Banking Integration and House Price Comovement *

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Abstract

The correlation of house price growth across US states has steadily increased over the 1976-2000 period. This paper shows that a significant part of this phenomenon is caused by the contemporaneous geographic integration of the US banking market, via the emergence of large banks. To this end, we first theoretically derive an appropriate measure of banking integration across state pairs and document that house price growth correlation is strongly related to this measure of financial integration. Its key insight is that, for banking integration to create comovement, overlapping banks have to be large. We then use bilateral cross-state banking deregulations as shocks to the banking integration of a state pair. Our IV estimates suggest that banking integration can explain up to one third of the rise in house price correlation over the period.

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1. Introduction

House prices across US states have become increasingly correlated. From 1976 to 1980, the average 5-years forward correlation of house price growth across state pairs was 11%; One third of the state pairs had negatively correlated house prices. Between 2000 and 2004, the average correlation has reached 44%; the fraction of negatively correlated state pairs has gone down to 10%. As shown in Figure 1, which is compiled using the OFHEO residential price index, house price synchronization has continuously increased over the past three decades.[1] Why this is happen? Over the same period, the US banking market has become increasingly integrated, through consecutive waves of deregulations that took place between the late 1970s and the mid-1990s (Kroszner and Strahan (1999)). We show that these two phenomena are related in that banking integration causes higher house price growth correlation. This is the main contribution of the paper.

The economic mechanism linking financial integration to house price correlation is straightforward. We build on the large literature on internal capital markets in banks, which documents that funding shocks to a bank holding company tend to propagate to its divisions, and affect their lending (see e.g. Peek and Rosengren (1997), Cetorelli and Goldberg (2012), Liberti and Sturgess (2013)). Because of this mechanism, when a bank simultaneously operates in several states, this creates a commonality in lending across these states. This, in turn, synchronizes house price movements, to the extent that bank lending affects house prices (Adelino et al. (2011), Loutskina and Strahan (2012), Favara and Imbs (2011)). Empirically establishing the causality from bank integration to house price growth correlation is more challenging. To address this challenge, we proceed in two steps.

[1] Our paper is the first one, to our knowledge, to document this long-term trend on US states, but a few papers have already provided evidence of the increase in house price correlation. Using the same data as us, but on the 2000s only, Cotter et al. (2011) have documented an increase in house prices correlation across US cities during the real estate boom. Using Case & Shiller data for 10 large cities, Kallberg et al. (2012) have also documented an increase in house price correlation in recent years. Finally, Hirata et al. (2012) have shown a long term increase in international house prices. On a different note, Van Nieuerburgh and Weill (2010) show that, over the same period, the dispersion of house prices levels *across* US cities has also gone up. This is perfectly consistent with the fact we document here: Prices co-vary more (our paper), but their levels differ more (theirs).

First, we develop a simple statistical model that links bank integration to house price growth correlation. This model is used to derive an empirically testable relationship between house price growth correlation and a relevant measure of bank integration. This measure captures the extent to which large banks overlap state-pairs. Formally, for each state pair (i, j), it is defined as the sum, across all banks operating in both states, of the products of their market shares in both state.[2]

The model also delivers two key insights that shed light on the link between bank integration and asset price comovement. First, the link between financial integration and house price correlation mostly goes through idiosyncratic bank lending shocks. If lending is mostly affected by aggregate shocks (e.g., because all banks securitize or rely on wholesale funding), then banking integration has no effect on house price comovement: Aggregate shocks affect all banks, whether they operate in segmented or integrated markets. However, when banks face idiosyncratic lending shocks, their overlap across states induces house prices comovement. For idiosyncratic shocks to matter, however, the market needs to be sufficiently concentrated. This leads to the second insight of the model: Bank integration only matters to the extent that banks operating across states are large enough. If banking markets becomes more integrated, but banks remain small, the law of large number will smooth out the impact of idiosyncratic shocks, and integration will have no effect on house price growth correlation. Put simply, granularity in bank integration is a necessary ingredient to create comovement in house prices. Our integration measure embodies both insights.

Second, we use interstate banking deregulations as shocks to financial integration between US state pairs, in order to establish that financial integration causally affects the comovement of house prices. We exploit the fact that these deregulations were essentially *bilateral*, and staggered between 1978 and 1994. Consistent with the findings in Michalski and Ors (2012), we find that these bilateral interstate banking deregulations had a strong

[2] It thus ranges from 0 when the two states are completely segmented – no common lending between the two states or market shares of each banks operating in both states close to 0 – to 1 when the two states are perfectly integrated – a single bank responsible for the whole lending activity in both states.

and immediate impact on our measure of financial integration (see also Goetz et al. (2013) for the use of these deregulations in a different context). We then show that these deregulations were immediately followed by a sharp increase in house price correlation (about 8 percentage points on across specifications). Finally, we use these deregulations as instruments for banking market integration. This IV estimate allows us to quantify the effect of integration on house price comovement. We defend the validity of these deregulations as instruments for banking integration at length in Section 4.1. We find an economically and statistically significant relationship between bank integration and house price correlation across state pairs. We perform numerous robustness checks. We finally use our cross-sectional estimate to shed light on the rise in house price comovement. Because of the very deregulations that we use as instruments in our panel regressions, we observe that bank integration increases dramatically between 1976 and 2000. This trend is mostly explained by the extension of the 20 largest Bank Holding Companies across state boundaries. Given our cross-sectional estimates, this movement may explain as much as one third of the rise in house price correlation over the period.

This paper contributes to three strands of the literature. First, our paper confirms the significant role that credit supply plays in the determination of housing prices. A series of recent papers have documented the impact of credit supply shocks on house prices. These papers have used instruments related to securitization demand by GSEs (Adelino et al. (2011), Loutskina and Strahan (2012)) or branching deregulations (Favara and Imbs (2011)). Our paper complements this literature by using an alternative instrument (interstate banking laws) and by focusing on the time series and cross-sectional properties of house price growth correlation across US states. In doing this, we also shed light on the key role of idiosyncratic bank shocks, and of bank granularity, to explain the second moments of home prices.

This paper also contributes to the literature on capital flows and contagion. The international finance literature documents increasing comovement in equity prices since the 1970s (see Forbes (2012) for a summary and new evidence from equity markets). Such comovement is typically interpreted as a consequence of capital market integration. When capital can flow more freely across borders, asset prices become more sensitive to shifts in global investor demand. In line with this interpretation, several papers have reported significant cross-sectional relationships between asset prices correlation and the intensity of capital flows between countries.[3] Within this literature, our paper provides analogous evidence for a new asset class (real estate), in a set of regions that experienced a drastic integration of capital markets (US states). Such integration occurred via the banking market and was driven primarily by bilateral, staggered, deregulations. These policy experiments in the context of otherwise relatively homogenous states, allow us to isolate the causal impact of capital (banking) flows on asset price comovement. This paper also relates to the related literature on the real effects of financial integration: GDP growth volatility across US states (Morgan et al. (2004)) and GDP growth comovement across E.U. member states (Kalemli-Ozcan et al. (2013)).

Finally, our paper is linked to Gabaix (2011), which shows that idiosyncratic shocks to large firms have the power to explain aggregate volatility. The evidence on such "granular origins of aggregate fluctuations" is, however, mixed. On the one hand, Foerster and Watson (2011) find no role for idiosyncratic volatility in explaining the volatility of US manufacturing output. On the other hand, Amiti and Weinstein (2013) find that banking concentration in Japan is large enough to give a significant role to idiosyncratic shocks on aggregate lending volatility. Van Nieuerburgh et al. (2013) also show that the concentration of customer networks is an important determinant of firm-level volatility and that at the macro level, the firm volatility distribution is driven by firm size dispersion. While these papers focus on volatility, our study provides evidence in favor of the "granular origins of comovement". Our statistical model clearly shows that integration can only affects asset price comovement via large banks. In the data, the increase in banking integration – which causes correlation – is

[3] In line with this literature, Quinn and Voth (2012) show that asset price correlation was large in the beginning of the 20^{th} century and decreased substantially before WWII. Hirata et al. (2012) provide evidence that many asset classes have become more correlated over time. But they link this evolution to macro shocks, not to credit supply.

mostly driven by the 20 largest banks. Hence, taken together with the above papers, our results suggest that, in bank lending perhaps more than in manufacturing output, idiosyncratic credit supply shocks are an important contributor to aggregate shocks.

Section 2 describes the data and documents the strong increase in house price comovement over the past 3 decades. Section 3 lays out a simple statistical model that highlights the role of financial integration on house price correlation and document the rise in bank integration in the US over the 1976-2000 period. Section 4 goes back to the data and shows the causal impact of bank integration on house price correlation in the cross-section of state pairs. Section 5 concludes.

2. Data

2.1. Data Construction

Our dataset is the balanced panel of all US state pairs from 1976 to 2000. It contains measures of house price comovement, labor income comovement, state-pair proximity in industry composition, a measure of state-pair banking integration. To compute these variables, we use three sources of data: quarterly house price index from OFHEO, state-level bank lending from the Call Reports, and state-level labor income from the BLS.

2.1.1. House Prices

We retrieve state-level, repeated-sales, house price indices from the OFHEO website for the period ranging from 1976 to 2000. These data are available quarterly for all US states since 1976. We stop in 2000 because our IV strategy is based on deregulations happening between the mid 1980s and 1995. As we will see below, Call Reports also impose a constraint on our time frame. We use these data to calculate quarterly residential real estate price growth. Our focus on state-level data (as opposed to MSA level data) is driven by two considerations: (1) our instrument – interstate banking deregulation – is defined at the state-pair level and

(2) the OFHEO data covers *all* states since 1976, but its coverage of MSA-level prices is complete only after 1994.

For each state pair, we use these data to compute the time series of house price correlation. More precisely, for each state-pair and each year, we compute the correlation of house price growths in each state of the pair, over the next 20 quarters (including the four quarters of the current year). This will be our main measure of house price comovement, but we will also show robustness for three additional measures. First, we also compute 3 year rolling correlations. This alternative proxy is noisier but more responsive to regime changes. Second, using the 20 quarters rolling window, we also compute the covariance of house price growths. Third, we compute the "beta" of prices in state i with respect to prices in j (Forbes and Rigobon (2002)). More accurately, for each state-pair (i, j), β^{ij} is the regression coefficient of house price growth in state i on house price growth in state j, taking the next 20 quarters as estimation sample.

Table I reports summary statistics for these comovement measures, for each one of the $50 \times 51/2 - 50 = 1,225$ state pairs between 1976 and 1996 (these statistics stop in 1996 because of our 5 year rolling window). So the sample has $21 \times 1225 = 25,725$ observations. The average house price growth correlation over a 5 year horizon is .185, with a median of .188. The correlation over a 3 year horizon is very similar, with a mean of .195 and a median of .207. Less than 30% of the observations have negative house price growth correlation. Section 2.2 discusses at more length the summary statistics of correlation as well as the trends in correlation.

