that particular state. Bank constraint is measured as $\frac{Liabilities}{Assets}$ in each year. We sum across these values at the state-year level to produce a measure of bank constraint at the state level for each year. We use the mean value of the state-bank constraint, in the years prior to deregulation as our measure of *Constrained*. All non-binary variables used in the regression are standardized to mean zero and variance one. Standard errors reported in parentheses are two-way clustered by state$_i$ and state$_j$.

Table 12: Baseline Specification Accounting for Shocks to Small and Large Firms

Δgdp_{it}	(1)	(2)	(3)	(4)	(5)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0164	-0.0141	-0.0172	-0.0100	-0.0138
	(0.0007)	(0.0015)	(0.0031)	(0.0041)	(0.0046)
$Post_{i,j,t} \times \Gamma^{ind}_{i,t-1}$		0.0033	0.0040	-0.0110	-0.0116
		(0.0225)	(0.0227)	(0.0208)	(0.0209)
$\Gamma^{ind}_{i,t-1}$		-0.0010	-0.0014	0.0206	0.0209
		(0.0166)	(0.0169)	(0.0138)	(0.0138)
$Post_{i,j,t}$	0.0783	0.0665	0.0720	0.1119	0.1157
	(0.0491)	(0.0502)	(0.0517)	(0.0569)	(0.0590)
$Post_{i,j,t} \times \Gamma^{ind,small}_{j,t-1}$			0.0069		0.0134
			(0.0045)		(0.0051)
$\Gamma^{ind,small}_{i,t-1}$				-0.0128	-0.0143
				(0.0171)	(0.0169)
$Post_{i,j,t} \times \Gamma^{ind,small}_{i,t-1}$				0.0233	0.0252
				(0.0243)	(0.0240)
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	56,758	40,872	40,872	29,260
R^2	0.6583	0.6897	0.6907	0.7463	0.7477

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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j. $\Gamma^{ind,small}_{j,t-1}$ ($\Gamma^{small}_{i,t-1}$) denotes the idiosyncratic shocks in state j (i) constructed by aggregating the Domar weighted labor productivity shocks of small firms – firms that are in not in the top 10 firms, by sales – in state j (i). $\Gamma^{ind}_{j,t-1}$ ($\Gamma^{ind}_{i,t-1}$) denotes the idiosyncratic shocks in state j (i) constructed by aggregating the Domar weighted labor productivity shocks of large firms – firms that are in the top 10 firms, by sales – in state j (i). 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$_j$.

Table 13: Estimation Accounting for Loan Loss Provision Shocks

Δgdp_{it}	(1)	(2)	(3)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0164	-0.0161	-0.0162
	(0.0007)	(0.0019)	(0.0022)
$Post_{i,j,t}$	0.0783	0.0773	0.0772
	(0.0491)	(0.0491)	(0.0492)
$Post_{i,j,t} \times LLP_{j,t-1}$		-0.0118	-0.0120
		(0.0012)	(0.0014)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times LLP_{j,t-1}$			0.0008
			(0.0039)
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	57,700	57,700	57,700
R^2	0.6583	0.6583	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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j. The unit of observation in each regression is a state$_i$-state$_j$-year pair. We account for annual loan loss provision for each state. We weight a bank's loan loss provision in each state by banks' share of lending in that particular state. We then sum across these values at the state year level to produce a measure of loan loss provision at the state level. All non-binary variables used in the regression are standardized to mean zero and variance one. Standard errors reported in parentheses are two-way clustered by state$_i$ and state$_j$.

Table 14: Baseline Specification with Controls

Δgdp_{it}	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0194	-0.0161	-0.0187	-0.0190	-0.0219	-0.0183	-0.0121
	(0.0005)	(0.0033)	(0.0084)	(0.0047)	(0.0030)	(0.0022)	(0.0068)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times$ Exports$_{i,j,pre}$		-0.0057					-0.0054
		(0.0020)					(0.0044)
$Post_{i,j,t} \times$ Exports$_{i,j,pre}$		-0.0071					-0.0099
		(0.0054)					(0.0052)
$\Gamma^{ind}_{j,t-1} \times$ Exports$_{i,j,pre}$		-0.0005					-0.0011
		(0.0006)					(0.0030)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times$ Imports$_{i,j,pre}$		-0.0019					-0.0000
		(0.0050)					(0.0074)
$Post_{i,j,t} \times$ Imports$_{i,j,pre}$		-0.0051					-0.0071
		(0.0095)					(0.0097)
$\Gamma^{ind}_{j,t-1} \times$ Imports$_{i,j,pre}$		0.0060					0.0014
		(0.0034)					(0.0061)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times$ Income$_{j,pre}$			0.0131				0.0102
			(0.0102)				(0.0083)
$Post_{i,j,t} \times$ Income$_{j,pre}$			0.0345				0.0436
			(0.0232)				(0.0326)
$\Gamma^{ind}_{j,t-1} \times$ Income$_{j,pre}$			-0.0047				-0.0015
			(0.0083)				(0.0074)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times$ Income Covariance$_{i,j,pre}$				-0.0067			-0.0084
				(0.0114)			(0.0145)
$Post_{i,j,t} \times$ Income Covariance$_{i,j,pre}$				0.0020			0.0143
				(0.0635)			(0.0831)
$\Gamma^{ind}_{j,t-1} \times$ Income Covariance$_{i,j,pre}$				0.0054			0.0017
				(0.0056)			(0.0063)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times$ GDP Covariance$_{i,j,pre}$					-0.0039		0.0007
					(0.0090)		(0.0113)
$Post_{i,j,t} \times$ GDP Covariance$_{i,j,pre}$					0.0036		0.0087
					(0.0168)		(0.0177)
$\Gamma^{ind}_{j,t-1} \times$ GDP Covariance$_{i,j,pre}$					0.0072		0.0055
					(0.0084)		(0.0097)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times$ Industry Similarity$_{i,j,pre}$						0.0022	-0.0020
						(0.0062)	(0.0088)
$Post_{i,j,t} \times$ Industry Similarity$_{i,j,pre}$						-0.0072	-0.0065
						(0.0235)	(0.0320)
$\Gamma^{ind}_{j,t-1} \times$ Industry Similarity$_{i,j,pre}$						-0.0072	-0.0052
						(0.0037)	(0.0054)
$Post_{i,j,t}$	0.0874	0.0879	0.0955	0.0871	0.0869	0.0875	0.0963
	(0.0518)	(0.0519)	(0.0552)	(0.0523)	(0.0523)	(0.0517)	(0.0551)
Region_i-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State_i-State_j FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State_j-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State_i-Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	53,445	53,445	53,445	53,445	53,445	53,445	53,445
R^2	0.6661	0.6661	0.6662	0.6661	0.6661	0.6661	0.6663

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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. The unit of observation in each regression is a state$_i$-state$_j$-year pair. We include additional control variables including Exports from state i to state j, Imports from state i to state j, personal income per capital in state j, the similarity in industry composition between states i and j, and covariance in personal income growth between states i and j measured before deregulation. 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$_j$.

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

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Appendix A Framework

A.1 Relationship between domestic growth and foreign shocks

This section develops a simple framework where the transmission of idiosyncratic 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.

$$\frac{\Delta l_{it}^{k}}{l_{i,t-1}^{k}} = a_t + \eta_t^k + \nu_{it} - \sum_{j \neq i}^{j \in I} \frac{l_{j,t-1}^{k}}{l_{t-1}^{k}} \nu_{jt} \tag{A.1}$$

Equation A.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 $\frac{l_{j,t-1}^{k}}{l_{t-1}^{k}}$ 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 $\Sigma_\eta = \sigma_\eta^2 1$, where 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, ν_{it}, and foreign shocks, ν_{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 A.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 ν_{it} is given by $\sigma_\nu^2 1$, where 1 denotes an identity matrix. We make additional assumptions that include $\mathbb{E}[a_t \eta_t^k] = 0$; $\mathbb{E}[a_t \nu_{it}] = 0 \; \forall \, i \in I$; $\mathbb{E}[\eta_t^k \nu_{it}] = 0 \; \forall i \in I$ and $\forall \, k \in K$;

$\mathbb{E}[\nu_{jt}\nu_{it}] = 0 \; \forall \; i \neq j$.

Economic growth in state i can be described by the equation A.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 $\mathbb{E}[\varepsilon_{it}\nu_{jt}] = 0$.

$$\frac{\Delta y_{it}}{y_{i,t-1}} = \mu \frac{\Delta l_{it}}{l_{i,t-1}} + \varepsilon_{it} \tag{A.2}$$

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

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

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 A.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 A.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.

A.2 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 7. 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 A.1.

$$\frac{\Delta y_{it}}{y_{i,t-1}} = \mu\{a_t + \nu_{it} + \sum_{k\in K} \eta_t^k \frac{l_{i,t-1}^k}{l_{i,t-1}} - \sum_{j\neq i} \nu_{jt} \sum_{k\in K} (\frac{l_{i,t-1}^k}{l_{i,t-1}} \times \frac{l_{j,t-1}^k}{l_{t-1}^k})\} + \varepsilon_{it} \tag{A.4}$$

A.2.1 Variance Equation

The variance of economic growth in state i using equation A.4 is given by equation A.5 where, $H_{it} \equiv \sum_{k\in K}\{\frac{l_{i,t-1}^k}{l_{i,t-1}}\}^2$, and $H_{kt}^{-i} \equiv \sum_{j\neq i}(\frac{l_{j,t-1}^k}{l_{t-1}^k})^2$. Equation A.5 connects domestic economic volatility with banking integration and foreign shocks, wherein the volatility of economic activity in state i increases as banking integration increases.

$$\mathrm{Var}[\frac{\Delta y_{it}}{y_{i,t-1}}] = \mu^2\sigma_a^2 + \mu^2\sigma_\eta^2 \times H_{it} + \mu^2\sigma_\nu^2(1 + \sum_{k\in K}(\frac{l_{i,t-1}^k}{l_{i,t-1}})^2 \times H_{kt}^{-i}) + \sigma_\varepsilon^2 \tag{A.5}$$

A.2.2 Covariance Equation

Next, we employ equation A.4 to derive the covariance equation. For simplicity in notation we present the covariance of economic growth for state 1 and 2 in equation A.6.

$$\begin{aligned}\mathrm{Cov}[\frac{\Delta y_{1t}}{y_{1,t-1}}, \frac{\Delta y_{2t}}{y_{2,t-1}}] = \mu^2\{\sigma_a^2 + \sigma_\eta^2(\sum_{k\in K}\frac{l_{1,t-1}^k}{l_{1,t-1}} \times \frac{l_{2,t-1}^k}{l_{2,t-1}}) - \sigma_\nu^2(\frac{l_{1,t-1}+l_{2,t-1}}{l_{2,t-1}})(\sum_{k\in K}\frac{l_{1,t-1}^k}{l_{1,t-1}} \times \frac{l_{2,t-1}^k}{l_{t-1}^k}) \\ + \sigma_\nu^2 \sum_{j\neq 1,2}(\sum_{k\in K}\frac{l_{1,t-1}^k \times l_{j,t-1}^k}{l_{1,t-1}\times l_{t-1}^k} \times \sum_{k\in K}\frac{l_{2,t-1}^k \times l_{j,t-1}^k}{l_{2,t-1}\times l_{t-1}^k})\}\end{aligned} \tag{A.6}$$

The net effect of financial integration on covariance seems ambiguous. However, the negative term associated with financial integration and idiosyncratic shocks is of order 3 whereas the positive term associated with financial integration and idiosyncratic shocks is of order 4. It remains a quantitative question whether the net effect of financial integration and idiosyncratic 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 7.

A.3 Equivalence between baseline and collapsed specification

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.

$$\Delta GDP_{it} = \beta_0 Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} + \beta_1 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{i,j,t}, i \neq j \tag{A.7}$$

ΔGDP_{it} denotes real GDP growth for state i, $\Gamma^{ind}_{j,t-1}$ 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 operate 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 $\Gamma^{ind}_{j,t-1}$ as it is absorbed within θ_{jt}. We also control for $\theta_i \times t$ denoting the linear trend specific to state i.[35] $\varepsilon_{i,j,t}$ 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. Furthermore, the state-pair level regression enables us to account for time-varying factors specific to the origin state of idiosyncratic shocks, as well as 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.

As a clarification, note that each state$_i$ appears $N-1$ times in the regression sample each year using the granular residual of each state$_j$ as a regressor at a time ($i \neq j$), where N is the total number of states in the sample. To implement this, we estimate $N-1$ equations for each state i as represented by the following system of equations:

$$\begin{aligned}
\Delta GDP_{i,t} &= \beta_0 Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} + \beta_1 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{j,t} + \varepsilon_{i,j,t} \\
&= \dots \\
&= \beta_0 Post_{i,k,t} \times \Gamma^{ind}_{k,t-1} + \beta_1 Post_{i,k,t} + \alpha_i \times \alpha_k + \theta_i \times t + \theta_{k,t} + \varepsilon_{i,k,t}
\end{aligned} \tag{A.8}$$

[35] Our results are robust to the exclusion of $\theta_i \times t$.