2.1.2. Geographic Dispersion of Banks

To measure bank lending at the state level, we use the Call Reports consolidated at the BHC level, from 1976 to 2000. These data are available quarterly and provide us, for each commercial bank, with its identification number (rssd9001), its total real estate loans (rcfd1410), its state of location (rssd9200), and the bank holding company (BHC) it is affiliated to (rssd9348) –if there is one. We then collapse real estate loans, each quarter, at the BHC-state level. For instance, if a BHC owns two commercial banks in Arizona (with real estate loans of $3bn and $5bn), we say that its total lending in this state is $8bn. When a commercial bank is independent, we keep the observation —as if the commercial bank was a BHC owning itself.

By performing this aggregation, we implicitly assume that commercial banks do not operate outside the borders of the state they are located in. This is a good approximation until the Riegle-Neal Act of 1994, which allowed BHCs to consolidate activities in several states into a single commercial bank (Morgan et al. (2004)).[4] After 1994, bank asset location information becomes noisier and noisier as larger banks progressively consolidate loans across state borders. With this shortcoming in mind, we choose to use the Call Reports data until 2000 in our main regressions. We do, however, systematically provide robustness checks on 1976-1994 only, to make sure that potential biases induced by Riegle-Neal do not affect our findings. As we shall see, it turns out that they do not.

We use the Call Reports to calculate our measure of banking integration of state pairs, whose summary statistics we report in Table I. We defer the definition of these measures to Section 3, as they will naturally emerge from our statistical model.

2.1.3. Fundamental Proximity Measures

For each state pair, each year, we first measure "fundamental comovement". In most regressions, we use the 5-year forward rolling correlation of personal income growth. The source is thequarterly data on personal income from the Bureau of Economic Analysis (BEA). Personal income is the income received by all persons from all sources: it is the sum of net earnings

[4] There are two alternative data sources that we could use to compute measures of banks integration, but these data are less suited to our study than the Call Reports. One is the FDIC data on deposits, that report, for each bank, the geographic dispersion of deposits. Unfortunately, these data are only available after 1993 and thus do not overlap with the interstate banking deregulation that we use as instruments. The other is HMDA (Home Mortgage Disclosure Act), which is a loan-application level dataset that covers most loan application in the US. Starting in 1990, HMDA is a very clean data source on mortgage issuances. The problem for us is that HMDA is substiantially noisier in the 1980s, in particular before 1988, where most of our pre-reform observations are. Also, coverage is partial in the beginnin of the sample.

by place of residence, property income, and personal current transfer receipts. As we did for home prices, we also calculate two alternative measures of fundamental comovement: The covariance and average "beta" of personal income growth over the next 20 quarters.

For each state pair and year, we also construct a measure of "economic proximity". Following Morgan et al. (2004), we calculate the distance in industry composition between the two states. The source is data from the BEA on state employment by industry. For each state in the pair, we first calculate the vector of employment shares in 20 industries and then compute the Euclidian distance between these two vectors. This number is large when the two states have very different industrial specialization. Summary statistics for these variables are reported in Table I. The average income correlation is high at .47 and it is negative for less than 5% of the observations.

2.2. Rising Correlations

As shown in the introduction, Figure 1 plots the year-by-year distribution of correlations across state pairs from 1976 to 1996. Note that due to the way we compute correlation (5 year forward rolling window), this figure uses house price data up to 2000. In the paper, we exclude the post 2000 data which we believe are shaped by different forces (Loutskina and Strahan (2012)). But the movement that we document is not subsequently reversed. After 2000, correlation increases even faster than it does up to 1996: In 2006, the average 5 year forward correlation of house price growth across US states is above 75%. Cotter et al. (2011) document the same fact over the 2000s on city-level data. However, since interstate banking deregulations end in 1995, our IV strategy is less meaningful after 2000.

Both the average and the median correlation increase from an average of 5% in the 76-80 period to an average of about 40% in the 1992-1996 period. In the same figure, we also report the evolution of the 25^{th} and 75^{th} percentiles of the distribution and confirm that the entire distribution shifts upwards over the period. Strikingly, the 25^{th} percentile of the distribution of house price correlation is negative until the late 1980s. To gauge the statistical significance of this trend, we regress the average –across state pairs – correlation and regress it on a trend, adjusting for the 5-years correlation in error terms with the Newey-West procedure. The fitted trend is equal to 0.015 with a t-stat of 5.3.

This fact resists numerous robustness checks that we do not report for brevity. In particular, the trend remains large and statistically significant using 3-year, instead of 5-year rolling correlations: +1.9 point per year, with a Newey-West adjusted t-stat of 5.4. Second, this trend is also present when we use MSA-level price indices from OFHEO. At the MSA level, average house price correlation across city pairs grows from .02 in 1980 to .18 in 1994. Like the trend using state-level prices, the increase is strongly significant statistically and economically, and continues into the 2000s.

3. A Framework to Measure Bank Integration

This Section develops a simple statistical framework to establish a testable relationship between house price comovement and a relevant measure of bank integration. Our framework allows for both aggregate and idiosyncratic shocks to the lending policy of banks (see Gabaix (2011)).

3.1. Basic Statistical Framework and Intuitions

Bank lending growth can be described as the sum of a bank-specific shock and an aggregate shock. Banks may operate in several states. $L^k_{i,t}$ is the lending of bank k in state i:

$$\frac{\Delta L^k_{i,t}}{L^k_{i,t-1}} = a_t + \eta_{k,t} \tag{1}$$

where $\eta_{k,t}$ is the idiosyncratic shock to the lending policy of bank k. The variance matrix of idiosyncratic shocks is given by $\Sigma_\eta = \sigma^2_\eta Id$. Bank-specific shocks can be interpreted as credit-supply shocks: For instance idiosyncratic bank funding shocks or bank-level decisions over lending growth. a_t is the aggregate shock to bank lending. It can be interpreted as a shock to the supply of wholesale funding or as a shock to the aggregate demand for securitized loans. σ_a^2 is the variance of a_t. Finally, note that the model can easily include state-specific shocks $\zeta_{i,t}$, like local credit demand shocks for instance. Including these shocks does not materially affect our mathematical derivations. We opted for the streamlined specification (1) for purely expositional purposes.

Our second assumption is that lending shocks affect house prices (Adelino et al. (2011); Loutskina and Strahan (2012); Favara and Imbs (2011)). We posit that house price growth in state i can be described by:

$$\frac{\Delta P_{i,t}}{P_{i,t-1}} = \mu \frac{\Delta L_{i,t}}{L_{i,t-1}} + \epsilon_{it} \tag{2}$$

where we assume that price shocks $\epsilon_{i,t}$ are independent of $\eta_{k,t}$ and a_t. The variance matrix of $\epsilon_{i,t}$ is given by: $\Sigma_\epsilon = \sigma_\epsilon^2 \big(\rho.J + (1-\rho)Id\big)$, where J is the squared matrix of ones. $L_{i,t}$ is aggregate lending by all banks active in state i: $L_{i,t} = \sum_k L_{i,t}^k$. μ is the elasticity of house prices to bank lending.

We then combine equations (1) and (2) to compute the variance-covariance matrix of house prices across states:

$$Var\left(\frac{\Delta P_{i,t}}{P_{i,t-1}}\right) = \sigma_\epsilon^2 + \mu^2\sigma_a^2 + \mu^2\sigma_\eta^2 \underbrace{\left(\sum_1^K \left(\frac{L_{i,t-1}^k}{L_{i,t-1}}\right)^2\right)}_{H_{ii}} \tag{3}$$

$$Cov\left(\frac{\Delta P_{i,t}}{P_{i,t-1}}, \frac{\Delta P_{j,t}}{P_{j,t-1}}\right) = \sigma_\epsilon^2\rho + \mu^2\sigma_a^2 + \mu^2\sigma_\eta^2 \underbrace{\left(\sum_1^K \frac{L_{i,t-1}^k}{L_{i,t-1}} \frac{L_{j,t-1}^k}{L_{j,t-1}}\right)}_{H_{ij}} \tag{4}$$

These two equations connect price volatility and covariance on the one hand, with bank market structure on the other hand. Equation (3) shows that house price volatility depends on bank concentration through idiosyncratic shocks only. In the absence of idiosyncratic shocks, the structure of the bank market has *no effect* on house price volatility. Since, in our model, banks all have the same exposure to the aggregate shock a_t, the aggregate exposure to a_t does not depend on market composition. When banks face idiosyncratic shocks, however, market structure matters. When banks are atomistic, the Herfindahl index H_{ii} is small: Idiosyncratic shocks cancel each other out and they do not contribute to aggregate uncertainty. When the lending activity is concentrated (the Herfindahl index H_{ii} is closer to 1), the largest banks are so prevalent that their shocks are not smoothed out. They contribution to aggregate fluctuations in lending.

The same intuition on the role idiosyncratic shocks helps to interpret the covariance equation (4). The first term captures the fundamental comovement $\rho_\epsilon \sigma_\epsilon^2$ that exists between house prices. The second term is the effect of the aggregate bank shock. Because banks operating in states i and j are subject to the same aggregate shock a_t, prices in these states tend to comove. Whether these banks overlap the two states, or are entirely different entities, the comovement induced by the common exposure to a_t is the same. This is why this second term does not involve the composition of the lending market. The third term represents the effect of idiosyncratic shocks on banks that overlap the two states. H_{ij}, the "co-Herfindahl" of states i and j is large when the same banks are large lenders in both states, and when the overlap is concentrated among a few banks. As in the variance equation, market integration has no effect on comovement, unless there are idiosyncratic shocks. But then, idiosyncratic shocks only matter when the market is concentrated enough. Hence, to generate meaningful comovement, idiosyncratic risk has to be borne by a few, large, overlapping banks.

We now calculate the correlation between house prices. We make the linear approximation that H_{ii} is small and obtain:

$$corr\Big(\frac{\Delta P_{i,t}}{P_{i,t}}, \frac{\Delta P_{j,t}}{P_{j,t}}\Big) = \left(\frac{\rho + \frac{\mu^2}{\sigma_\epsilon^2}\sigma_a^2}{1 + \frac{\mu^2}{\sigma_\epsilon^2}\sigma_a^2}\right) + \left(\frac{\frac{\mu^2}{\sigma_\epsilon^2}\sigma_\eta^2}{1 + \frac{\mu^2}{\sigma_\epsilon^2}\sigma_a^2}\right) H_{ij} - \left(\frac{\left(\rho + \frac{\mu^2}{\sigma_\epsilon^2}\sigma_a^2\right)\frac{\mu^2}{\sigma_\epsilon^2}\sigma_\eta^2}{\left(1 + \frac{\mu^2}{\sigma_\epsilon^2}\sigma_a^2\right)^2}\right) \frac{H_{ii} + H_{jj}}{2} \tag{5}$$

Equation (5) contains all the effects just discussed in the variance-covariance equations. The first term captures the effect of the aggregate banking shock. It increases when σ_a goes up, for given house price fundamental volatility σ_ϵ. This formalizes the intuition that a more volatile "common factor" to bank lending would lead to larger house price correlation. The second term of (5) is the focus of our cross-sectional analysis: it captures the impact of idiosyncratic shocks (it disappears if $\sigma_\eta = 0$). Idiosyncratic shocks generate more correlation when more banks overlap the two states, all the more so when these banks are large. The third term captures the variance effect: If states i and j both have concentrated banking markets, they will be sensitive to the idiosyncratic shocks of their big banks and will therefore be volatile, which for given covariance lowers the correlation. In our empirical analysis, to focus on the role of the co-Herfindahl H_{ij}, we will absorb these terms through state-year dummies.

3.2. Bank Integration Measures in the Data

We now go back to the data to calculate our measure of bank integration, the co-Herfindahl index $H_{ij,t}$. For each state pair (i, j) and each year t, we are able to calculate $H_{ij,t} = \sum_k s^k_{i,t} s^k_{j,t}$, where k is the index of BHCs that have some lending activity in both states i and j. $s^k_{i,t}$ is the market share of k in state i. It is equal to real estate loans held by k in state i, divided by all real estate loans held by BHCs active in state i.

We report descriptive statistics on the co-Herfindahls in Table I. Looking at descriptive statistics in Table I, we observe that the average co-Herfindahl is small (0.002), and is equal to zero until the 75% percentile. This comes from the fact that, since regulation was so effective at preventing bank integration, the co-Herfindahl is almost always zero before deregulation. At the same time, because our sample starts as soon as 1976, 36% of the observations correspond to state pairs before deregulation, even though, in 1996, 100% of the state pairs have deregulated (Michalski and Ors, 2012). Conditional on deregulation, the average co-Herfindahl is 0.006, compared to 0.001 prior to deregulation. This observation serves as the basis for our IV strategy: We explore the link between deregulation and bank integration more in depth in Section 4.1.

We show, in Table II, that bank integration rises sharply during the period, and thus has the power to explain the rise in house price comovement (as can be directly seen from equation (5)). As is clear from column 1 of this Table, the average $H_{ij,t}$ is multiplied by more than 3 during the period that we consider. The increase really starts after 1985, which corresponds to the timing of interstate banking laws that we use as shocks to financial integration (see Section 4). We then decompose the co-Herfindahl into the contribution of the 20 largest BHCs by total assets nationwide (variable rcfd2170 in the Call Reports), and the contribution of all other BHCs.[5] Columns 2 and 3 of Table II report the averages of the two components by sub-period. The numbers are consistent with the idea that bank integration increased in two steps. At first, in the 1980s, small banks merged and began to overlap in a few states but remained small and regional. Indeed, during this period our integration measure rises when we take all banks, while the top-20 bank contribution remains flat. In the 1990s, a few nationwide players emerged: Essentially all of the increase in bank integration is accounted for by the largest BHCs in the country.

An alternative potential explanation for the rise in house price comovement is that banks themselves have comoved more and more over the period. In equation (5), this effect would arise via an increase in aggregate volatility σ_a. This would happen for instance because banks relied more and more on the wholesale market to fund their mortgage issuance. As a result, common shocks to the demand for securitized loans, or common supply shocks to the wholesale funding, may have made bank lending more and more synchronized at the nationwide level. We discuss this effect in Appendix B, and show that, in the data, the opposite happens: we calculate σ_a as the rolling volatility of average lending growth, and find

[5]More specifically, we write:

$$H_{ij,t} = \sum_{k \in \text{Top } 20} s_{i,t}^k s_{j,t}^k + \sum_{k \notin \text{Top } 20} s_{i,t}^k s_{j,t}^k$$

where the first term is the contribution of the top 20 BHCs and the second term the residual.

that it decreases strongly over the period. The aggregate component of bank lending became smaller over the period, therefore unable to explain the increase in house price comovement over the period that we focus on.

3.3. Bank Size and Volatility

In our derivations, we assume that bank-level idiosyncratic shocks do not decrease with bank size. This is done mostly to simplify exposition. In Appendix A, we extend our analytical and empirical analyses to the case where bigger banks are less volatile. We find that the size-volatility relationship is not strong enough to significantly affect our conclusions. In this Section, we only provide the intuitions, and encourage interested readers to read the Appendix A for a more thorough analysis.

First, notice that larger banks tend to have less volatile loan growth. Among non-financial firms, there is a well-known negative relationship between size and volatility (see for instance Moskowitz and Vissing-Jorgensen (2002)). It can be related to the well-documented failure of Gibrat's law, i.e. that larger firms have slower growth. In the case of banks, this may arise because larger entities can smooth out shocks to smaller entities. Demand shocks are automatically dampened by the aggregation of accounts. Internal capital markets may help diversify away idiosyncratic funding shocks. Looking at our data, we find that indeed, larger banks are less volatile. But the relationship between size and volatility is not very strong. The upper bound of our estimates (see Appendix A) suggests that multiplying bank size by 1000 leads to a reduction in loan growth volatility by about 3.8 percentage points in the cross-section. This is a statistically significant effect, yet not a very large one.

Even if it is small, this relationship may affect our measurement of bank integration. For our measure of bank integration $H_{ij,t}$ to be large, we need cross-state lending to be concentrated into a few large banks. If, however, large banks are less volatile, this effect is attenuated. To understand it, take the limit case where large banks are a large collection of smaller banks. Then, idiosyncratic shocks to these small banks are diversified away, so that large banks have no idiosyncratic risk. In this case, they do not contribute at all to house price comovement –and therefore should not appear in the measure of bank integration. The argument is more general. When larger banks are less volatile, the Co-Herfindahl $H_{ij,t}$ is an upward biased measure of effective banking integration. This bias is small if bank shocks are close to being homoskedastic. If this approximation is wrong, however, estimating equation (5) generates incorrect estimates.

To check that this is not the case, we amend the definition of $H_{ij,t}$ to correct for the fact that larger banks are less volatile. As shown in Appendix, this amounts to putting a smaller weight, determined by the link between volatility and size, on the market shares products of larger banks. We show in Appendix A that this amended version of bank integration is strongly correlated with our simplified measure H_{ij} (the correlation coefficient is .78). We then re-run the estimations of our main table (Table VI), using the amended integration measure, and find similar effects. Comforted by such robustness, we choose, in order to simplify exposition, to focus in the main text on the approximation where bank shocks are homoskedastic.

4. Empirical Tests

In this Section, we show that more integrated banking markets lead to higher house price correlations. To this end, we estimate equation (5). Since bank integration and house price comovement may share common unobserved determinants, we use state pair-level bilateral reforms as instruments for integration. We first describe these reforms and show their validity as instruments for financial integration in the comovement regression. We then turn to OLS and IV estimates.

4.1. Bilateral Deregulations Increase Banking Integration

We discuss here the first stage of our IV strategy. To instrument $H_{ij,t}$ in the correlation regression, we use interstate banking deregulations as shocks to financial integration. We rely on data compiled by Amel (2000) and Michalski and Ors (2012). Between 1978 and 1994, various states allowed banks from other states to enter their banking markets via M&As. These deregulations typically, but not always, took place on the basis of reciprocity. 33.8% of the state pairs deregulations were "national non-reciprocal": one state would allow banks from all other states to enter its market. 21.6% were "national reciprocal": one state would open its market only to states that open their markets too. The third most common deregulation method was through "bilateral reciprocal" agreements (8.8%). We refer the reader to Michalski and Ors (2012) for more details on these deregulations. In 1995, the Riegle-Neal Act generalized interstate banking to all state pairs that had not deregulated before.

We believe these bilateral deregulations make sensible instruments for four distinct reasons. First, the timing coincides exactly: We show graphically as well as econometrically that both bank integration and house price correlation pick up right in the aftermath of these banking deregulations. Secondly, the fact that many deregulations were national in nature (reciprocal or non reciprocal) suggests that states did not pick the pairs they would belong too. Bilateral reciprocal agreement could create such a concern but they are a small minority. Third, the political economy of these reforms does not seem to have involved the mortgage market, but rather the relative lobbying effort of small banks, who favored the status-quo of segmented banking markets, and small firms, who wanted increased banking competition Kroszner and Strahan (1999). Fourth, we include in our specifications a large number of controls and fixed effects. We add the full set of state pair fixed effects, state-year fixed effects for each state in the state pair. We also control for the proximity in industrial composition, as well correlation of state-level incomes.[6]

[6] It is also possible to include state pair-specific trends, but given available Stata procedures, this comes at

Looking at the raw data, we find that these reforms have a strong impact on the level of bank integration in a state-pair. In Figure 2, we make as little treatment of the data as possible. We restrict our attention to state pairs that deregulate the same year and plot the mean integration measure $H_{ij,t}$ as a function of the number of years relative to the year of deregulation. To control for the aggregate evolution in banking integration, we adjust every year the measure of $H_{ij,t}$ by subtracting the mean co-Herfindahl for those state-pairs that will not deregulate in the next 5 years. These states serve as a benchmark for what happens to integration $H_{ij,t}$ in the absence of interstate banking deregulation. As can be seen from the graph, the average adjusted co-Herfindahl is flat before the reform and close to zero, and then starts to pick up right at the time of the bilateral banking deregulation. The deregulations therefore impulse a clean break in the pattern of banking integration, which suggests that they will be powerful instruments.

In our regression analyses, we need to introduce a "smoothed" version of the co-Herfindahl. More precisely, for each state pair-year in our sample, we define the five year rolling average of $H_{ij,t}$: $H^{m}_{ij,t} = \sum_{k=0}^{k=4} H_{ij,t+k}$. We do this because our regressions link the co-Herfindahl with a rolling measure of house price correlation. Because it is rolling, this measure only responds progressively to sudden regulatory shocks. This is why it is internally consistent to average the co-Herfindahl over the same window. In the paper, we therefore only report regression results using the "smoothed" measure of integration. Notice that, however, our results do not depend on this assumption, and remain strongly significant when we use the "spot" co-Herfindahl.

Let us now investigate the first stage regression statistically. For a state pair (i, j) in year t, we estimate the following equation:

the cost of not controlling for state pair fixed effects. The reason is that there are 1,225 state pairs and some 2,000 state-years, so that we would need a procedure that combines triple fixed effects and a large number of trends. To bypass this limitation, we have reestimated our model without state-year dummies but with state pair trends. When we do this, our results remain strongly significant statistically, but a bit smaller economically. To clarify exposition, we focus on only one specification in the main text. These alternative tables are, however, available from the authors upon request.

$$H^m_{ij,t} = \alpha_{ij} + POST^m_{ij,t} + \delta_t + controls_{ij,t} + \nu_{ij,t} \quad (6)$$

where $POST^m_{ij,t}$ is the 5 year forward rolling average of a dummy equal to 1 when both states in the pair have opened their banking markets to the other state. We smooth the POST dummy because we use the "smoothed" integration $H^m_{ij,t}$ as our dependent variable. Again, equation (6) yields similar estimates without the smoothing procedure (as Figure 2 can attest), but we want to remain consistent with the second stage regression that uses rolling correlations. α_{ij} is a state pair fixed effect, designed to control for composition effects that arise from the fact that some pairs may deregulate before others. δ_t are year fixed effects that capture nationwide trends in bank integration potentially unrelated to the reforms. $controls_{ij,t}$ are here to capture time-varying measures of state similarity that may correlate with the reform. We include: the 5-years forward correlation of state-level labor income growths, proximity in industry structure, and the log of states i and j's total labor incomes. In our most restrictive specification, we also include state i-year fixed effects as well as state j-year fixed effects, so that all the identification comes from changes in correlation and deregulation within a given state-year. We cluster error terms $\nu_{ij,t}$ at the state pair (i, j) level.