Adding all of the equations for state i yields the following:

$$
\begin{aligned}
(N-1)\Delta GDP_{i,t} &= \beta_0 \left(\sum_j Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \right) + \beta_1 \sum_j Post_{i,j,t} \\
&\quad + \sum_j \alpha_i \times \alpha_j + (N-1)\theta_i \times t + \sum_j \theta_{j,t} + \sum_j \varepsilon_{i,j,t} \qquad \text{(A.9)} \\
\implies \Delta GDP_{i,t} &= \frac{\beta_0}{N-1} \left(\sum_j Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \right) + \frac{\beta_1}{N-1} \sum_j Post_{i,j,t} \\
&\quad + \left(\theta_i \times t + \frac{1}{N-1} \cdot \sum_j \alpha_i \times \alpha_j \right) + \frac{1}{N-1} \cdot \sum_j \theta_{j,t} + \frac{1}{N-1} \cdot \sum_j \varepsilon_{i,j,t} \\
&= \beta_0^* \left(\sum_j Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \right) + \beta_1^* \sum_j Post_{i,j,t} + \beta_2^* \sum_j \Gamma^{ind}_{j,t-1} + \theta_i^* \times t + \theta_t^* + \varepsilon^*_{i,t}
\end{aligned}
$$

$$\text{(A.10)}$$

where, $\frac{1}{N-1} \cdot \sum_j \theta_{j,t} = \beta_2^* \cdot \frac{1}{N-1} \cdot \sum_j \Gamma^{ind}_{j,t-1} + \theta_t^*$

Equation A.10 can be estimated at state-year (i, t) level and the interpretation of the estimate of interest, i.e., the coefficient of the interaction term of Post and foreign idiosyncratic shocks, is similar to the estimate obtained from the system of equation in specification 3.

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.

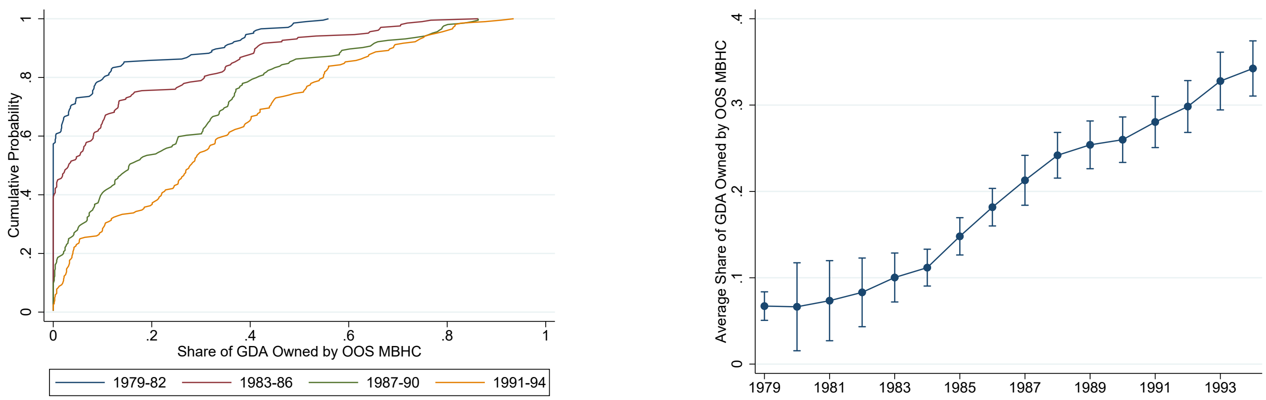
B.1 Data

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 estimate 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 generating 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 ≈ 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	0.1966	0.0753	0.0708	0.0706
	(0.0443)	(0.0324)	(0.0291)	(0.0304)	(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

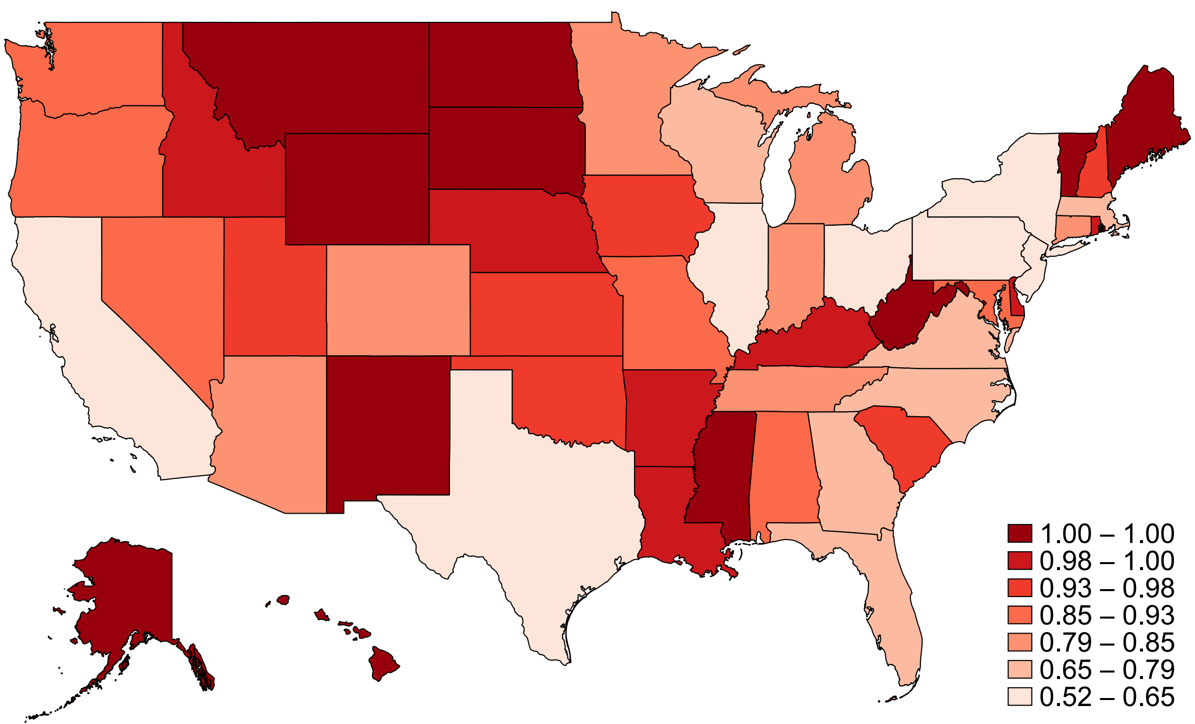
The table reports the regression of the share of gross domestic assets (GDA) owned by out-of-state (OOS) MBHCs on the Post (=1) variable. The variable Post (=1) takes a value of 1 after the median deregulation year. Median deregulation year is defined as the year by when that state deregulated with at 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.

Appendix C Properties of Idiosyncratic Shocks

C.1 Presence of Fat Tails

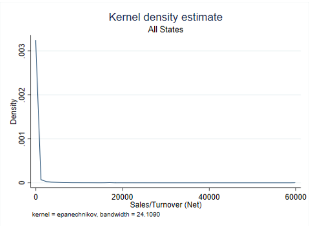
We begin our analysis by verifying that each state is dominated by large firms. We examine the ratio of sales by top 10 firms by sales to the sales of all firms for each state and find strong evidence of dominance of state-level economies by large firms. Figure C.1 shows the average proportion of sales 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 headquartered 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

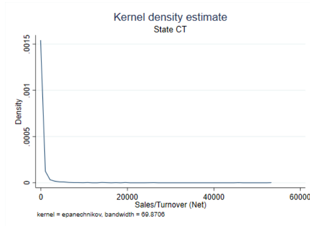


The figure plots the cross-sectional distribution of sales of top 10 firms in the state to the sales of all firms in that state between 1978 to 1995. We report the time-series average of the sales ratio of top 10 firms for each state. The legend denotes the ratio of sales of top 10 firms in the state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

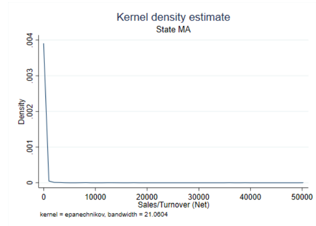
Figure C.2: Sales Distribution for HQ Firms in Each State



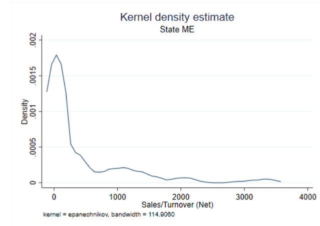
(a) All States



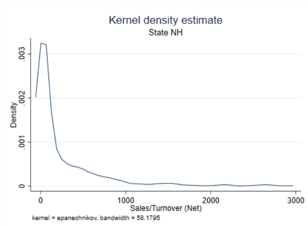
(b) Connecticut



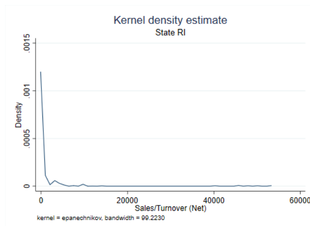
(c) Massachusetts



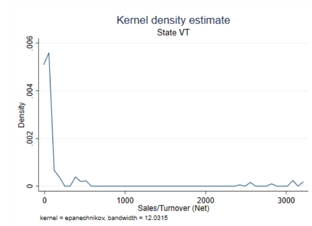
(d) Maine



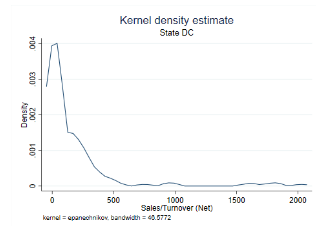
(e) New Hamphshire



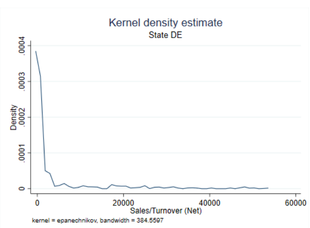
(f) Rhode Island



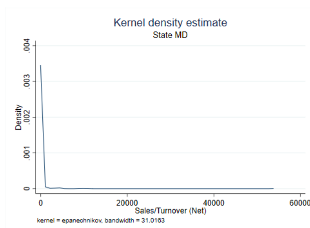
(g) Vermont



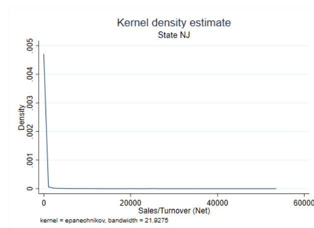
(h) DC



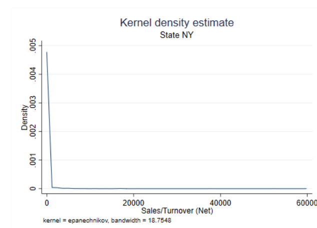
(i) Delaware



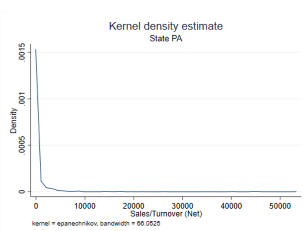
(j) Maryland



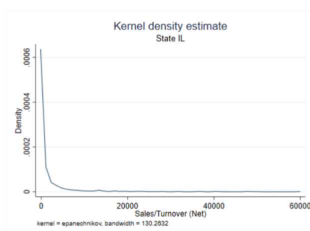
(k) New Jersey



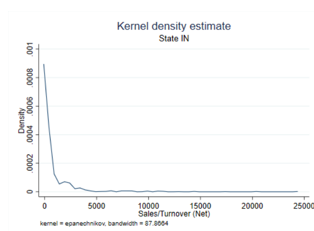
(l) New York



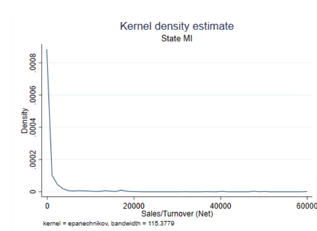
(m) Pennsylvania



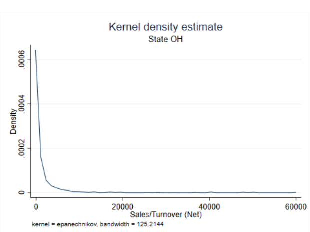
(n) Illinois



(o) Indiana



(p) Michigan



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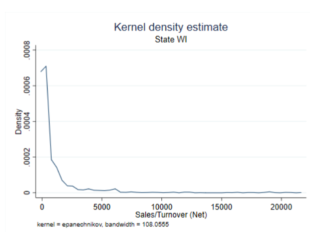

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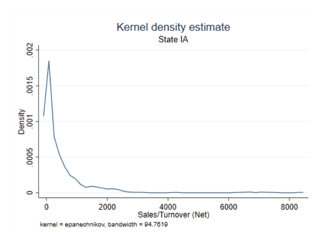

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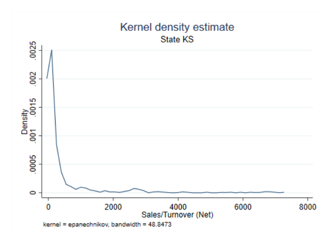
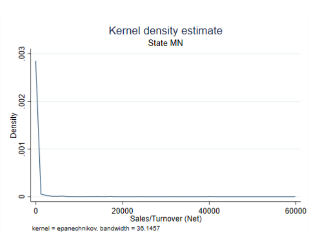
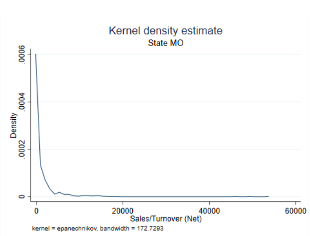


(t) Kansas



(u) Minnesota



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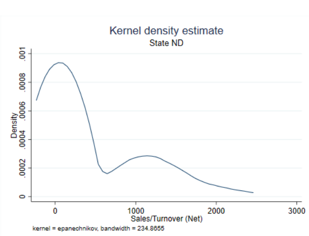

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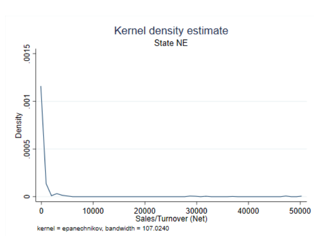

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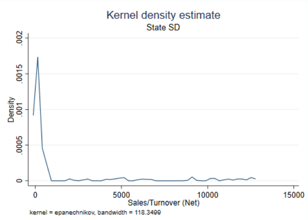
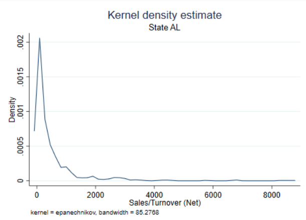
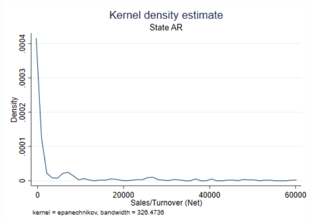


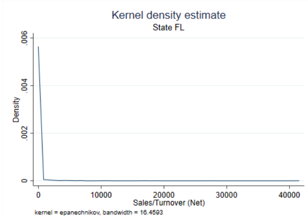
(a) South Dakota



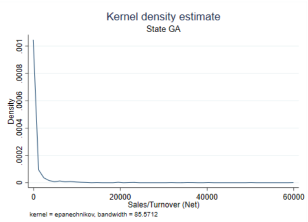
(b) Alabama



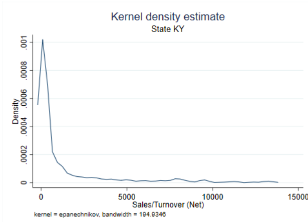
(c) Arkansas



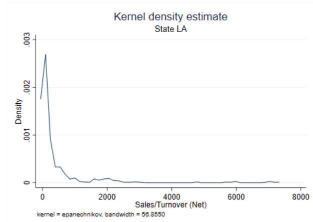
(d) Florida



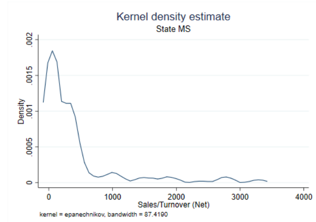
(e) Georgia



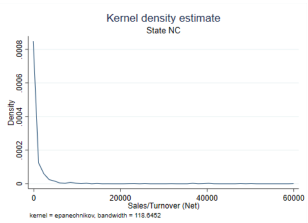
(f) Kentucky



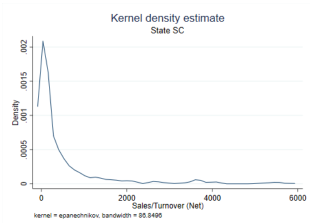
(g) Louisiana



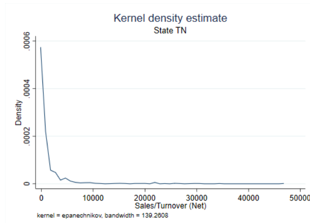
(h) Minnesota



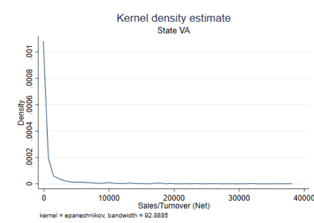
(i) North Carolina



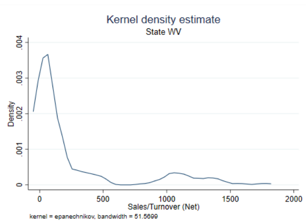
(j) South Carolina



(k) Tennessee



(l) Virginia



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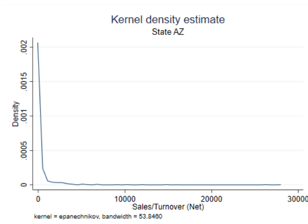
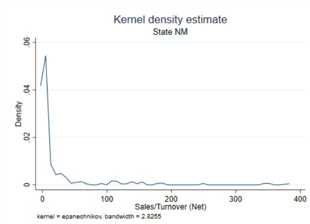
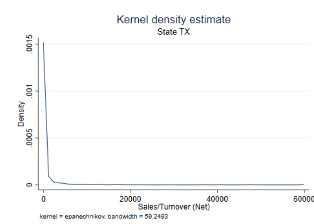


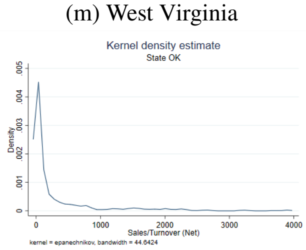
(n) Arizona



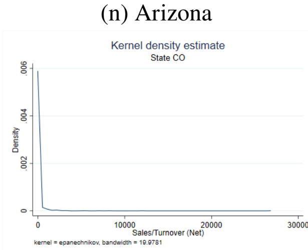
(o) New Mexico



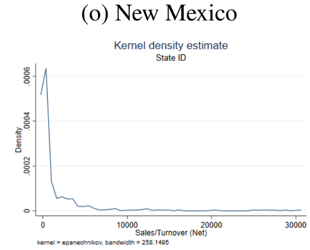
(p) Texas



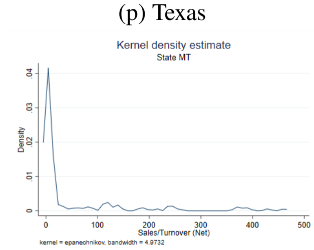
(q) Oklahoma



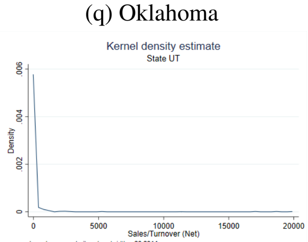
(r) Colorado



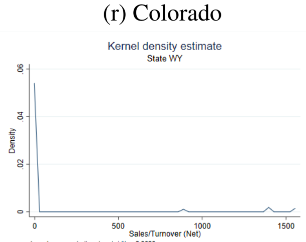
(s) Idaho



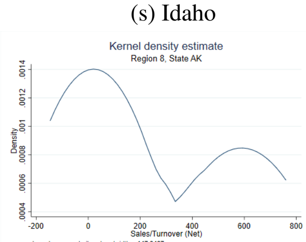
(t) Montana



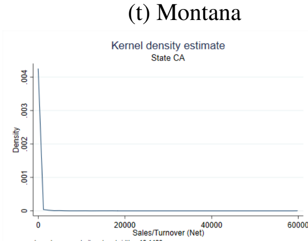
(u) Utah



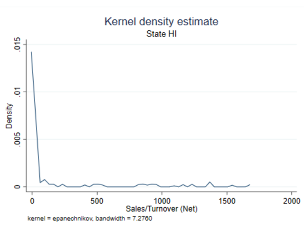
(v) Wyoming



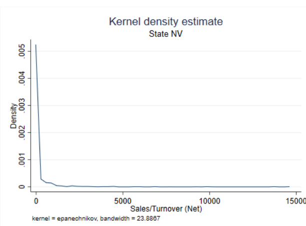
(w) Alaska



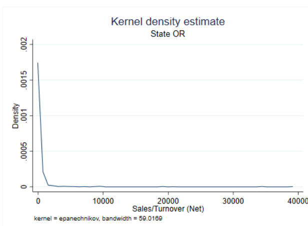
(x) California



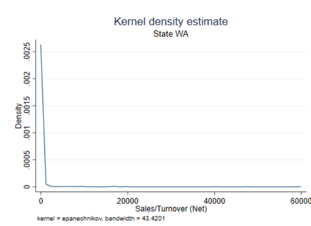
(a) Hawaii



(b) Nevada



(c) Oregon

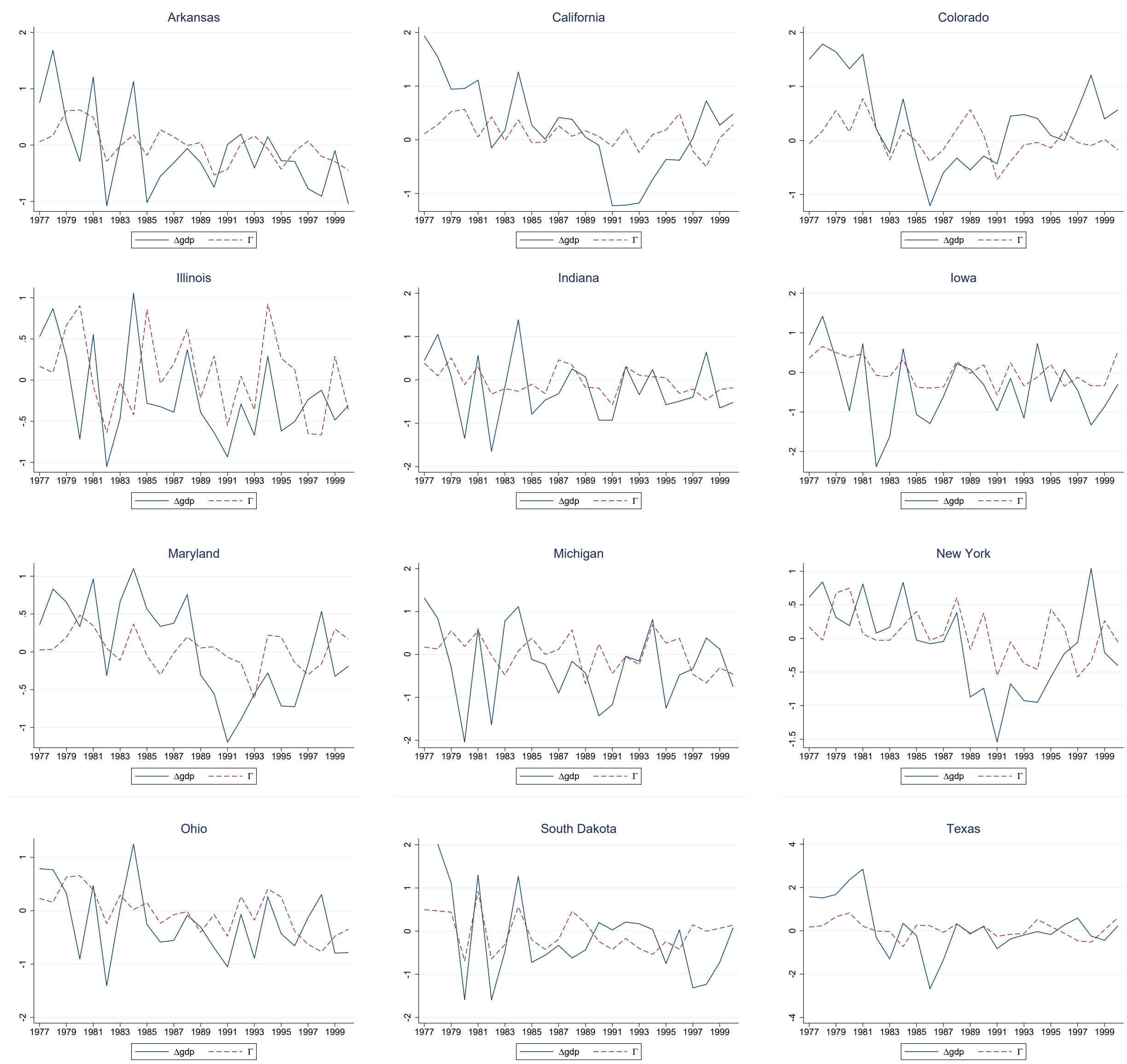


(d) Washington

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

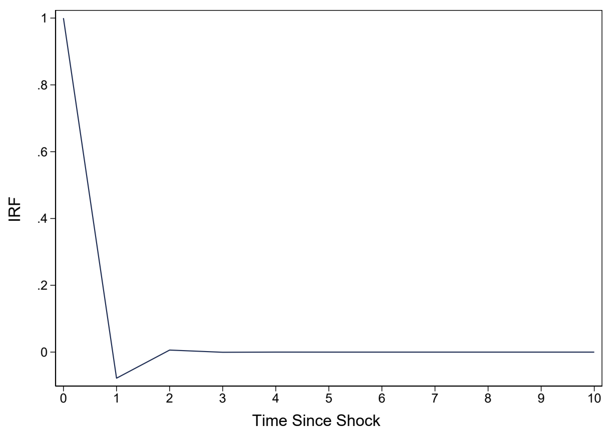


The figure plots the relation between idiosyncratic shocks Γ_t and subsequent annual economic growth Δgdp_{t+1} for some selected states. All variables are standardized to mean 0 and variance 1. The sample period spans from 1977 to 2000.