We report estimates of (6) in Table III. The first column only has time fixed effects and no other controls. Notice that we are only using 25,725 observations which correspond to the 1976-1996 period, as our smoothed co-Herfindahl $H^m_{ij,t}$ requires 5 years of Call Reports to be computed.

Consistently with the graphical evidence, $POST^m_{ij,t}$ is strongly significant at 0.013 and a t-stat of 8.6. Hence, bank integration in deregulated state pairs is 0.013 higher than in state pairs that have not yet deregulated. As previously noted, this number is quite large (approximately one sample standard deviation), which suggests that the reforms had a massive impact on our variable of interest. Column 2 further controls for the sizes of state i and state j (measured through log income), the similarity in industry composition, as well as the 5-year forward correlation of personal incomes between the two states. The estimate does not change at all. Column 3 adds state-pair fixed effects. The point estimates drops a bit but remains strongly significant at .7 percentage points. This is still a large effect, about one half of a sample standard deviation of $H_{ij,t}$. Column 4 finally includes, in addition to the state-pair fixed effects, state-year fixed effects for both states in the state pair. The coefficient increases back up to almost 1 percentage point (with a t-stat of 7.8). Columns 5-6 replicate the specifications in columns 3-4, except that now the sample used to compute co-Herfindahls $H_{ij,t}$ stops in 1994, the last full year before Riegle-Neal is implemented. We do this important robustness check because the location of BHC assets becomes ill-measured in the Call Reports after this date. Notice that sample size drops to 18,375 observations, which corresponds to the 1976-1990 period: This is again because we are using five year forward rolling averages. Even after such a drastic reduction of the sample –only 17% of the observations correspond to POST bilateral reforms– the estimate remains strongly significant and qualitatively similar.

4.2. Bilateral Reforms Increase House Price Comovement

Before turning to IV regressions, we verify that interstate banking deregulations have directly caused an increase in house price correlation. Since we know that deregulations increased bank integration, and if we conjecture that integration affects comovement, as in equation (5), then deregulations should directly impact comovement. In this Section, we test for the presence of this reduced form relationship. The advantage of this reduced form approach is that it does not rest on the validity of the Call Reports data to measure the location of bank assets.

We first look at the raw data in Figure 3. We follow the same methodology as in Figure 2. We focus on those state-pairs where both deregulations occur the same year, and plot, for each date relative to the deregulation (from 10 years before to 6 years after), the average house price correlation across state pairs. Again, to control for the aggregate evolution of house price growth correlation, this average correlation is measured relative to the mean correlation in the same year in those state-pairs that will not deregulate in the next five years. Figure 3 shows that following the deregulation of interstate banking, house price growth correlation picks up by an average of 20 percentage points. This sharp increase occurs a couple of years after the deregulation. Since our correlation measure is forward year rolling, this means that banking reforms started to affect the correlation structure of house prices 2 years after implementation. Notice the fact that the mean-adjusted correlation is flat in the pre-reform period, which strongly indicates that reforms were not endogenous to some changes in housing market integration.

We now test for this relationship in a regression framework. We estimate the following equation:

$$\rho_{ijt} = \alpha_{ij} + POST^{m}_{ijt} + \delta_t + controls_{ijt} + \nu_{ijt} \tag{7}$$

where ρ_{ijt} is the 5-years rolling forward correlation of house price growth. Because this correlation is computed as a 5-years forward rolling window, we use a post-deregulation dummy that is also averaged out over the next 5 years: as in equation (6), $POST^{m}_{ijt}$ is the 5 year forward rolling average of a dummy equal to 1 when both states in the state pair have opened their banking market to the other state. Again, this smoothed dummy allows to cope with the fact that the correlation is calculated on a rolling basis over the same interval.

Table IV contains the estimates and is organized like the first four columns of Table III. Column 1 only has year fixed effects: In state pairs where interstate banking is deregulated, we find that house price growth correlation goes up by 7.8 percentage points relative to state-pairs that are not yet integrated (t-stat of 4). Columns 2 adds the time-varying state-pair level controls (log of personal income in state 1 and 2, proximity in industry structure, state-pair income correlation). As expected, income correlation has a large and significant predictive power on house price growth correlation, but does not affect our coefficient of interest very much. Column 3 adds the state-pair fixed effects, so that the identification is now within state-pair. We find that when interstate banking is deregulated, a state-pair experiences an increase in house price growth correlation of 5.8 percentage points relative to a state-pair that does not deregulate in the same time period. This is a large economic effect that explains about 18% of the sample standard deviation in house price growth correlation.

In Column 4, we add state-year fixed effects for both states of the pair (ij, t). In terms of equation (5), state-year dummies fully control for changes in state-specific volatilities (the H_{ii} terms in the equation) that affect the correlation. The results in Column 4 show that far from reducing our effects, these additional controls make our point estimate of the coefficient of interest larger at almost 10 percentage points. The effect is again strongly significant with a t-stat of 4.6.

We graphically show our econometric results in Figure 4. In this Figure, we re-run the fully saturated specification of Table IV, column 4, except that we introduce one dummy per year from 7 years before to 1 year after the deregulation. This window is asymmetric to account for the fact that our correlation measure is forward rolling. To make the Figure easier to read, these dummies are not smoothed (as the $POST^m_{ij,t}$ is). We then retrieve the estimate of each dummy variable and report it in the Figure, along with its 95% confidence interval. This Figure delivers two insights. First, before the deregulation, house price correlation is flat. Second, there is a clean break in trend as the reform starts. The correlation react 2 years before the banking markets become integrated, which is reasonable given that correlations are computed using a five year *forward* rolling window. This suggests that house prices start responding to integration some 3 years after the reform.

To check that we are conservative enough in estimating our standard errors, we have also performed a placebo analysis (see Bertrand et al. (2004)). The procedure is the following. First, for each state pair, we randomly draw deregulation dates with replacement from the empirical distribution of deregulation dates. We then re-run the regression of column 3, Table IV on these simulated data. We then retrieve the point estimate of $POST^m_{ij,t}$ and store it. We perform this procedure 100 times, and plot the distribution of these estimates in Figure 5. While our actual result is .058, the average estimate from the placebo regressions is .0005. We reject the null of 0 at the 10% (resp 5%) confidence level for only 7% (resp. 4%) of the simulations. These simulations give us confidence that our treatment of standard errors is adequate and does not lead to overestimating precision of our estimates.

Table V provides robustness checks on this reduced form regression. All the robustness checks reported in this Table use the fully saturated specification of Table IV, Column 4 –but of course they also hold for simpler specifications. Column 1 restricts the estimation period to 1976-1994. There are two important motivations for this robustness check. First, the Riegle-Neal Act of 1994 constitutes a shock to all state-pairs which might have affected house price correlations. While this effect should in principle be captured by our year fixed-effects, there might some state-pair specific reaction to the Riegle-Neal Act that could contaminate our estimates. Restricting the sample window to 1976-1994 allows us to make sure this is not the case. The second reason for this robustness checks is that, in some of our OLS and IV specifications, we check that our estimates also hold in the pre Riegle-Neal period, because after 1994 Call Reports used to calculate the co-Herfindahl are less reliable. The estimation in column 1, Table V ensures that the reduced form estimate also works for this restricted period: the coefficient remains similar at 12 percentage points (t-stat of 4).

In Table V, column 2, restricts the sample to a window of 5 years around the bilateral deregulation of interstate banking. We find an even larger effect of about 16 percentage points. These narrower sample periods limit the possibility that other state-pair level events occurring far away from the deregulations bias our estimates. Columns 3 excludes the 5 years preceding the bilateral deregulation of interstate banking from our estimation window. The reason for this robustness check is that the five years preceding a reform constitute "contaminated" years: Part of the correlation is computed using house price growth data before the reform while the remaining part uses data measured after the reform. As we explain above, this is the reason why our POST dummy is also averaged out over the next five years in equation (6) and (7). Excluding these years thus check for the robustness of this averaging choice. The coefficient we estimate decreases marginally to 8 percentage point (t-stat of 3.7). Column 4 adds an additional control variable ("After First Deregulation"), which is the five year forward average of a dummy equal to 1 after the first unilateral deregulation of the state pair. Indeed, for approximately half of the state pairs, interstate banking deregulation is not symmetric at first: one state allows banking from the other state without reciprocity. Column 4 shows that all of the rise in house price growth correlation following the deregulation of interstate banking takes place after both states in the pair have opened their banking market to banks from the other state. The "After First Deregulation" variable is insignificant and small, while the point estimate of the After Deregulation variable is unchanged.

Columns 5-7 test robustness using alternative measures of house price comovement. Column 5 shows that our results are robust to the horizon we use to compute the various correlations by using a 3-year rolling window instead of a 5-year rolling window to compute the correlation of house price growth and income growth. The estimate we obtain with a 3-year horizon is twice larger — 20 percentage points — but is also noisier (t-stat of 2.3). Column 6 shows the effect of the deregulation of interstate banking on house price comovement measured as the average beta of house price growth in the state pair. This measure has been used in part of the literature on financial contagion (Forbes and Rigobon (2002)).[7]. We find again a strong effect of interstate banking deregulation on house price comovement as the deregulation leads to an 8.7 percentage points increase in average beta. This is economically large (28% of the sample standard deviation of average beta). Finally, Column 7 uses the covariance of house price growth as our dependent variable. Since the covariance is not a scaled measure, its empirical distribution is much noisier and contains a non-trivial amount of outliers. We deal with this issue by windsorizing the covariance of income growth and house price growth using the median plus/minus five times the interquartile range as thresholds for the distributions. Our result is robust to, instead, windsorizing at the 1^{th} percentile or the 5^{th} percentile. We find a large and significant increase in house price growth

[7] Section 2.1 describes the construction of our average beta measure

covariance following the deregulation of interstate banking in a state-pair. The effect is almost 8 percentage points, which represent 19% of the sample standard deviation of house price growth covariance.

4.3. Bank Overlap and House Price Comovement: OLS and IV

We now estimate equation (5) on the set of state pairs. Our econometric specification is given by:

$$\rho_{ijt} = \alpha_{ij} + b.H^m_{ijt} + c.X_{ijt} + \delta_{jt} + \delta_{it} + \nu_{ijt} \tag{8}$$

where $H^m_{ij,t}$ is the 5 year forward rolling average of $H_{ij,t}$. The control variables X are the difference in industry composition between the two states in the pair and the 5-year forward correlation of income growth. δ_{jt} and δ_{it} are state-j year and state-i year fixed effects. As in our previous specifications, we use 5-years forward rolling averages of integration and concentration. In line with Table III, we instrument bank integration H^m_{ijt} using the interstate banking deregulation variable $POST^m_{ij,t}$.