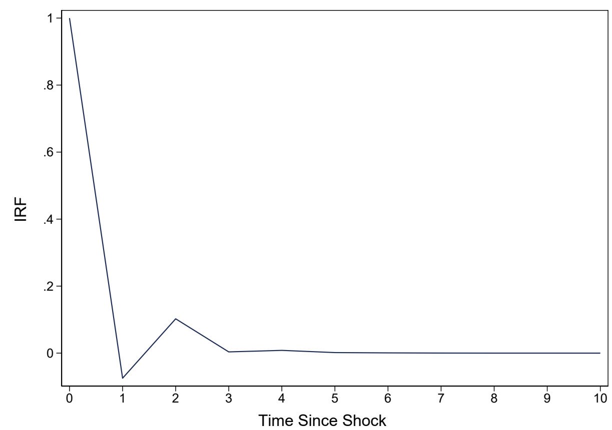
C.3 Persistence of Idiosyncratic shocks

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



(a) IRF from an AR(1) model for Γ



(b) IRF from an AR(3) model for Γ

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

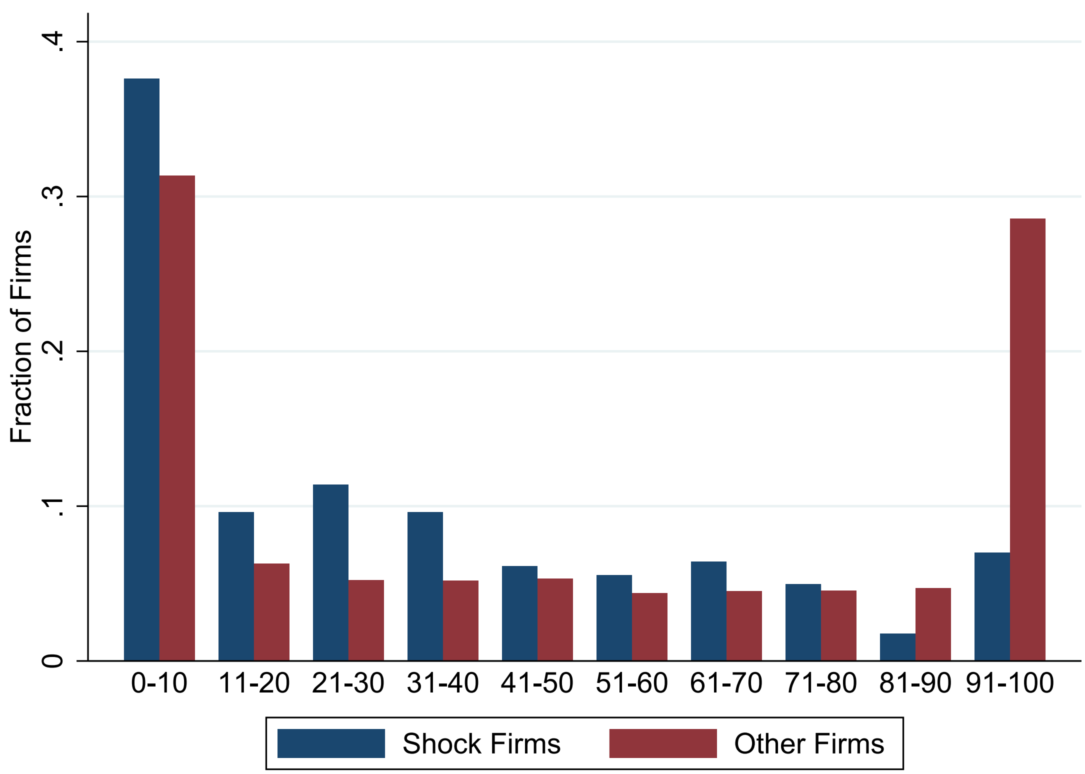
This section compares the ratio of bank debt to total debt for firms used to construct state level idiosyncratic shocks (shock firms) to all other firms in the S&P Capital IQ database. The data on bank debt and total debt comes from Capital IQ database. Due to data limitations we can only compare the 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	

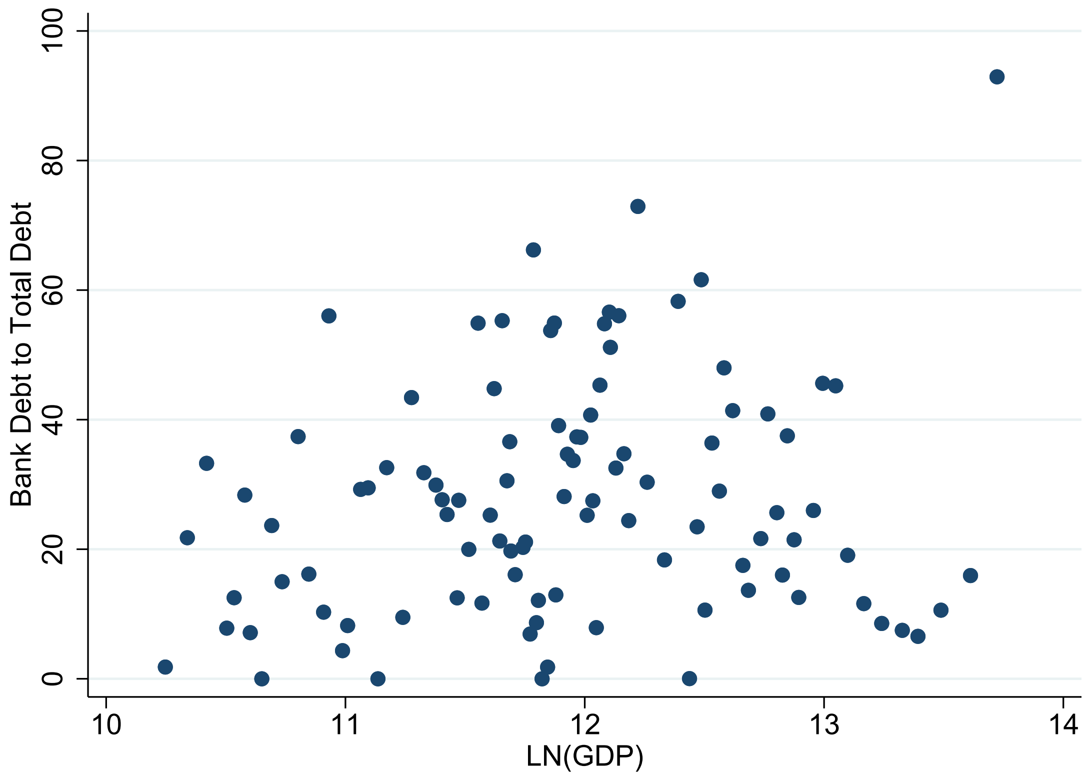
This table reports mean, median and the standard deviation for the bank debt to total debt ratio in percentage. Shock firms refer to the top 10 firms in each state used to construct state-level idiosyncratic shocks. All other firms not used to construct state-level idiosyncratic shocks are classified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

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.

C.5 Effect of Idiosyncratic Shocks on Bank Capital

Table C.2: Effect of Idiosyncratic Shocks on Bank Capital

Panel A: Bank Constraint$_{j,t}$	(1)	(2)	(3)
$\Gamma^{ind}_{j,t-1}$	-0.0013	-0.0005	-0.0027
	(0.0040)	(0.0032)	(0.0021)
Year FE		Yes	Yes
State FE			Yes
N	1,154	1,154	1,154
R^2	0.0000	0.3573	0.7714

Panel B: Bank Deposits$_{j,t}$	(1)	(2)	(3)
$\Gamma^{ind}_{j,t-1}$	-0.0115	-0.0049	0.0157
	(0.0165)	(0.0165)	(0.0119)
Year FE		Yes	Yes
State FE			Yes
N	1,154	1,154	1,154
R^2	0.0002	0.1133	0.7578

This table reports the effect of idiosyncratic shocks on bank constraint (Panel A) and bank deposits (Panel B). The main independent variable is $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. The unit of observation is at the state-year level. We account for the degree of bank constraint for each state by weighting a bank's level of constraint in each state by the bank's share of lending in that particular state. Bank constraint is measured as $\frac{Liabilities}{Assets}$ in each year. We sum across these values at the state-year level to produce a measure of bank constraint at the state level for each year. Bank deposits are measured as $\frac{Deposits}{Assets}$ in each year. We sum across these values at the state-year level to produce a measure of bank deposits at the state level for each year. All non-binary variables used in the regression are standardized to mean zero and variance one. Standard errors reported in parentheses are clustered by state$_j$.

Appendix D Framework for IV Design

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), $\phi^{NB}_{i,j}$, 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), $\phi^{B}_{i,j}$, 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 D.1 and D.3 respectively yielding equation D.2 and D.4 under the assumption of separability.[36]

$$g_i = f(L_i, U_i, g_j, U_j, \phi^{NB}_{i,j}, \epsilon_i) \tag{D.1}$$

$$= f_1(L_i) + f_2(U_i, \epsilon_i) + f_3(g_j, \phi^{NB}_{i,j}, U_j) \tag{D.2}$$

$$L_i = h(g_i, g_j, \phi^{B}_{i,j}, V_i, V_j, \eta_i) \tag{D.3}$$

$$= h_1(g_i, \eta_i, V_i) + h_2(g_j, \phi^{B}_{i,j}, V_j) \tag{D.4}$$

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, $\tilde{\phi}^{B}_{i,j}$, exogenous shocks to the banking integration of state-pair (i, j). Specifically, we assume that the instrument has the form: $L_i = m[\Gamma_j, \tilde{\phi}^{B}_{i,j}] \equiv z_{i,j}$. 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 $h_2(.)$ using $z_{i,j}$ onto $f_1(.)$ 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, $Post_{i,j,t}$.[37] We estimate the effect of shocks to loan supply on economic growth via a two stage least

[36] 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, $\phi^{NB}_{i,j}$, U_j), as in equation D.2. 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, $\phi^{B}_{i,j}$, V_j) as in equation D.4

[37] $log(l_{i,t})$ 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.

square estimation (2SLS) in the following setup where equation D.5 and D.6 represent the first and the second stage respectively.[38]

$$log(l_{i,t}) = \alpha_2 + \beta_2 \Gamma_{j,t-1} \times Post_{i,j,t} + \beta_3 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \varepsilon_{ijt} \tag{D.5}$$

$$\Delta gdp_{i,t} = \alpha_1 + \beta_1 \hat{log}(l_{i,j,t}) + \alpha_i \times \alpha_j + \theta_i \times t + \theta_{jt} + \mu_{ijt} \tag{D.6}$$

We want to highlight that the structure of the first-stage equation mirrors our baseline specification, with equation D.5 estimated at the state-pair level. This yields $N1$ equations per state and year (N being the total number of states). The predicted value of $log(l_{i,t})$ based on shocks in state j is then used in the second-stage specification. Consequently, the second stage is also estimated at the state-pair level, resulting in $N1$ equations per state and year, with the predicted lending in state i based on shocks in state j, denoted as $\hat{log}(l_{i,j,t})$, as the key variable.

D.1 Economic Magnitude of the Effect from 2SLS specification

This section presents the details of calculating the economic magnitude of the effect based on the 2SLS coefficients presented in Table 7.

$$\frac{\Delta y - \mathbb{E}(\Delta y)}{\sigma(\Delta y)} = \alpha + \beta \log x + \varepsilon \tag{D.7}$$

Taking expectation of equation D.7 for $x = x$ and $x = x + dx$, we get the following under the assumption $\mathbb{E}[\varepsilon] = 0$:

$$\mathbb{E}\left[\frac{\Delta y - \mathbb{E}(\Delta y)}{\sigma(\Delta y)}\right] = \alpha + \beta \mathbb{E}[\log x] \tag{D.8}$$

$$\mathbb{E}\left[\frac{\Delta y' - \mathbb{E}(\Delta y)}{\sigma(\Delta y)}\right] = \alpha + \beta \mathbb{E}[\log(x + dx)] \tag{D.9}$$

Subtracting equation D.9 from equation D.8 gives the following:

[38]Note 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.

$$
\begin{aligned}
\mathbb{E}\left[\frac{\Delta y' - \mathbb{E}(\Delta y)}{\sigma(\Delta y)}\right] - \mathbb{E}\left[\frac{\Delta y - \mathbb{E}(\Delta y)}{\sigma(\Delta y)}\right] &= \beta\{\mathbb{E}[\log(x + dx)] - \mathbb{E}[\log x]\} \\
\mathbb{E}\left[\frac{\Delta y' - \Delta y}{\sigma(\Delta y)}\right] &= \beta\left\{\mathbb{E}\left[\log\left(x\left(1 + \frac{dx}{x}\right)\right)\right] - \mathbb{E}[\log x]\right\} \\
&= \beta\left\{\mathbb{E}[\log(x)] + \mathbb{E}\left[\log\left(1 + \frac{dx}{x}\right)\right] - \mathbb{E}[\log x]\right\} \\
&= \beta\mathbb{E}\left[\log\left(1 + \frac{dx}{x}\right)\right] \\
&\approx \beta\mathbb{E}\left[\frac{dx}{x}\right] \\
\mathbb{E}\left[\Delta y' - \Delta y\right] &\approx \beta\mathbb{E}\left[\frac{dx}{x}\right] \times \sigma(\Delta y)
\end{aligned}
\tag{D.10}
$$

Put $\sigma(\Delta y) = 0.03254$ (from Table 2) in equation D.10 we get the following change in Δy for 1 percentage point (pp) change in x:

$$\mathbb{E}\left[\Delta y' - \Delta y\right] = 0.03254 \times \beta$$

The following table provides the economic magnitude of the effect in percentage points for three values of β based on different specifications in Table 7:

Coefficient Type	Strictest Specification	Smallest Magnitude	Largest Magnitude
Source	Column 8	Column 2	Column 4
$\sigma(\Delta y)$	0.03	0.03	0.03
β	4.14	1.88	7.60
Economic Magnitude of Effect in pp	**0.13**	**0.06**	**0.25**

Table D.1: OLS Regression

Δgdp_{it}	(1)	(2)	(3)
$log(C\&I - Loan_{i,t})$	-0.0086	0.0741	0.0695
	(0.0347)	(0.0759)	(0.0813)
$\text{Post}_{i,j,t}$	0.2203	0.0363	0.0489
	(0.0794)	(0.0826)	(0.0709)
$\Gamma^{ind}_{i,t-1}$			0.0025
			(0.0171)
$\Gamma^{ind}_{i,t-2}$			-0.0048
			(0.0145)
Constant	0.0463		
	(0.5895)		
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	50,950	50,950	50,563
R^2	0.0117	0.6943	0.7145

This table presents the estimates from the OLS regression of GDP growth in state i on the natural logarithm of lending in state i while controlling for banking deregulation between state i and state j. $\Gamma^{ind}_{j,t-1}$ denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. The unit of observation in each regression is a state_i-state_j-year pair. Observations are weighted by the share of exports from state i to state j, using the 1977 Commodity Flow Survey Data. All non-binary variables except $log(C\&I - Loan_{i,t})$, 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.

Appendix E 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.

E.1 Baseline Results

Table E.1: Robustness: Collapsed Version of the Specification

Δgdp_{it}	(1)	(2)	(3)	(4)
$\frac{\sum_j Post_{i,j,t}}{N-1} \times \frac{\sum_{j,j\neq i} \Gamma^{ind}_{j,t-1}}{N-1}$	-0.1928	-0.1978	-0.1335	-0.1285
	(0.0505)	(0.0522)	(0.0540)	(0.0546)
$\frac{\sum_{j,j\neq i} \Gamma^{ind}_{j,t-1}}{N-1}$	0.0667	0.0675	0.0003	0.0391
	(0.0257)	(0.0258)	(0.1879)	(0.2009)
$\frac{\sum_j Post_{i,j,t}}{N-1}$	0.3062	0.3251	0.2161	0.2038
	(0.0769)	(0.0822)	(0.1264)	(0.1240)
State$_i$ FE		Yes	Yes	Yes
Region$_i$-Year FE			Yes	Yes
State$_i$-Linear Trend				Yes
N	1,173	1,173	1,173	1,173
R^2	0.0252	0.1405	0.6119	0.6586

This table reports the results from collapsing the baseline specification at the state$_i$ and year level. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is the interaction term of $\frac{\sum_{j,j\neq i} \Gamma^{ind}_{j,t-1}}{N-1}$ and $\frac{\sum_j Post_{i,j,t}}{N-1}$. $\frac{\sum_{j,j\neq i} \Gamma^{ind}_{j,t-1}}{N-1}$ denotes the average of idiosyncratic shocks in all state j, where $j \neq i$. The state-level idiosyncratic shocks are constructed by aggregating the Domar weighted labor productivity shocks of the top 10 firms, by sales in state j after accounting for industry-year fixed effects. $\frac{\sum_j Post_{i,j,t}}{N-1}$ refers to the index of deregulation for state$_i$ at time t, and is calculated as the fraction of states with which state$_i$ has deregulated banking. The unit of observation in each regression is at the state$_i$-year level. All non-binary variables used in the regression are standardized to mean zero and variance 1. Standard errors reported in parentheses are clustered by state$_i$.

Table E.2: Rolling GDP Growth Correlation and Deregulation

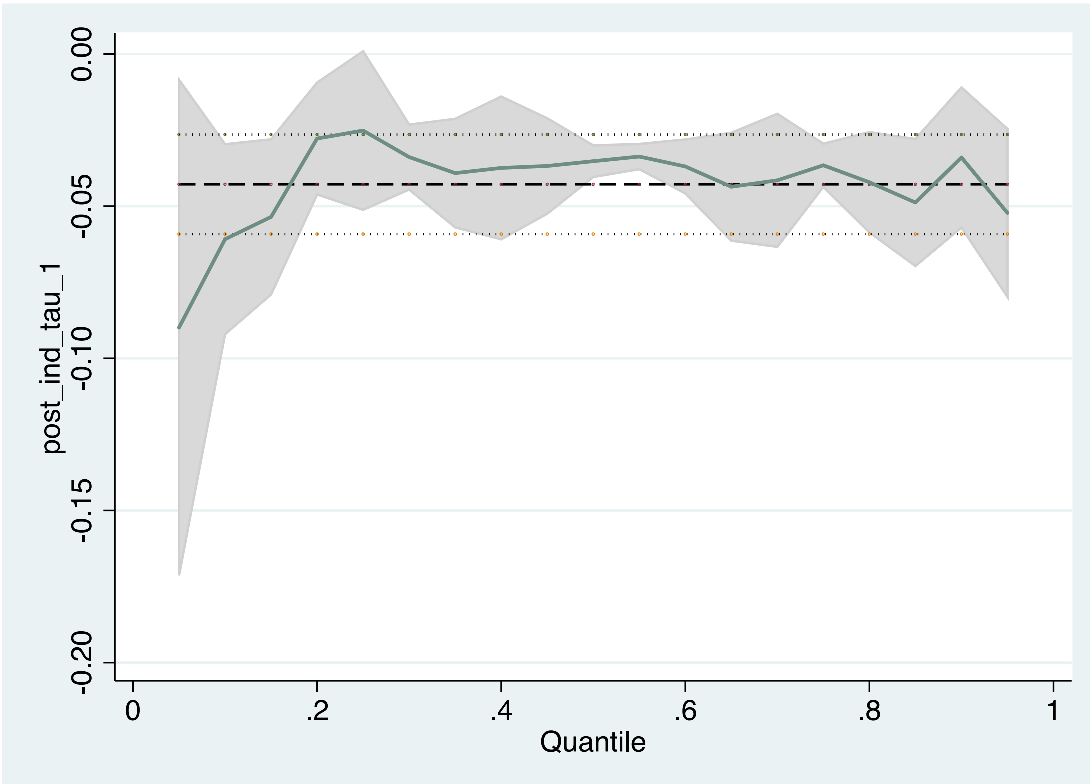
$\Delta Corr(gdp_{it}, gdp_{jt})$	(1)	(2)	(3)	(4)	(5)	(6)
	5 years	6 years	7 years	8 years	9 years	10 years
$Post_{i,j,t}$	-0.0276	-0.0275	-0.0253	-0.0206	-0.0177	-0.0149
	(0.0069)	(0.0099)	(0.0103)	(0.0096)	(0.0076)	(0.0062)
State_i-State_j FE	Yes	Yes	Yes	Yes	Yes	Yes
State_j-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State_i-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	55,300	55,300	55,300	55,300	55,300	55,300
R^2	0.6882	0.7293	0.7584	0.7818	0.8000	0.8160

This table reports the results from the estimation of the following regression specification:

$$\text{corr}(\text{gdp}_{it}, \text{gdp}_{jt}) = \beta_0 Post_{i,j,t} + \alpha_i \times \alpha_j + \theta_{it} + \theta_{jt} + \varepsilon_{ijt}, i \neq j$$

The dependent variable is the rolling GDP growth correlation. The rolling correlation with GDP is calculated over a window of 5-10 years, with the specific window size indicated in columns 1-6, respectively. The unit of observation in each regression is at the state$_i$-state$_j$-year level. Standard errors reported in parentheses are two-way clustered by state$_i$ and state$_j$.

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

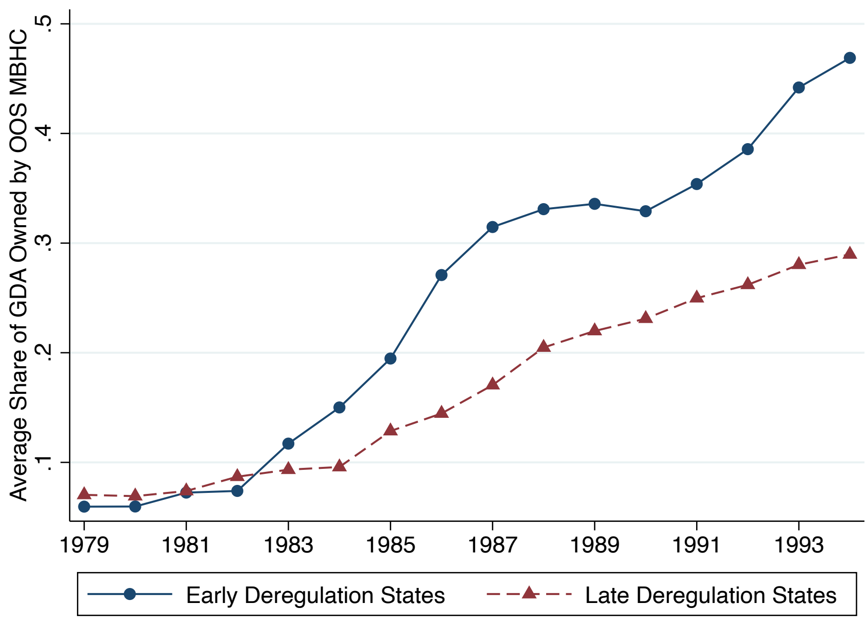


The figure plots the point estimate for the difference in the relation between GDP growth in state i and idiosyncratic shocks in state j where $i \neq j$ in the pre and post deregulation period. *Pre* refers to a sample of all state-pairs before banking integration. *Post* refers to a sample of all state-pairs 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.

E.2 Weighted Regression Results

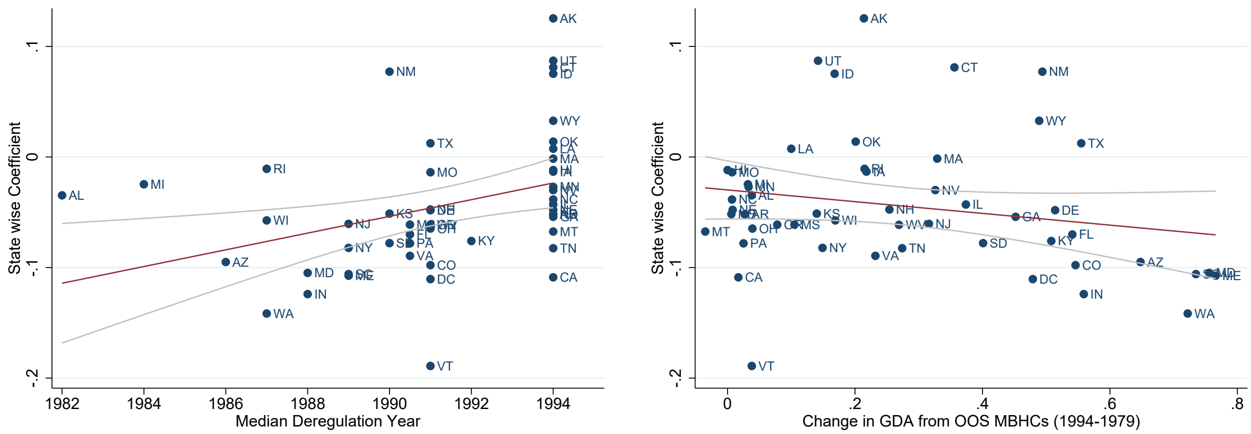
Table E.3 reports the results from a weighted estimation. We compute the share of exports from state i to state j, and the share of imports coming from state j to state i using the 1977 Commodity Flow Survey Data. The share measures the magnitude and the direction of real linkages from i to j. Columns (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.

Figure E.2: 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 E.3: 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 estimated presented in Figure 4 and the median year of deregulation (Figure E.3a) and the change in the share of gross domestic assets owned by out-of-state MBHCs (Figure E.3b). 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.

Table E.3: Weighted Estimation (Weighted by Exports/Imports)

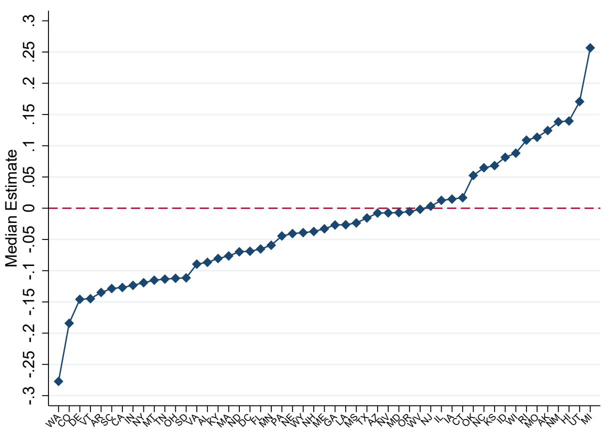
Δgdp_{it}	(1)	(2)	(3)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0164	-0.0583	-0.0397
	(0.0007)	(0.0244)	(0.0156)
$Post_{i,j,t}$	0.0783	0.0452	0.0816
	(0.0491)	(0.0767)	(0.0603)
Region$_i$-Year FE	Yes	Yes	Yes
State$_i$-State$_j$ FE	Yes	Yes	Yes
State$_j$-Year FE	Yes	Yes	Yes
State$_i$-Linear Trend	Yes	Yes	Yes
N	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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. 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$_j$.

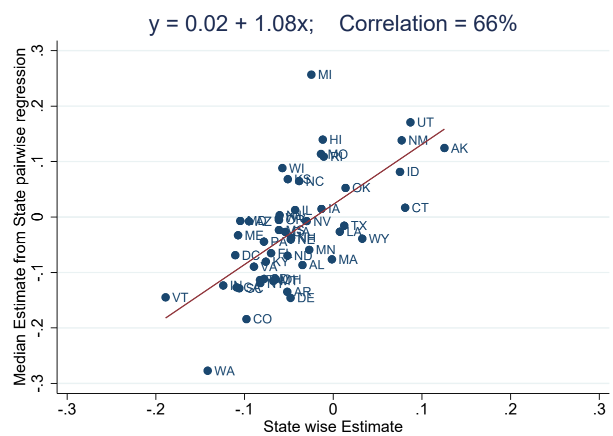
E.3 Heterogeneous Treatment Effects

Furthermore, to ensure that the estimates are not driven by extreme values, Figure E.4a 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. The state-level estimates from this exercise are qualitatively similar to the ones obtained from the state-wise estimation reported in Figure 4. In fact, the correlation between these state-level estimates and the estimates described earlier is 66%, see Figure E.4b.