Table VI presents the regression estimates. Columns 1 and 2 use the whole sample for estimation: 1976-2000, which leads, as before, to 25,725 observations. This long period has the advantage of covering all deregulations, and by 2000, all states pairs have deregulated since at least 5 years. The drawback of this long period is that we use Call Report information on bank asset location over 1995-2000 which is much less reliable. As a robustness check, we therefore re-run the regressions on 1976-1994 and report the OLS and IV results in columns 3 and 4. As in previous regressions using this restricted sample, the number of observations logically drops to 18,375.

The standard errors of our IV coefficients are estimated using a bootstrap method. This method helps us to easily cope with the simultaneous use of IV and our very large number of fixed effects (more than 3,000). To implement it, we repeat the following procedure 100 times. Each round, we first draw with replacement 1,225 state pair histories from our sample. We then run our first stage regression with state pair and state-year fixed effects, retrieve the predict value of integration, and run the second state regressions. We finally obtain a point estimate. We repeat the procedure 100 times, and use the standard deviation of these estimates to calculate the t-values we report in Table VI, columns 2 and 4.

In column 1, the OLS estimation provides a point estimate of 1.8 (t-stat of 4.3). A one standard-deviation increase in the co-Herfindhal leads to a 7% standard deviation increase in house price growth correlation. The IV estimation, reported in column 2, provides a coefficient that is 6 times larger (13) but also noisier (t-stat of 4.5). This suggests that OLS are downward biased, probably due to measurement error (our measure of banking integration imperfectly proxies for the actual banking integration of the state-pair). Given our IV estimate, a one s.d. increase in co-Herfindahl leads to a 17% s.d. increase in house price correlation.

Taking these cross-sectional estimates to the time-series, we find that the rise of bank integration has the power to explain approximately one third of the overall increase in house price comovement between 1976 and 1996. From Table II, we see that the average co-Herfindahl H_{ijt}^m increases from .0017 to .0055 over this period. Given a coefficient estimate of 13, our estimation thus explains an increase in house price correlation of $0.38 \times 13 \approx 5$ percentage points over this period, compared to an overall observed increase in correlation by about 15 ppt over the same period (see Figure 1). As shown in Table II, the emergence of the 20 largest banks in the country explains almost all of this evolution.

5. Conclusion

This paper has shown that the integration of the US banking market in the 1980s and the 1990s has led to synchronization of house prices across US states. We thus provide evidence that freeing capital flows – at least through the banking system – can lead to significant contagion across geographic regions. In doing so, we highlight the importance of idiosyncratic risk in shaping the relationship between bank integration and asset prices comovement. This paper thus contributes to the international finance literature on the link between contagion and capital market movements.

More broadly, the paper documents that interstate banking deregulations led to a large wave of capital market integration in the US (see also Morgan et al. (2004); Loutskina and Strahan (2012)), with a few large banks slowly becoming the national key-players. This suggests that these deregulations can be further used as natural experiments to test macroeconomic models regarding the economic effects of capital markets integration.

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6. Tables and Figures

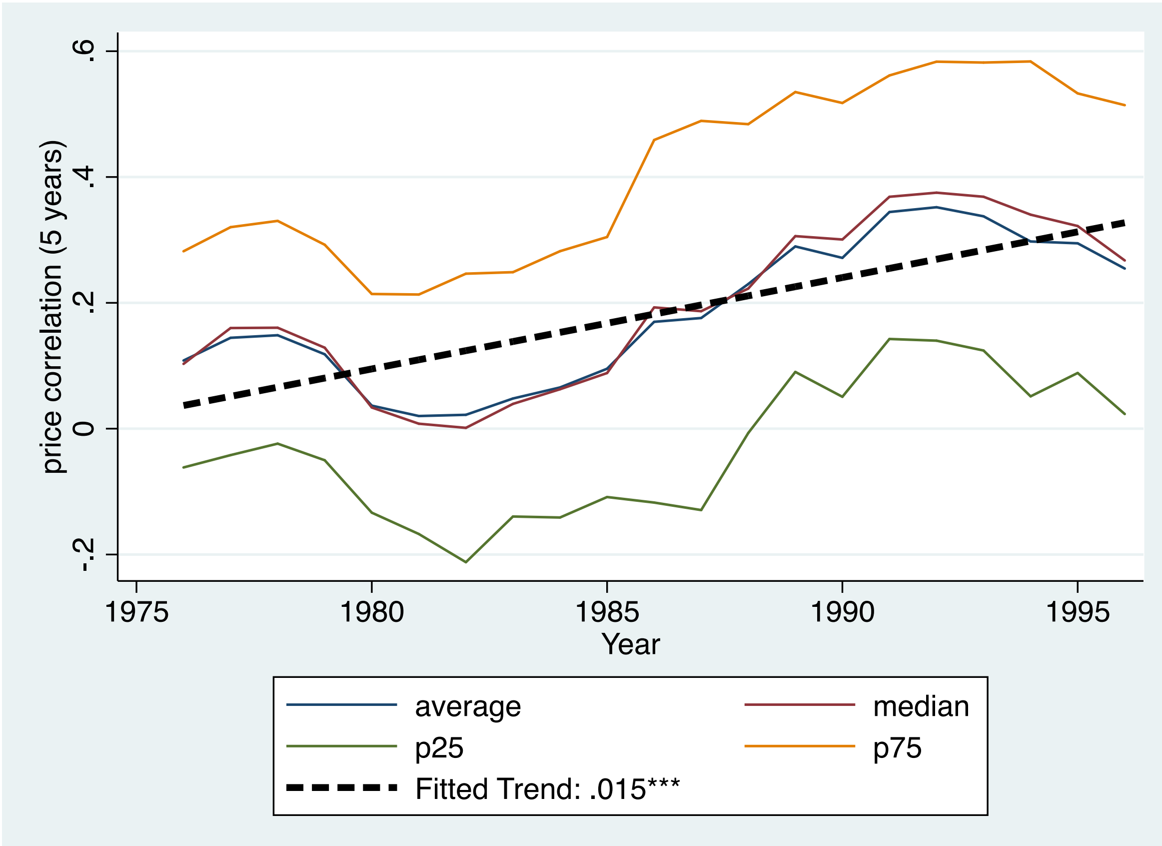

Figure 1: Pairwise correlation of real estate price growth across US States: 1976-1996..
Source: OFHEO real estate price index. *Note*: This figure plots the mean, median, 25^{th} and 75^{th} percentiles of the distribution of pairwise correlations of real estate price growth across US States for the 1976-1996 period. Correlation is computed using a 5-years forward rolling window with quarterly data.

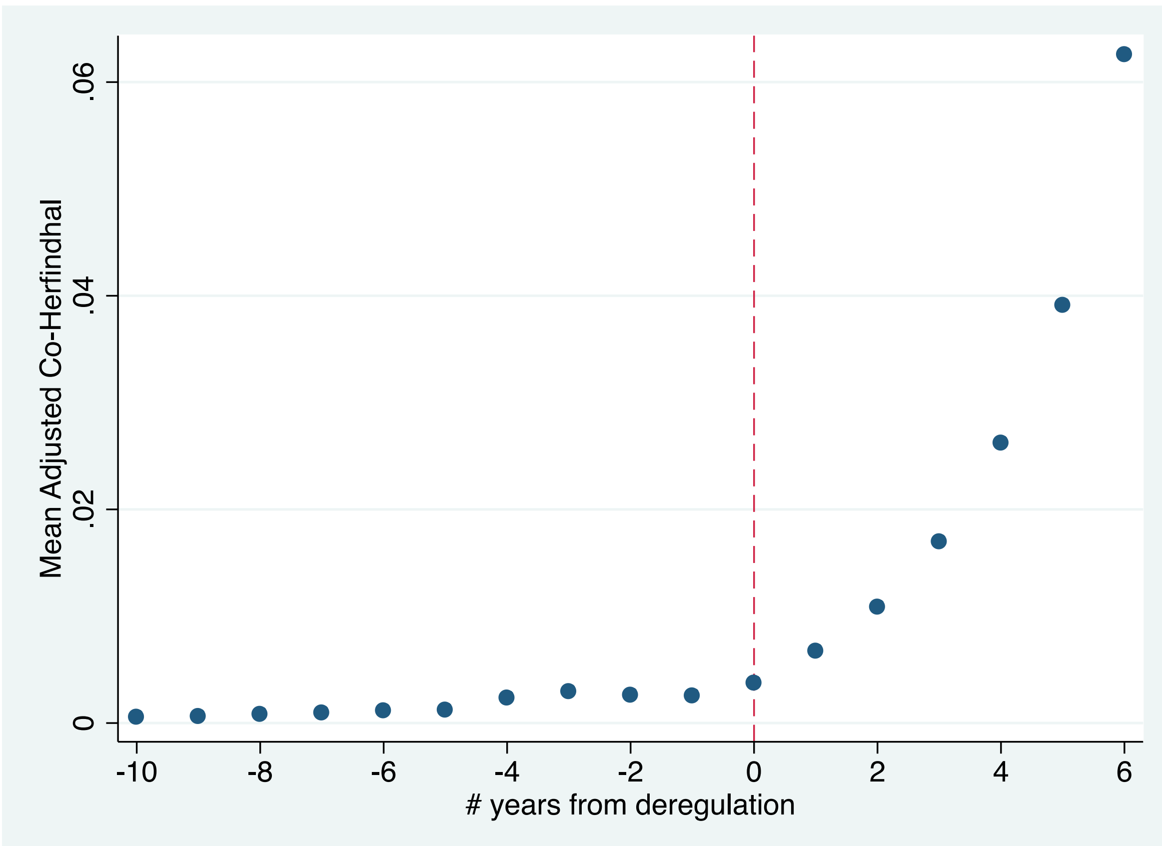

Figure 2: **Banking Integration and Interstate Banking Deregulation.**
Source: Call Reports. *Note*: This figure plots the average adjusted-Co-Herfindhal of banking assets across pairs of US states as a function of the distance to deregulation of interstate banking in the state-pair. Co-Herfindhals are adjusted by the median co-Herfindhal of states in the same year that will not deregulate in the next five year. The sample is restricted to the set of US state-pairs where both states deregulate in the same year. The co-Herfindhal H_{ij} is defined in Section 3.