Figure E.4: Median Estimates from the State Pairwise Regression & its Correlation with Estimates from the State-wise Regression in Figure 4



(a) Median Estimates from the state pairwise regression



(b) Scatter plot of estimates from state-wise regression and state-pairwise regression

The figure E.4a plots the median value of the estimates obtained from state-pairwise regression of economic growth in state i on the interaction term of post and idiosyncratic shocks in state j, the level terms of both post and idiosyncratic shocks in state j. For each state we take the median value of all the state-pairwise estimates and plot them in increasing order. The figure E.4b plots the relation between the two state-level estimates. The figure plots the median value of the estimates obtained from state-pairwise regression of economic growth in state i on the interaction term of post and idiosyncratic shocks in state j, the level terms of both post and idiosyncratic shocks in state j. For each state we take the median value of all the state-pairwise estimates and plot them in increasing order. This is plotted along the Y-axis. The state-level estimates obtained from the state-pairwise regression are plotted along the X-axis.

Table E.4: Baseline Specification with Time-Varying Controls

Δgdp_{it}	(1)	(2)	(3)	(4)	(5)	(6)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0185	-0.0173	-0.0212	-0.0263	-0.0134	-0.0195
	(0.0012)	(0.0034)	(0.0085)	(0.0046)	(0.0045)	(0.0108)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times \text{Exports}_{i,j,pre}$		-0.0024				-0.0048
		(0.0084)				(0.0081)
$Post_{i,j,t} \times \text{Exports}_{i,j,pre}$		-0.0159				-0.0054
		(0.0052)				(0.0058)
$\Gamma^{ind}_{j,t-1} \times \text{Exports}_{i,j,pre}$		-0.0074				-0.0068
		(0.0078)				(0.0075)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times \text{Exports}_{i,j,post}$		0.0006				0.0027
		(0.0094)				(0.0093)
$Post_{i,j,t} \times \text{Exports}_{i,j,post}$		0.0088				0.0058
		(0.0078)				(0.0122)
$\Gamma^{ind}_{j,t-1} \times \text{Exports}_{i,j,post}$		0.0095				0.0096
		(0.0093)				(0.0090)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times \text{Imports}_{i,j,pre}$		0.0072				0.0117
		(0.0115)				(0.0108)
$Post_{i,j,t} \times \text{Imports}_{i,j,pre}$		0.0136				0.0010
		(0.0148)				(0.0121)
$\Gamma^{ind}_{j,t-1} \times \text{Imports}_{i,j,pre}$		-0.0198				-0.0199
		(0.0068)				(0.0075)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times \text{Imports}_{i,j,post}$		0.0072				0.0117
		(0.0115)				(0.0108)
$Post_{i,j,t} \times \text{Imports}_{i,j,post}$		0.0136				0.0010
		(0.0148)				(0.0121)
$\Gamma^{ind}_{j,t-1} \times \text{Imports}_{i,j,post}$		-0.0198				-0.0199
		(0.0068)				(0.0075)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times \text{Income}_{j,t}$			0.0103			0.0126
			(0.0165)			(0.0176)
$Post_{i,j,t} \times \text{Income}_{j,t}$			-0.0062			0.0103
			(0.0640)			(0.0649)
Income Covariance$_{i,j,t}$				0.2569		0.2718
				(0.0589)		(0.0631)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times \text{Income Covariance}_{i,j,t}$				-0.0122		-0.0099
				(0.0070)		(0.0072)
$Post_{i,j,t} \times \text{Income Covariance}_{i,j,t}$				0.0135		0.0040
				(0.0922)		(0.0961)
$\Gamma^{ind}_{j,t-1} \times \text{Income Covariance}_{i,j,t}$				-0.0058		-0.0108
				(0.0096)		(0.0116)
Industry Similarity$_{i,j,t}$					0.3700	0.4431
					(0.2067)	(0.2130)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1} \times \text{Industry Similarity}_{i,j,t}$					0.0163	0.0215
					(0.0132)	(0.0187)
$Post_{i,j,t} \times \text{Industry Similarity}_{i,j,t}$					0.0299	0.0046
					(0.0413)	(0.0452)
$\Gamma^{ind}_{j,t-1} \times \text{Industry Similarity}_{i,j,t}$					-0.0123	-0.0122
					(0.0053)	(0.0085)
$Post_{i,j,t}$	0.0928	0.0936	0.0929	0.0908	0.1000	0.0861
	(0.0500)	(0.0501)	(0.0489)	(0.0827)	(0.0500)	(0.0856)
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	54,048	54,048	54,048	54,048	54,048	54,048
R^2	0.6568	0.6570	0.6568	0.6624	0.6579	0.6640

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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j after accounting for industry-year fixed effects. The unit of observation in each regression is a state$_i$-state$_j$-year pair. We include additional time-varying control variables including Exports from state i to state j in 1977 (*pre*-deregulation) and 1993 (*post*-deregulation), Imports from state i to state j in 1977 (*pre*-deregulation) and 1993 (*post*-deregulation), personal income per capital in state j, the similarity in industry composition between states i and j, and 15-year forward-rolling covariance in personal income growth between states i and j. 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$_j$.

E.4 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*.[39] Figure E.2 shows that the average share of gross domestic assets owned 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 E.3a 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 E.3b 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 E.5 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

[39] 1991 is the median value for all states.

in the median deregulation year, increases the state-level point estimate by 0.008.[40] 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 4.3.1. 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 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.

Table E.5: State-level Estimates, Deregulation Timing and Out-of-State Banking Expansion

Dep Var: State-level Estimate	(1)	(2)	(3)
Median Deregulation Year	0.1237		0.0846
	(0.0507)		(0.0456)
Δ Asset		0.0197	0.0532
		(0.1316)	(0.1411)
Δ Asset^2		-0.4271	-0.3639
		(0.1122)	(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 Asset^2. The state-level estimated 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.

[40] $\Delta\beta_s = 0.1237 \times \sigma_{\beta_s} = 0.1237 \times 0.061 = 0.008$.

E.5 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 7 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 7 are downward biased.

Another concern regarding linkages is the potential for positive shocks in one state to translate into negative shocks in another state, particularly if they share similar industry compositions. For instance, if oil-producing firms drive aggregate GDP growth in both Texas and Kansas, a positive shock in the oil sector in Texas (e.g., the discovery of new oil fields) could lead to a negative shock for the oil sector in Kansas. This could result in increased GDP growth in Texas, but decreased GDP growth in Kansas. This negative correlation due to industry similarity could influence our results. To address this concern, we control for industry similarity between the two states in Table 14 and find that our results remain robust despite this potential transmission of shocks.

In light of these considerations, one may question the validity of the exclusion restriction. However, our findings suggest that even if this strong identifying assumption is relaxed, the magnitude of our estimates is either downward biased or unlikely to substantially alter our primary results.

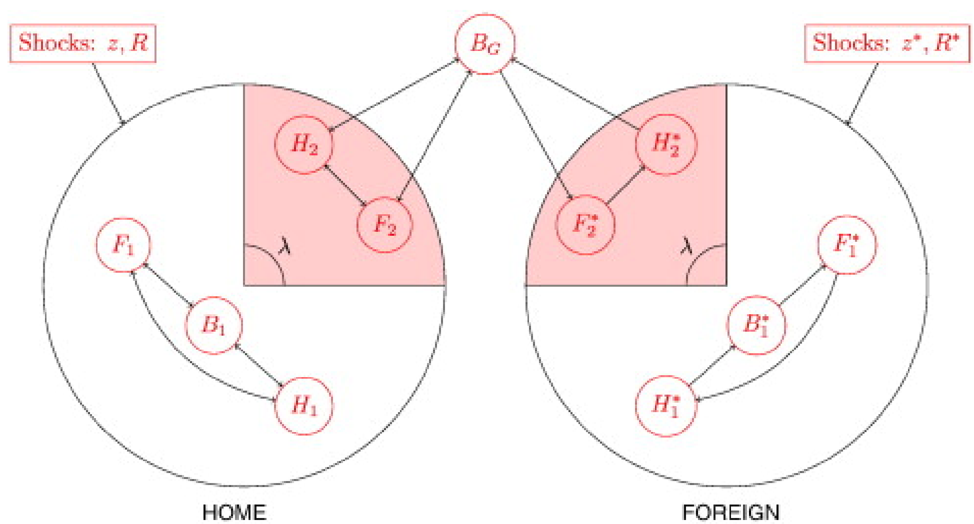
Appendix F Theoretical Model

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

F.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

Figure F.1: The structure of the economy



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

drive economic fluctuations: a standard productivity 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.

F.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 segement 2 of both the countries:

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

F.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^e_{it} on bank loans

$$d_{it} = e^{z_t} F(k_{it}, l_{it}) - R^e_{it} w_{it} l_{it} - x_{it}$$

$$k_{it+1} = (1-\delta) k_{it} + x_{it} - \phi k_{it} [\frac{x_{it}}{k_{it}} - \delta]^2$$

$$\begin{bmatrix} z_t \\ z^*_t \end{bmatrix} = A_z \begin{bmatrix} z_{t-1} \\ z^*_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon^z_t \\ \epsilon^z_t * \end{bmatrix}$$

where R^e_{it} 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 $[\epsilon^z_t, \epsilon^{z*}_t]$ is a vector of iid innovations with mean 0, standard deviation σ^z_ϵ and correlation ρ^z_ϵ. 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:

$$R^e_{2t} = R^{e*}_{2t}$$

F.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 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:

$$L_{1t} = w_{1t} l_{1t}; \quad L_{1t}^* = w_{1t}^* l_{1t}^*$$
$$L_{2t} = w_{2t} l_{2t}; \quad L_{2t}^* = w_{2t}^* l_{2t}^*$$

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.

F.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 $\forall t$:

$$\bar{m}R_{1t}^{m} + (1-\bar{m})R_{1t}^{e} = R_{1t} + \iota$$

$$\bar{m}R_{1t}^{m*} + (1-\bar{m})R_{1t}^{e*} = R_{1t}^{*} + \iota$$

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

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 $\forall t$

$$c_{1t} + x_{1t} + (D_{1t+1} - D_{1t}) = e^{z_t}F(k_{1t}, l_{1t}) + \frac{D_{1t+1}}{R_{1t}}(\bar{m}(R_t^m - 1) - \iota)$$

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

$$c_{2t} + c_{2t}^{*} + x_{2t} + x_{2t}^{*} + (D_{2t+1} - D_{2t})(D_{2t+1}^{*} - D_{2t}^{*}) =$$

$$= e^{z_t}F(k_{2t}, l_{2t}) + e^{z_t^*}F(k_{2t}^{*}, l_{2t}^{*}) + \frac{D_{2t+1}^{*} + D_{2t+1}}{R_{2t}}(\frac{\bar{m}}{2}(R_t^m + R_t^{m*} - 2) - \iota)$$

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) $\forall t$.

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

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

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

F.3 Parameterization and Theoretical Findings

Functional forms and baseline parameter values

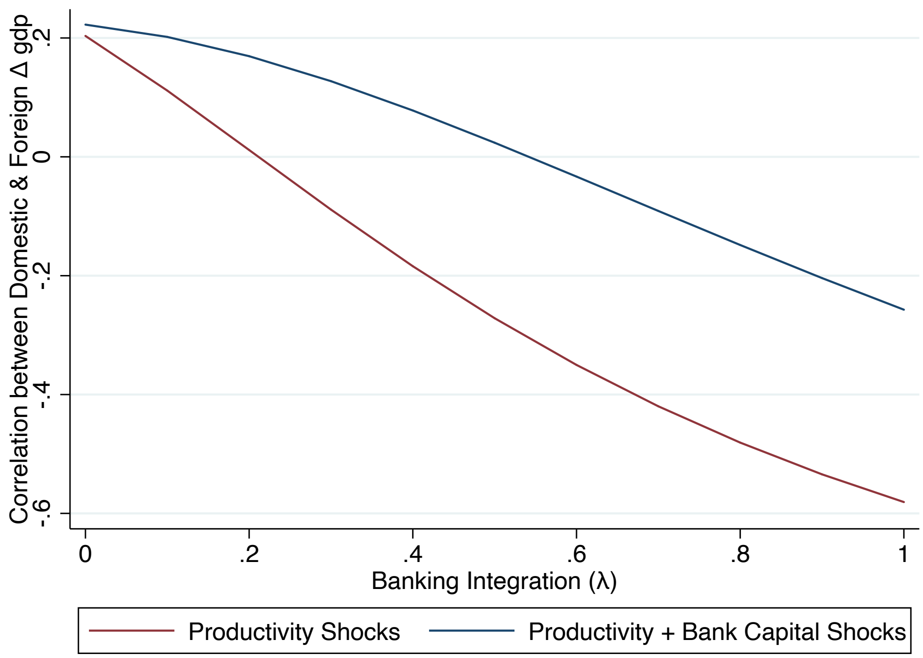
- **Utility:** U(c, l) = log(c)-Al

- **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 F.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 idiosyncratic shocks (Kalemli-Ozcan, Papaioannou, and Perri (2013)).

Figure F.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 G Robustness

Table G.1: Robustness - Alternative Specification

Δgdp_{it}	(1)	(2)	(3)	(4)
$\sum_{j\neq i} Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0196	-0.0095	-0.0125	-0.0125
	(0.0037)	(0.0056)	(0.0052)	(0.0054)
$\sum_{j\neq i} \Gamma^{ind}_{j,t-1}$	0.0070	-0.0070	-0.0023	-0.0022
	(0.0021)	(0.0168)	(0.0174)	(0.0179)
$\sum_{j\neq i} Post_{i,j,t}$	0.0063	0.0039	0.0041	0.0041
	(0.0016)	(0.0032)	(0.0025)	(0.0026)
Region$_i$ × Year FE		Yes	Yes	Yes
State$_i$ FE			Yes	
State$_i$-Linear Trend				Yes
# Obs	1,173	1,173	1,173	1173
R^2	0.0285	0.5171	0.6122	0.6124

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 $\sum_{j\neq i} Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$ which denotes the aggregated value of idiosyncratic productivity shocks to top 10 firms in state i interacted with $Post_{i,j,t}$. All non-binary variables used in the regression are standardized to mean zero and variance 1. The unit of observation in each regression is a state$_i$-year. Standard errors reported in parentheses are clustered by state$_i$.

Table G.2: Alternative Shock Specification

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

Δgdp_{it}	(1)	(2)	(3)	(4)	(5)	(6)
$Post_{i,j,t} \times \Gamma^{ind,state}_{j,t-1}$	-0.0669	-0.0020	-0.0069	-0.0088	-0.0281	-0.0276
	(0.0223)	(0.0006)	(0.0016)	(0.0006)	(0.0109)	(0.0105)
$\Gamma^{ind,state}_{j,t-1}$	0.0746	-0.0001	0.0022	0.0027		
	(0.0165)	(0.0003)	(0.0006)	(0.0004)		
$Post_{i,j,t}$	0.2441	0.0086	0.0770	0.0776	0.0880	0.0806
	(0.0645)	(0.0789)	(0.0604)	(0.0471)	(0.0527)	(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	0.0201	0.3094	0.5168	0.6113	0.6115	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 $\Gamma^{ind,state}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j, after accounting for industry-year and state-year fixed effects. 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$_j$.

Table G.3: Can Idiosyncratic Shocks to Small Firms Predict Shocks to Large Firms?

$\Gamma^{ind}_{j,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Gamma^{small,ind}_{j,t}$	-0.0374			-0.0238	-0.0136	-0.0078	-0.0209	-0.0209
	(0.0652)			(0.0645)	(0.0601)	(0.0587)	(0.0635)	(0.0640)
$\Gamma^{small,ind}_{j,t-1}$		0.0944		0.0791	0.0692	0.0732	0.0773	0.0773
		(0.0796)		(0.0852)	(0.0760)	(0.0747)	(0.0698)	(0.0703)
$\Gamma^{small,ind}_{j,t-2}$			-0.0890	-0.0766	-0.0829	-0.0790	-0.0970	-0.0970
			(0.0715)	(0.0746)	(0.0673)	(0.0669)	(0.0666)	(0.0671)
Year FE					Yes	Yes	Yes	Yes
State FE						Yes	Yes	
Region X Year FE							Yes	Yes
State-Linear Trend								Yes
N	803	803	803	803	803	803	803	803
R^2	0.0011	0.0072	0.0063	0.0122	0.0874	0.1137	0.2856	0.2856

This table reports the results from a regression of idiosyncratic shocks to large firms at time t on lags of idiosyncratic shocks to small firms. $\Gamma^{ind}_{j,t}$ denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j, at time t. $\Gamma^{ind,small}_{j,t}$ denotes the idiosyncratic shocks in state j, constructed by aggregating the Domar weighted labor productivity shocks of small firms – firms that are not in the top 10 firms, by sales – in state j at time t. Standard errors are robust.

G.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 G.4. 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 G.5. $\Gamma_{j,t-1}$ 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 G.4: Robustness - Constructing $\Gamma^{ind}_{j,t-1}$ using only positive firm-level shocks

Δgdp_{it}	(1)	(2)	(3)	(4)	(5)	(6)
$Post_{i,j,t} \times \Gamma^{ind-pos}_{j,t-1}$	-0.0825	-0.0031	-0.0052	-0.0076	-0.0168	-0.0148
	(0.0157)	(0.0008)	(0.0017)	(0.0002)	(0.0053)	(0.0047)
$\Gamma^{ind-pos}_{j,t-1}$	0.0618	0.0012	0.0026	0.0037		
	(0.0166)	(0.0003)	(0.0004)	(0.0001)		
$Post_{i,j,t}$	0.2535	0.0086	0.0766	0.0771	0.0860	0.0785
	(0.0643)	(0.0789)	(0.0604)	(0.0471)	(0.0526)	(0.0492)
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	0.0181	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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales 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$_j$.

Table G.5: Robustness - Alternative Construction of Γ

Δgdp_{it}	(1) $\Gamma^{ind-20}_{j,t-1}$	(2) $\Gamma^{ind-30}_{j,t-1}$	(3) $\Gamma^{ind-avg}_{j,t-1}$	(4) $\Gamma^{norm}_{j,t-1}$
$\text{Post}_{i,j,t} \times \Gamma^{*}_{j,t-1}$	-0.0159	-0.0162	-0.1178	-0.0037
	(0.0011)	(0.0009)	(0.0636)	(0.0019)
$\text{Post}_{i,j,t}$	0.0782	0.0782	0.0777	0.0778
	(0.0491)	(0.0491)	(0.0491)	(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 ($\Gamma^{ind-20}_{j,t-1}$) in other states in column (1), to top 30 firms ($\Gamma^{ind-30}_{j,t-1}$) in column (2), the a time-series average of idiosyncratic production shocks to top 10 firms ($\Gamma^{ind-avg}_{j,t-1}$) 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.

The point estimates of the interaction term in columns 1 and 2 of Table G.5 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 outsized 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 G.6. 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 G.6: Robustness - Alternative Samples

	(1)	(2)	(3)	(4)	(5)
Δgdp_{it}	All	>95%	>90%	>80%	>70%
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0164	-0.0195	-0.0154	-0.0145	-0.0176
	(0.0007)	(0.0026)	(0.0054)	(0.0054)	(0.0058)
Post$_{i,j,t}$	0.0783	0.0870	0.1028	0.0987	0.1284
	(0.0491)	(0.0547)	(0.0522)	(0.0503)	(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 $\Gamma^{ind}_{j,t-1}$ 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$_j$.

Table G.7: Robustness - Accounting for Shocks to Small Firms

Δgdp_{it}	(1)	(2)	(3)	(4)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0187	-0.0190		
	(0.0023)	(0.0031)		
$Post_{i,j,t}$	0.0824	0.0825	0.0823	0.0821
	(0.0505)	(0.0505)	(0.0506)	(0.0505)
$Post_{i,j,t} \times \Gamma^{ind,small}_{j,t-1}$		0.0045		
		(0.0031)		
$Post_{i,j,t} \times (\Gamma^{ind}_{j,t-1} - \Gamma^{ind,small}_{j,t-1})$			-0.0152	
			(0.0036)	
$Post_{i,j,t} \times \Gamma^{Res}_{j,t-1}$				-0.0186
				(0.0022)
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	41,550	41,550	41,550	41,550
R^2	0.6608	0.6608	0.6608	0.6608

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 in columns 1 and 2 is $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales in state j. $\Gamma^{ind,small}_{j,t-1}$ ($\Gamma^{small}_{i,t-1}$) denotes the idiosyncratic shocks in state j (i) constructed by aggregating the Domar weighted labor productivity shocks of small firms – firms that are in not in the top 10 firms, by sales – in state j (i). The unit of observation in each regression is a state$_i$-state$_j$-year pair. The key dependent variable in column 3 is the difference of $\Gamma^{ind}_{j,t-1}$ and $\Gamma^{ind,small}_{j,t-1}$ interacted with the Post variable. The key dependent variable in column 4 is the interaction of $\Gamma^{Res}_{j,t-1}$ and Post. $\Gamma^{Res}_{j,t-1}$ denotes the residuals from the regression of the large-firm shocks on small-firm shocks at the state-level. 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$_j$.

G.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 1. For each firm, we run the following regression of $g_{it}^{(i)}$ on macroeconomic shocks for each year.

$$g_{it}^{(i)} = \alpha_i + \beta_i \Delta\Omega_t + \varepsilon_{it} \tag{G.1}$$

$\Delta\Omega_t$ 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.G.8 and G.9 provide a brief summary of the macroeconomic shocks employed here.

Table G.8: Summary of Data Sources for Macroeconomic Variables

Description	Sources	Measure
Change in Effective Federal Funds Rates	FRED St. Louis Fed	$\Delta EFFR_t$
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	ΔUnemployment 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 G.9: 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

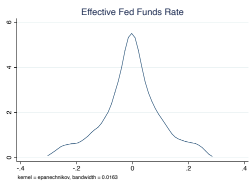
This table presents the summary statistics for the macroeconomic variables of interest from 1977-2000.

The firm-level regression allows the firms to have heterogeneous exposure to macroeconomic shocks. Figure G.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 sensitives 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.

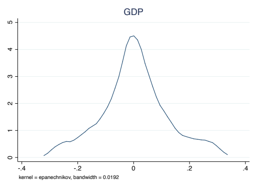
The ε_{it} for the top 10 firms in each state are extracted from equation G.1, and aggregated at the state-level using Domar weights as in equation 2. Figure G.2 presents a binscatter plot of our standard measure of state-level idiosyncratic shock, $\Gamma_{j,t}^{industry}$ and the idiosyncratic shock 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 G.10 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 column 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.

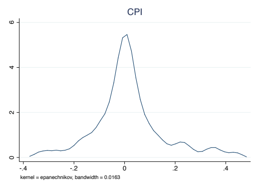
Figure G.1: Kernel Densities of Heterogeneous Exposures of firm-level shocks to Macroeconomic Variables



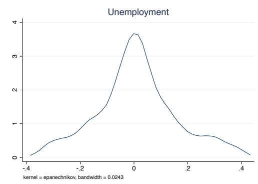
(a) Δ FFR$_t$



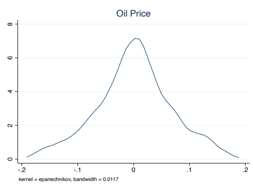
(b) GDP Growth Rate



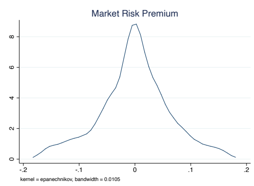
(c) CPI growth Rate



(d) Δ UR$_t$



(e) Hamilton Oil Price Shock

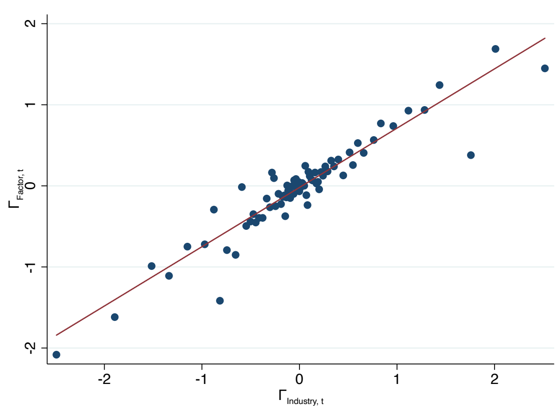


(f) Market Risk Premium

	p25	Median	p75	Mean	Std. Dev.
β_{FF}	-0.648	-0.013	0.719	-0.000	1.000
β_{GDP}	-0.339	0.182	0.567	0.000	1.000
β_{CPI}	-0.644	-0.392	0.227	0.000	1.000
β_{Unemp}	-0.435	0.007	0.786	-0.000	1.000
$\beta_{Hamilton}$	-0.744	0.186	0.837	0.000	1.000
β_{Market}	-0.539	-0.130	0.328	0.000	1.000

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 G.8 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 G.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 G.10: Baseline Results with Factor Structure of Shocks

Δgdp_{it}	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_{i,j,t} \times \Gamma^{factor}_{j,t-1}$	-0.0170	-0.0136	-0.0133	-0.0146	-0.0149	-0.0151
	(0.0022)	(0.0033)	(0.0040)	(0.0037)	(0.0039)	(0.0048)
$\text{Post}_{i,j,t}$	0.0784	0.0783	0.0783	0.0781	0.0783	0.0781
	(0.0491)	(0.0492)	(0.0491)	(0.0492)	(0.0492)	(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. $p < 0.1$, $p < 0.05$, $p < 0.01$

G.3 Placebo Test

G.3.1 Randomizing the Timing of Deregulation

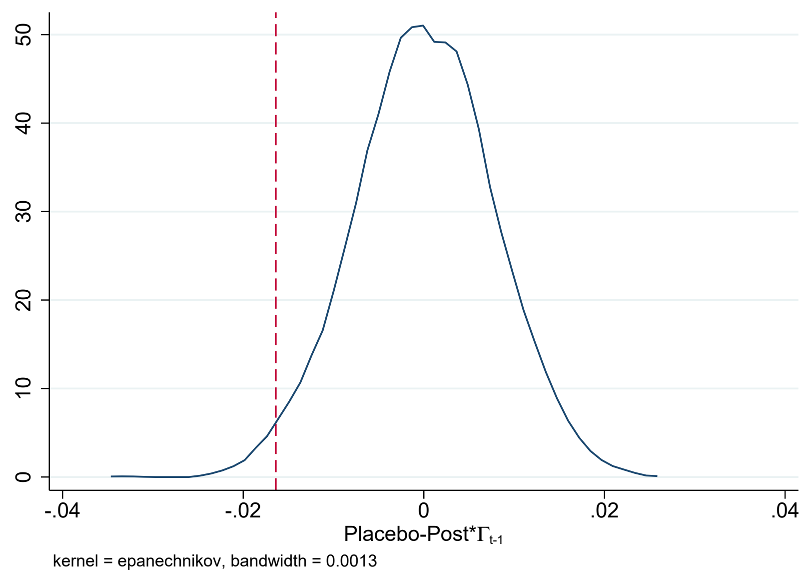
We conduct a placebo test wherein we randomize the timing of banking integration. A placebo deregulation year is generated for each state-pair (i, j) from a uniform distribution between 1982 and 1994. The baseline specification is estimated using the generated placebo year. We estimate this process 3,500 times. Appendix Figure G.3 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 variables is identical across state-pairs.