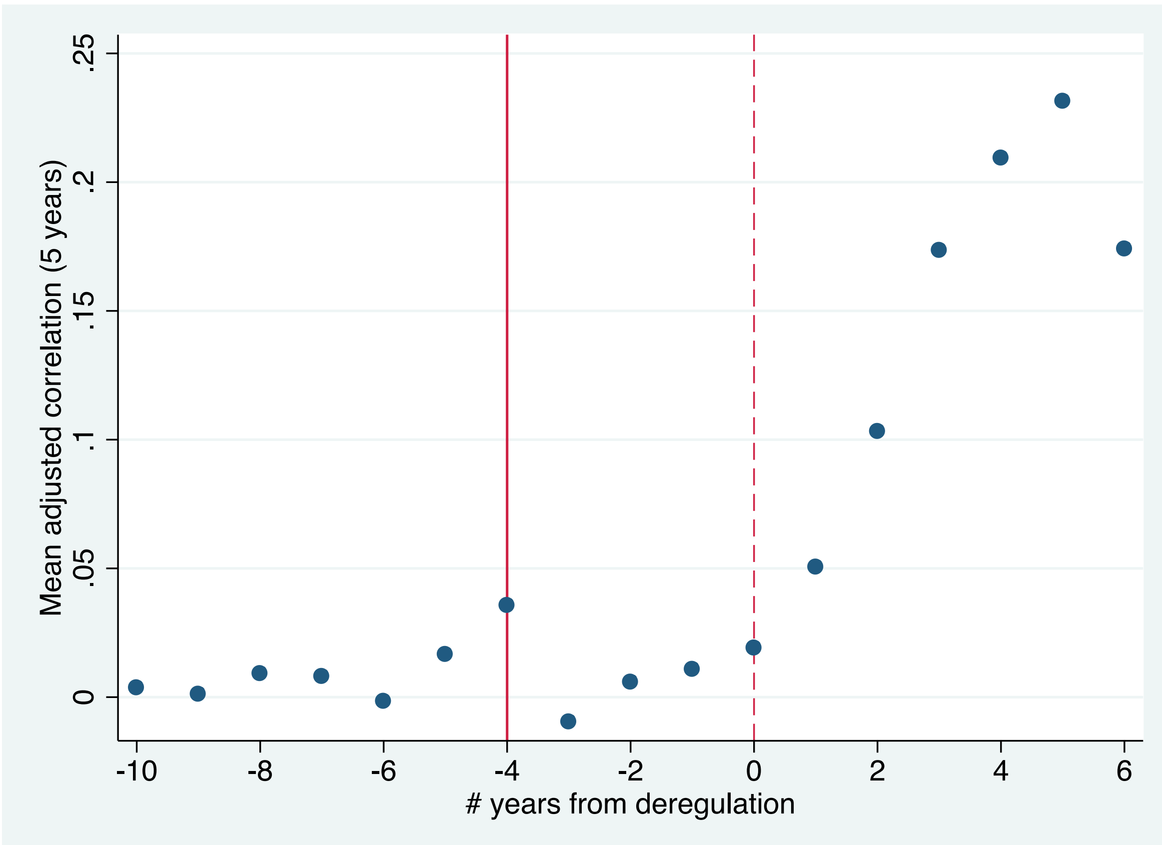

Figure 3: **Real Estate Price Correlation and Interstate Banking Deregulation**
Source: Call Reports. *Note*: This figure plots the average adjusted-house price growth correlationacross pairs of US states as a function of the distance to deregulation of interstate banking in the state-pair. House price growth correlation are adjusted by the mean correlation for states that will not deregulate in the next five year. The sample is restricted to the set of US state-pairs where both states deregulate in the same year.

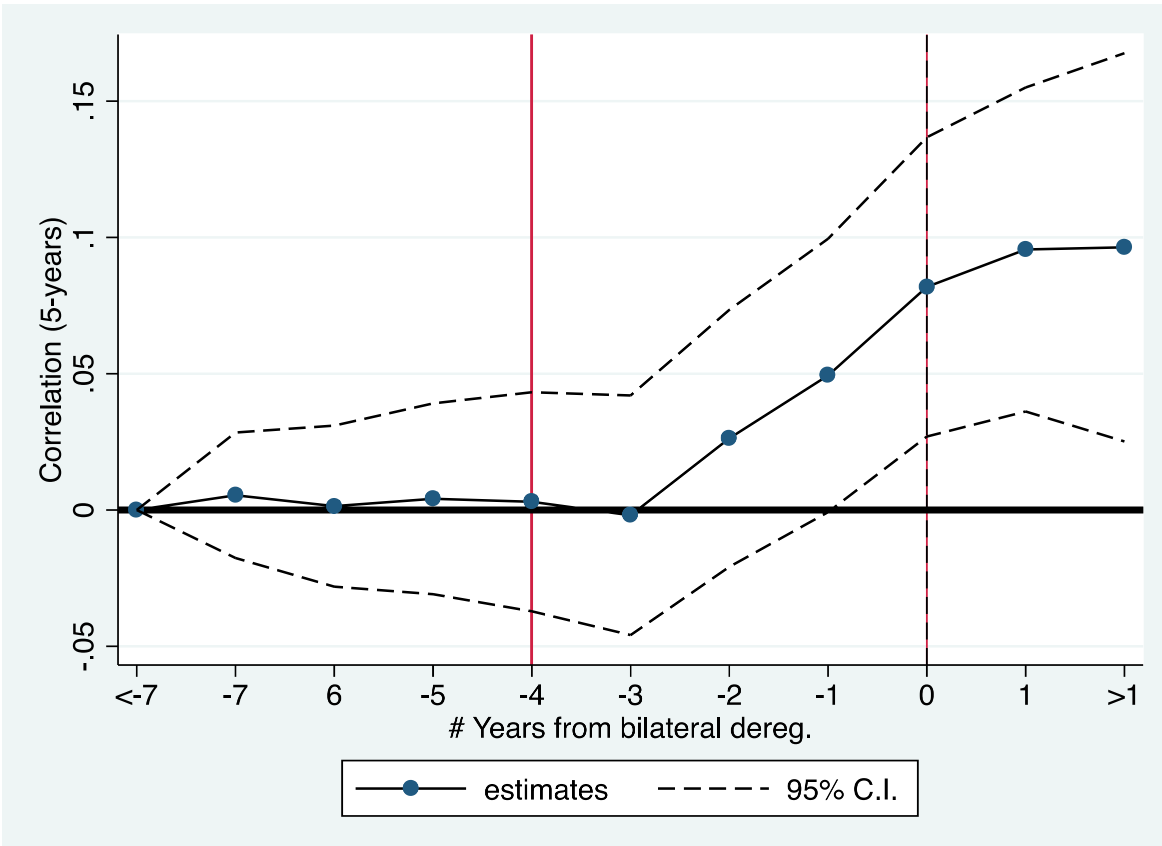

Figure 4: **Real Estate Price Correlation and Interstate Banking Deregulation: Regression Results**

Source: OFHEO real estate price index. *Note*: This figure plots the coefficient estimates (and the corresponding confidence interval) for the δ_k coefficients in the reduced-form regression: $\rho_{ij}^t = \sum_{k=-6}^{2} \delta_k \mathbb{I}_{t=T_{ij}+k} + \delta_{>2}\mathbb{I}_{t>T_{ij}+2} + \alpha_{ij} + \gamma_t + \kappa_{it} + \kappa_{jt} + \lambda \mathbb{I}_{t>\tau_{ij}} + \beta X_{ij}^t + \epsilon_{ij}^t$ where ρ_{ij}^t is the five-years forward correlation of real estate price growth in state-pair (i,j), T_{ij} is the year of bilateral deregulation of interstate banking for state-pair ij, X contains Log(Income 1), Log(Income 2), Differences in industry composition and Income Correlation, as defined in Table I and τ_{ij} is the year of the first interstate banking deregulation in state-pair (i,j).

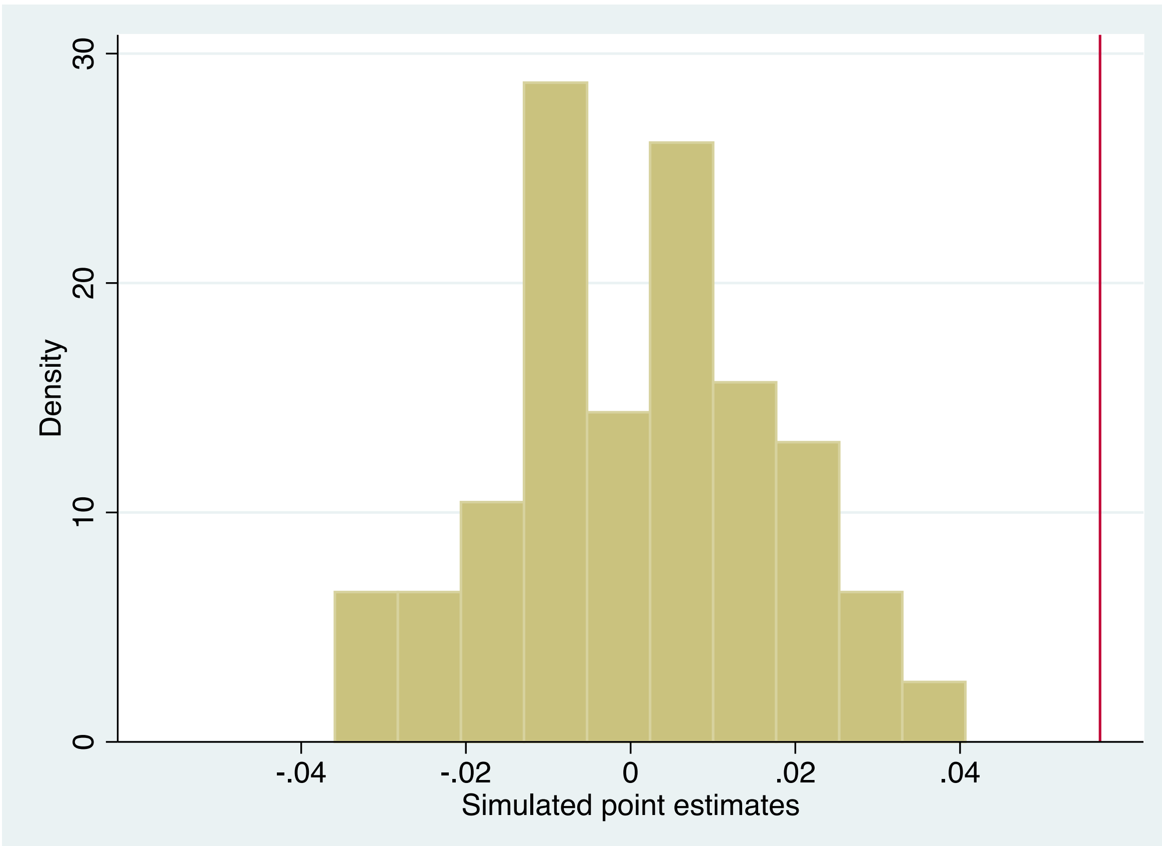

Figure 5: **Empirical Distribution of Placebo Estimates**
Note: This figure reports the empirical distribution of the point estimates recovered in these placebo regressions. We randomly draw deregulation dates with replacement from the empirical distribution of deregulation dates. We then re-run the analysis of column 3, Table IV on these placebo deregulations. We repeat this procedure 100 times.

Table I: Summary Statistics

Source: OFHEO real estate price index, BLS and Call Reports, 1976-2000. *Note:*. The first 10 variables are only defined for 1976-1996; The last two over 1976-2000. "Price Correlation (5 years)" is the pairwise correlation of real estate price growth across US states computed over a 5 year forward rolling windows with quarterly data. "Price Correlation (3 years)" uses a 3 year forward rolling window. "Price Beta (5 years)" is defined as $\frac{\beta^{i\to j}+\beta^{j\to i}}{2}$, where $\beta^{i\to j}$ is the beta of house price growth in state i on house price growth in state j, using a 5 year forward rolling windows and quarterly data. "Price Covariance (5 years)" is the pairwise covariance of real estate price growth across US states computed over a 5 year forward rolling windows with quarterly data. "Income Correlation (5 years)" is the pairwise correlation of income growth across US states computed over a 5 year forward rolling windows with quarterly data. "Income Correlation (3 years)" uses a 3 year forward rolling window. "Income Beta (5 years)" is computed as "Income Correlation (5 years)" but using income growth instead of house price growth. "Income Covariance (5 years)" is the pairwise covariance of income growth across US states computed over a 5 year forward rolling windows with quarterly data. Log(Income i) (resp. Log(Income j)) is the log of personal income in state i (resp. j) of the pair. "Industry composition difference" is defined as $\sum_{s=1}^{9}(\sigma_1^s-\sigma_2^s)^2$ where σ_i^s is the share of workers in state i working in industry i.industries across US states. "Co-Herfindhal" is defined for a state pair (i,j) as $\sum_k s_k^i \times s_k^j$, where s_k^i is the market share of bank k in state i, in terms of outstanding real estate loans.

Variable	Mean	Std. Dev.	p(10)	p(25)	p(50)	p(75)	p(90)	Obs.
Price Correlation (5 years)	0.185	0.328	-0.250	-0.049	0.188	0.426	0.625	25,725
Price Correlation (3 years)	0.195	0.373	-0.311	-0.078	0.207	0.486	0.687	25,725
Price Beta (5 years)	0.227	0.428	-0.302	-0.056	0.238	0.525	0.755	25,725
Price Covariance (5 years)	0.411	1.600	-0.954	-0.067	0.185	0.730	2.726	25,725
Income Correlation (5 years)	0.477	0.250	0.127	0.321	0.515	0.668	0.771	25,725
Income Correlation (3 years)	0.465	0.310	0.021	0.278	0.525	0.706	0.818	25,725
Income Beta (5 years)	0.539	0.305	0.151	0.367	0.574	0.734	0.852	25,725
Income Covariance (5 years)	0.568	0.568	0.106	0.247	0.427	0.733	1.211	25,725
$\text{Log(Income)}_{i,t}$	10.863	1.097	9.363	9.995	10.879	11.725	12.307	25,725
$\text{Log(Income)}_{j,t}$	10.878	1.098	9.404	10.031	10.868	11.619	12.350	25,725
Industry Comp. Difference	0.017	0.023	0.002	0.004	0.009	0.019	0.040	30,625
Co-Herfindahl $H_{ij,t}$	0.003	0.013	0.000	0.000	0.000	0.000	0.005	30,625

Table II: Evolution of Bank Integration

Source: OFHEO real estate price index, BLS and Call Reports, 1976-2000. *Note:*. This Table reports the evolution of the average "Co-Herfindhal", defined for a state pair (i, j) as $\sum_k s_{i,t}^k \times s_{j,t}^k$, where $s_{i,t}^k$ is the market share of bank k in state i in year t. For each state pair, the Co-Herfindahl is decomposed into two parts. The first one is the contribution of the 20 largest BHCs by total assets, i.e. $\sum_{k'} s_{i,t}^{k'} \times s_{j,t}^{k'}$, where k' are BHCs who belong to the top 20 by total assets nationwide. The second component is the residual, i.e. the contribution of all other banks. Column (1) reports the average co-Herfindahl by period, across state pair-years in the period. Column (2) does the same with the top 20 contribution. Column (3) does the same with the residual.

	All BHCs	Top 20	Others
1976-1980	.0017	.0016	.00013
1981-1985	.0018	.0013	.00052
1986-1990	.0027	.0015	.0012
1991-1995	.0057	.0046	.0011
1996-2000	.0055	.0047	.00081

Table III: Bank Integration and Banking Deregulation

Source: OFHEO house price index and Call Reports. Sample period: 1976-2000 in columns 1-4, 1976-1994 in columns 5-6. Note: The dependent variable is, for each US state-pair, the five year forward rolling average of the co-Herfindhal. After Deregulation is the 5 year forward rolling average of a dummy variable equal to 1 in the years following the bilateral deregulation of interstate banking. Log(Income i) is the log of the 5 year moving average of state i's personal income. Income Correlation is the pairwise correlation of personal income growth across US states computed every quarter over a 5 year rolling windows using quarterly data. Differences in industry composition is defined as $\sum_{s=1}^{9}(\sigma_1^s - \sigma_2^s)^2$ where σ_i^s measures the share of workers in state i working in industry i. All specifications include year fixed effects. Column (3)-(6) include state-pair fixed effects. Columns (4) and (6) include state-year fixed effects. Columns (5)-(6) are restrict the sample period to 1976-1994, since the bank asset location information is less reliable in Call Reports after the Riegle-Neal Act of 1994. Standard errors are clustered at the state-pair level. T-statistics reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5 and 1% levels of significance.

	H_{ij}^m					
	1976-2000				1976-1994	
	(1)	(2)	(3)	(4)	(5)	(6)
After Deregulation	.013***	.013***	.0053***	.0075***	.0072***	.0099***
	(9.7)	(9.7)	(7.7)	(7.6)	(7.2)	(7.7)
Log(personal income) in state 1		-.00063**	.0056***		.0073***	
		(-2.2)	(3.1)		(5.2)	
Log(personal income) in state 2		-.00051*	.0096***		.0083***	
		(-1.7)	(4.8)		(4.5)	
Diff. in Ind. Comp.		-.0013	.063**	.099**	.06***	.1**
		(-.13)	(2.5)	(2.1)	(3.1)	(2.4)
Income Correlation		.0034***	-.00045	-.0017***	-.000066	-.00038
		(4)	(-1.1)	(-2.8)	(-.19)	(-.75)
Observations	25725	25725	25725	25725	18375	18375
R2	.091	.098	.75	.79	.83	.86
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-pair FE	No	No	Yes	Yes	Yes	Yes
State i × Year FE	No	No	No	Yes	No	Yes
State j × Year FE	No	No	No	Yes	No	Yes

Table IV: Banking Deregulation and House Price Growth Correlation
Source: OFHEO house price index. Sample period: 1976-2000. Note: The dependent variable is the pairwise correlation of real estate price growth across US states computed every quarter over a 5 year rolling windows using quarterly data. After Deregulation is the 5 year moving average of a dummy variable equal to 1 in the years following the bilateral deregulation of interstate banking. Log(Income i) is the log of the 5 year moving average of state i's personal income. Income Correlation is the pairwise correlation of personal income growth across US states computed every quarter over a 5 year rolling windows using quarterly data. Differences in industry composition is defined as $\sum_{s=1}^{9} (\sigma_1^s - \sigma_2^s)^2$ where σ_i^s measures the share of workers in state i working in industry i. All specifications include year fixed effects. Column (3), (4) and (5) include state-pair fixed effects. Column (4) include state-pair specific trends. Column (5) includes state-year fixed effects for each state in the pair. Standard errors are clustered at the state-pair level. T-statistics reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5 and 1% levels of significance.

	House Price Growth Correlation			
	(1)	(2)	(3)	(4)
After Deregulation	.078***	.069***	.058***	.099***
	(4)	(3.9)	(3.3)	(4.6)
Log(personal income) in state 1		.025***	.18***	
		(6)	(3)	
Log(personal income) in state 2		.019***	.21***	
		(4)	(3.9)	
Diff. in Ind. Comp.		-.11	.96	-.35
		(-.5)	(1.3)	(-.32)
Income Correlation		.19***	.075***	.11***
		(12)	(4.8)	(4.7)
Observations	25725	25725	25725	25725
R2	.12	.16	.39	.53
Year FE	Yes	Yes	Yes	Yes
State-pair FE	No	No	Yes	Yes
State i × Year FE	No	No	No	Yes
State j × Year FE	No	No	No	Yes

Table V: Banking Deregulation and House Price Growth Correlation: Robustness Checks
Source: OFHEO house price index. Sample period: 1976-1994 in column (1) and 1976-2000 in all other columns. Note: The dependent variable is the pairwise correlation of real estate price growth across US states. It is computed every quarter over a 5 year rolling window using quarterly data in columns (1), (2), (3), (4) and (6) and using a 3 year rolling window in column (5). After Deregulation is the 5 year moving average of a dummy variable equal to 1 in the years following the bilateral deregulation of interstate banking. After First Deregulation is the 5 year moving average of a dummy variable equal to 1 in the years following the first deregulation of interstate banking across the two states in the pair. Income Correlation is the pairwise correlation of personal income growth across US states computed every quarter over a 5 year rolling windows using quarterly data. Income beta is the average beta of income growth of state i on income growth of state j, computed over a 5 year rolling windows using quarterly data, averaged over the pairs (i, j) and (j, i) Differences in industry composition is defined as $\sum_{s=1}^{9} (\sigma_1^s - \sigma_2^s)^2$ where σ_i^s measures the share of workers in state i working in industry i. All specifications include state-pair fixed effects as well as state-year fixed effects for each state in the pair. Column (2) only includes a window of 5 years around the bilateral deregulation of interstate banking in the state-pair. Column (3) excludes the five years before the bilateral deregulation of interstate banking in the state-pair. Column (4) explicitly controls for the behavior of price growth correlation in the years following the first deregulation of interstate banking in the state-pair. Column (5) computes the price growth correlation, as well as the income correlation, using a 3 year rolling window. Column (6) uses as a dependent variable the average beta of real estate price growth of state i on real estate price growth of state j, computed over a 5 year rolling windows using quarterly data, averaged over the pairs (i, j) and (j, i). Column (7) uses as a dependent variable the covariance of real estate price growth of state-pairs, computed over a 5 year rolling windows using quarterly data. Standard errors are clustered at the state-pair level. T-statistics reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5 and 1% levels of significance.

	Correlation					Beta	Covariance
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
After Deregulation	.12***	.16***	.081***	.1***	.2**	.087***	.076***
	(4.5)	(4.5)	(3.7)	(3.5)	(2.3)	(3.1)	(4.4)
Diff. in Ind. Comp.	7.5***	-21***	.45	-.35	1.7	-.39	-.66
	(5.7)	(-7.5)	(.4)	(-.32)	(.28)	(-.27)	(-.78)
Income Correlation	.17***	.13***	.11***	.11***			.011
	(6.3)	(4.3)	(4.2)	(4.7)			(.82)
After First Deregulation				-.0054			
				(-.17)			
Income Covariance					.039		
					(.53)		
Income Beta						.11***	
						(4.7)	
Observations	18375	11166	20825	25725	25725	25725	28175
R2	.52	.74	.54	.53	.41	.48	.49
State-pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State i × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State j × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table VI: House Price Growth Correlation and Banking Integration: OLS and IV Estimation

Source: OFHEO house price index and Call Reports. Sample period: 1976-2000 (columns 1,2), and 1976-1994 (columns 3,4). Note: Data is a panel of state pairs. The dependent variable is the five year forward rolling correlation of house price growth. Differences in industry composition is defined as $\sum_{s=1}^{9}(\sigma_1^s - \sigma_2^s)^2$ where σ_i^s measures the share of workers in state i working in industry i. We then take the five year forward rolling average of this measure. Income Correlation is the pairwise correlation of personal income growth across US states computed every quarter over a 5 year rolling windows using quarterly data. All specifications include year-, state pair-, and state-year- fixed effects. Column (1) and (3) provide OLS estimation. Columns (2) and (4) provides IV estimation where a state pair's co-Herfindhal is instrumented with interstate banking deregulation as in Column (5) and (6) of Table III. Because of the large number of fixed effects, we there is no procedure in Stata that calculates the s.e. exactly in TSLS regressions. Hence, standard errors are obtained through a bootstrap procedure: We make one draw from the sample, then estimate the first stage equation and construct the predictor of integration. Then, we regress correlation on this predictor, and retrieve the point estimate. We repeat the procedure 100 times, and take the empirical standard deviation of these estimates as our measure of the standard error. We use this s.e. to construct the t statistics reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5 and 1% levels of significance.