G.3.2 Randomizing idiosyncratic shocks

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.[41] 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 G.4 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.

[41] The 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

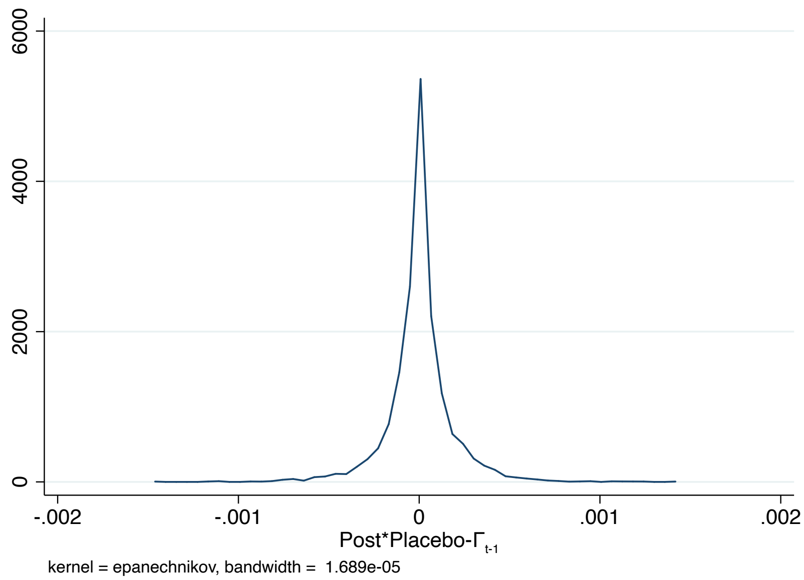
Figure G.3: Placebo Test: Randomization of the Timing of Deregulation



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 $Placebo - Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$ 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 G.4: Placebo Test: Randomization of $\Gamma^{ind}_{j,t-1}$



Min	p1	p5	p25	p50	p75	p95	p99	Max	Mean	St Dev
-0.0014	-0.0006	-0.0003	-0.0001	0.0000	0.0001	0.0003	0.0006	0.0014	0.0000	0.0002

The figure plots the kernel density of the point estimates of $Post_{i,j,t} \times Placebo - \Gamma^{ind}_{j,t-1}$ obtained from the 3,500 Monte-Carlo simulations. We generate a random data for $Placebo - \Gamma^{ind}_{j,t-1}$ 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 $Placebo - \Gamma^{ind}_{j,t-1}$. The table underneath The figure gives the numbers associated with the distribution of the estimates plotted in figure.

G.4 Geography-based Measurement Error

G.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:

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

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

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 G.11. 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 G.11: Robustness - Value Added Measure of Γ

Δgdp_{it}	(1)	(2)
$Post_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0044	
	(0.0013)	
$Post_{i,j,t} \times \Gamma^{norm}_{j,t-1}$		-0.0061
		(0.0012)
$\text{Post}_{i,j,t}$	0.0885	0.0884
	(0.0490)	(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

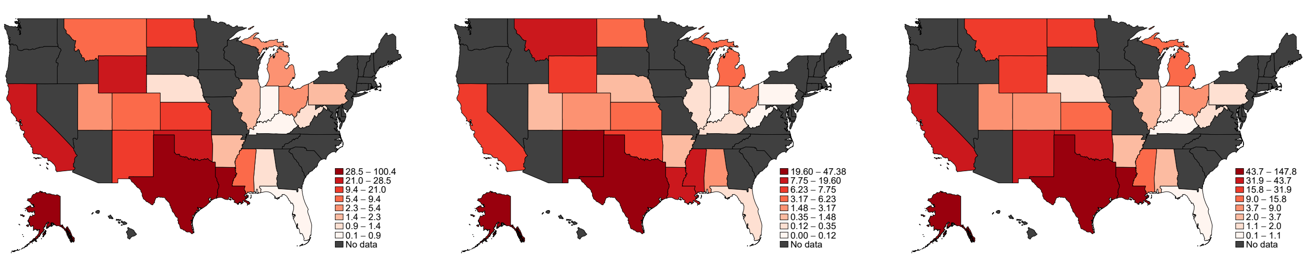
This table presents the estimates for baseline specification with alternative construction of Γ using the value-added measure. The dependent variable is the change in the real GDP growth rate in percentage. The main independent variable is $\Gamma^{ind}_{j,t-1}$ and $\Gamma^{norm}_{j,t-1}$ which denote 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.

G.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 G.5 for the geographic distribution of these discoveries, and Figure G.6 for detailed summary statistics, the time series variation of oil discoveries.

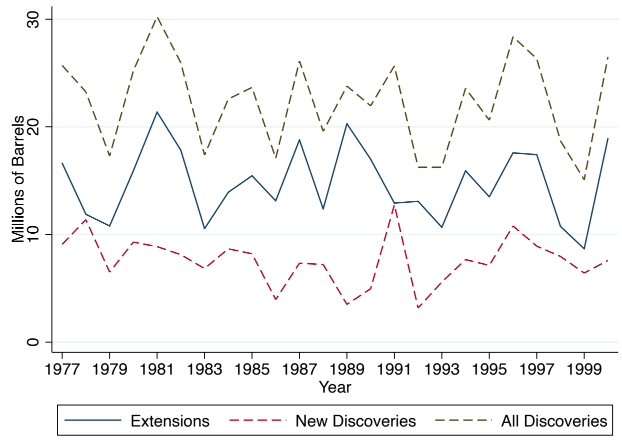
Figure G.5: Geographic Dispersion of Oil Discoveries (1977-2000)



(a) Extensions (b) New Discoveries (c) All Discoveries

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.

Figure G.6: Oil Discovery: Summary Statistics & Average Over Time

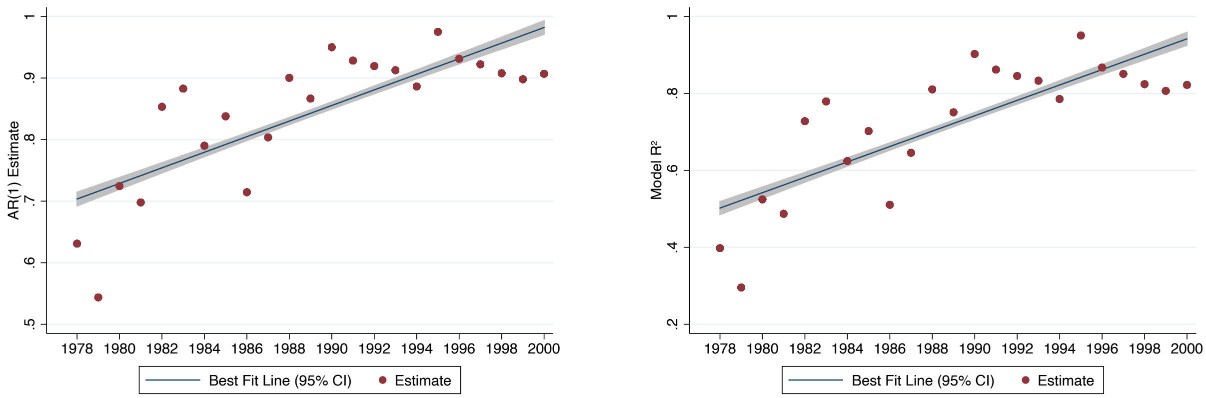


	N	% Zeros	p25	Median	p75	Mean	Std. Dev.
Extensions	576	23.6%	1	4	14	14.81	31.24
New Discoveries	576	40.6%	0	1	8	7.58	17.95
All Discoveries	576	21.4%	1	6	26	22.38	43.69

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.

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 sin nature. Third, the oil discovery shocks become more predictable towards the second half of the sample. We 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 G.7. 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).

Figure G.7: Predictability of Oil Shocks



(a) AR(1) estimate over time

(b) Model R^2

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.

Table G.12 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 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 G.8. 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 G.12 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

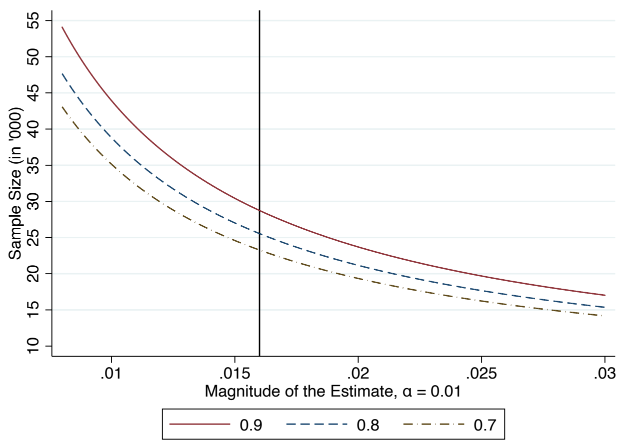
Table 3. This lends support to our argument that the geography-based measurement error is likely to bias our estimate towards finding an effect of lower magnitude.

Table G.12: Robustness - Measuring Γ Using Oil Discovery Shocks

Δgdp_{it}	(1) Baseline	(2) Extensions	(3) New Disc.	(4) All Disc.
Post$_{i,j,t}\times\Gamma_{j,t-1}$	-0.0103	-0.0132	-0.0157	-0.0364
	(0.0018)	(0.0212)	(0.0373)	(0.0382)
Post	0.0739	0.1207	0.0990	0.0953
	(0.0574)	(0.0812)	(0.0637)	(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$_j$.

Figure G.8: 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.

G.5 Addressing Concerns Related to Migration

This section presents two tests addressing the concern that the baseline result is not driven by interstate 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 3, to include the region$_i\times$ region$_j\times$year fixed effects, and region$_i\times$state$_j\times$year, where region refers to the BEA economic region of the state.[42] This test assumes that within US migration is likely to be smoothly distributes 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 G.13 reports these results. Column (1) estimate the baseline specification, equation 3, for reference. Column (2) and (3) augment the baseline specification with region$_i\times$region$_j\times$year fixed effects, and region$_i\times$state$_j\times$year respectively. The point estimate of the interaction term of Post$_{i,j,t}$ and $\Gamma^{ind}_{j,t-1}$ 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 random-region$_i\times$random-region$_j\times$year fixed effects, and random-region$_i\times$state$_j\times$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 Post$_{i,j,t}$ and $\Gamma^{ind}_{j,t-1}$ while including the random-region$_i\times$random-region$_j\times$year fixed effects, and random-region$_i\times$state$_j\times$year fixed effects. Table G.15 reports the mean, median, standard deviation and t-statistic of the distribution of estimates. The mean and the median values reported in Table G.15 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.

[42]We refer the readers to Table G.14 for the delineation of states into eight different economic regions by the Bureau of Economic Analysis.

Table G.13: Robustness - Addressing Migration Concerns Using Region Interaction Fixed Effects

$\Delta gdp_{i,t}$	(1)	(2)	(3)
$\text{Post}_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0164	-0.0170	-0.0208
	(0.0007)	(0.0025)	(0.0060)
$\text{Post}_{i,j,t}$	0.0783	0.0793	0.0834
	(0.0491)	(0.0503)	(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 $\text{Region}_i \times \text{Region}_j \times$Year fixed effects in column (2), and $\text{Region}_i \times \text{State}_j \times$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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales 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.

Table G.14: 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 G.15: 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 $\Gamma^{ind}_{j,t-1}$ 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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales 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 $\Gamma^{ind}_{j,t-1}$ 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.

G.6 Dropping the states of South Dakota and Delaware

This section reports the estimation results of the baseline specification, equation 3 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 G.16 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 G.16: Robustness - Removing South Dakota & Delaware from the Sample

$\Delta gdp_{i,t}$	(1)	(2)	(3)	(4)
$\text{Post}_{i,j,t} \times \Gamma^{ind}_{j,t-1}$	-0.0164	-0.0153	-0.0180	-0.0167
	(0.0007)	(0.0034)	(0.0003)	(0.0019)
$\text{Post}_{i,j,t}$	0.0783	0.0685	0.0750	0.0652
	(0.0491)	(0.0493)	(0.0487)	(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 $\Gamma^{ind}_{j,t-1}$ which denotes the idiosyncratic shocks in state j constructed by aggregating the Domar weighted labor productivity shocks of top 10 firms, by sales 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.