	House Price Correlation			
	1976-2000		1976-1994	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
H_{ij}	1.8***	13***	2.5***	12***
	(4.3)	(3.8)	(3.2)	(4.4)
Difference in Industry Composition	-.51	-2*	7.4***	5.8***
	(-.48)	(-1.7)	(5.6)	(3.3)
Income Correlation	.11***	.14***	.17***	.18***
	(4.8)	(5.8)	(6.2)	(6.9)
Observations	25725	25725	18375	18375
State-pair FE	Yes	Yes	Yes	Yes
State i × Year FE	Yes	Yes	Yes	Yes
State j × Year FE	Yes	Yes	Yes	Yes

APPENDIX

A. Bank size and Shock Volatility

In this Appendix, we explain how heteroskedastic bank shocks affect our calculations and estimates. The issue is the following: If larger banks have smaller idiosyncratic shocks, their effect on comovement should be smaller than in our baseline model. We first expose this effect theoretically, and use the derivation to account for the fact that bank size is negatively correlated with volatility. We show that this adjustment does not affect our results very much.

To see how the link between bank size and volatility affects our derivations, let us assume that the bank-specific idiosyncratic shock is a decreasing function of bank size: $f(L^k_{t-1})\eta_k$ instead of η_k. f is a function such that $f' < 0$. The rest of the correlation structure is the same as in the baseline model. In this new model, the volatility of bank shocks is given by $\sigma_\eta.f(L^k_{t-1})$.

In this case, the covariance equation (3) becomes:

$$cov\left(\frac{\Delta P_{i,t}}{P_{i,t-1}}, \frac{\Delta P_{j,t}}{P_{j,t-1}}\right) = \rho_\epsilon\sigma^2_\epsilon + \mu^2\sigma^2_a + \mu^2\sigma^2_\eta\sum_1^K\left(f(L^k_{t-1})\right)^2\left(\frac{L^k_{i,t-1}}{L_{i,t-1}}.\frac{L^k_{j,t-1}}{L_{j,t-1}}\right)$$

The new determinant of comovement is the sum of local market shares products of overlapping banks, weighted by a decreasing function of bank size. Hence, overlapping banks contribute less to comovement if they are big, because big banks are less volatile. Hence, the size-volatility relationship affects the way we measure bank integration, all the more so when f is more sensitive to bank size.

To find out about function f, we regress the volatility of loan growth on the log of bank size. We split our sample into four 5-year periods: 1980-1984, 1985-1989, 1990-1994 and 1995-1999. For each of these periods, we restrict ourselves to BHCs continuously present in the Call Reports for all 20 quarters. Within each of these periods, and for each of these banks, we then calculate the standard deviation of quarterly loan growth using all 20 quarters, and the log of total loans at the first quarter of the period. We then regress loan growth volatility –normalized by 4.2% which is the average volatility – on beginning of period log bank assets. In doing so, we assume that $f(x) = a + b\log(x)$, and that $\sigma_\eta = 4.2\%$.

We find that, indeed, larger banks are slightly less volatile than small ones, but that the sensitivity is small. We report, in Figure A.1, scatter plots for each of the four subperiods, using total assets as our loan measure. The sensitivity of volatility to size is present, but decreasing over time. To analyze significance, we report regression results in Table A.I. Across all subperiods, the largest (negative) value for coefficient b is -0.3. It means that multiplying bank size by 1000 reduces volatility by $\log(1000) \times 0.3 \approx .3.8$ percentage points. Thus, the correction for the bank size effect is a priori unlikely to have major effects on our results.

But to check this, we go one step beyond: We take the estimate size-volatility relation, and recalculate the new integration measure K_{ij} using the formula suggested by the previous equation:

$$K_{ij} = \sum_{1}^{K} (a - b\log(L^k_{t-1}))^2 \left(\frac{L^k_{i,t-1}}{L_{i,t-1}} . \frac{L^k_{j,t-1}}{L_{j,t-1}} \right) \tag{9}$$

where a and b are estimated on the pooled panel of BHCs used in Table A.I, separately for measures using total assets and real estate loans only. Running this pooled regression, we find $a = 2.98$ and $b = 0.232$, which we plug in the above formula. These numbers are consistent with those of Table A.I.

We then explore the correlation between this adjusted measure K_{ij} and the integration measure H_{ij} that we use in the main text. We show a scatter plot in Figure A.2. Note first that, in contrast to H_{ij}, the adjusted K_{ij} does not have to mechanically be between 0 and 1. But more importantly, both measures are very highly correlated, with a linear correlation of .78. Thus, because volatility is not very sensitive to bank size, the measure of bank integration that we use in the main text is a good proxy for the size-adjusted measure.

As a final robustness check, we re-estimate the relationship between correlation and integration with the new integration measure. We re-estimate the results reported in Table VI, except that we use K_{ij}, instead of H_{ij}, as our main explanatory variable. As we do for H_{ij}, we compute the five year forward rolling average of K_{ij} to account for the fact that correlation is itself estimated on a 5 year forward rolling window (see Section 4.1). We use the same instruments as in the main text (bilateral banking deregulations), and run regressions using both 1976-2000 and 1976-1994 samples. As in Table VI, we report both OLS and IV estimates in Table A.II. We find that the estimates have the same level of statistical significance and very similar economic sizes. This suggests that the simplifying approximation that bank volatility does not depend on size –approximation that we make in the text– is correct.

Figure A.1: Bank Size and Bank Volatility - Scatter Plots

Source: Call Reports. *Note*: We first split our sample into 4 subperiods. Within each of these periods, we focus on the balanced panel of banks that report loan figures in the Call Reports for each of the 20 quarters. Then, we calculate, for each bank, the log of real estate loans at the first quarter of the period, and the standard deviation of quarterly home loan growth over the period. We then plot the second variable against the first one, for each subperiod separately. The red line if the fitted univariate regressions. Regression results corresponding to these plots are reported in Table A.I.

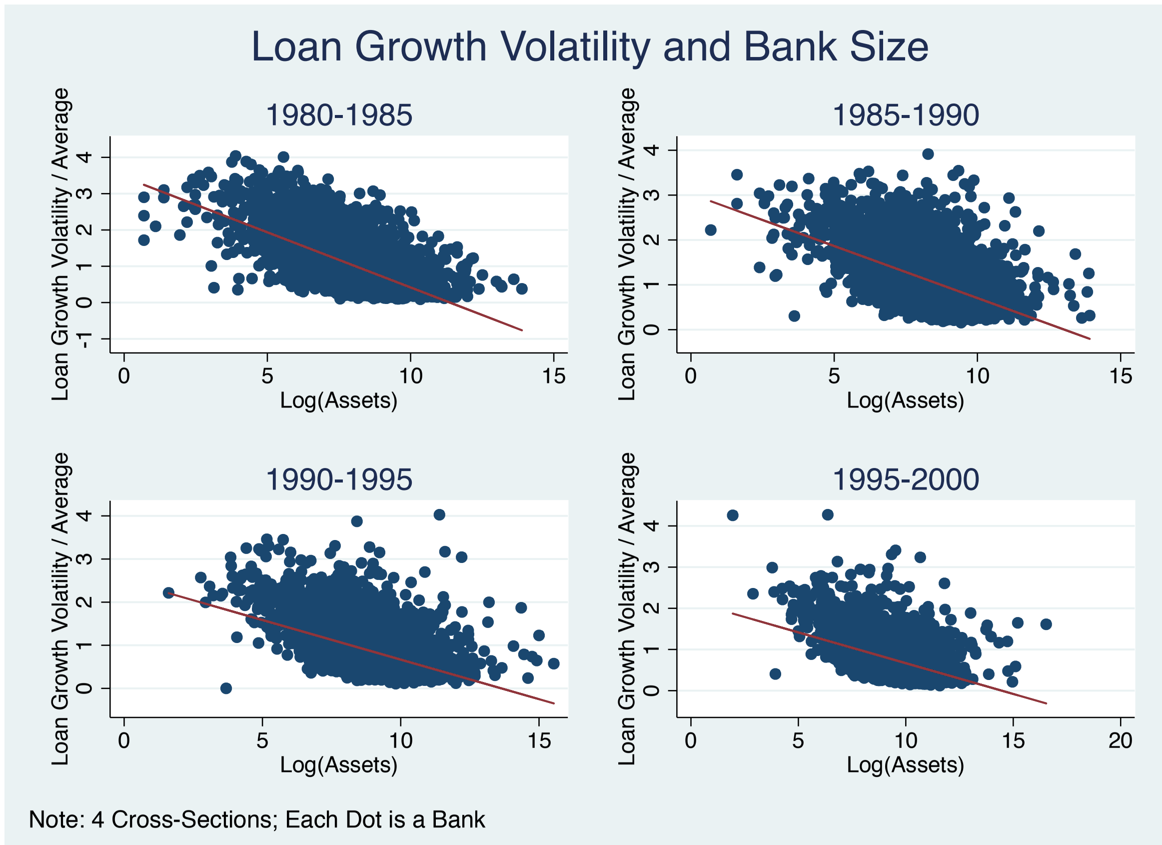

Figure A.2: Measuring Integration: With and Without Bank Size Adjustment

Source: Call Reports. *Note*: This Figure graphically illustrate the correlation between the co-Herfindahl and the size-volatility-adjusted measure of integration. On the y-axis, we report the unadjusted overlap measure H_{ij} that we use in the paper, given by:

$$\sum_{1}^{K} \left(\frac{L_{i,t-1}^{k}}{L_{i,t-1}} . \frac{L_{j,t-1}^{k}}{L_{j,t-1}} \right)$$

, while on the x-axis, we report the bank size-adjusted measure given by:

$$\sum_{1}^{K} (a - b \log(L_{t-1}^{k}))^{2} \left(\frac{L_{i,t-1}^{k}}{L_{i,t-1}} . \frac{L_{j,t-1}^{k}}{L_{j,t-1}} \right)$$

where a and b are estimated as in Table A.I., but after pooling all subperiods together. This alternative definition accounts for the fact that overlaps should matter less for bigger banks –which are less volatile. The univariate linear correlation is .78.

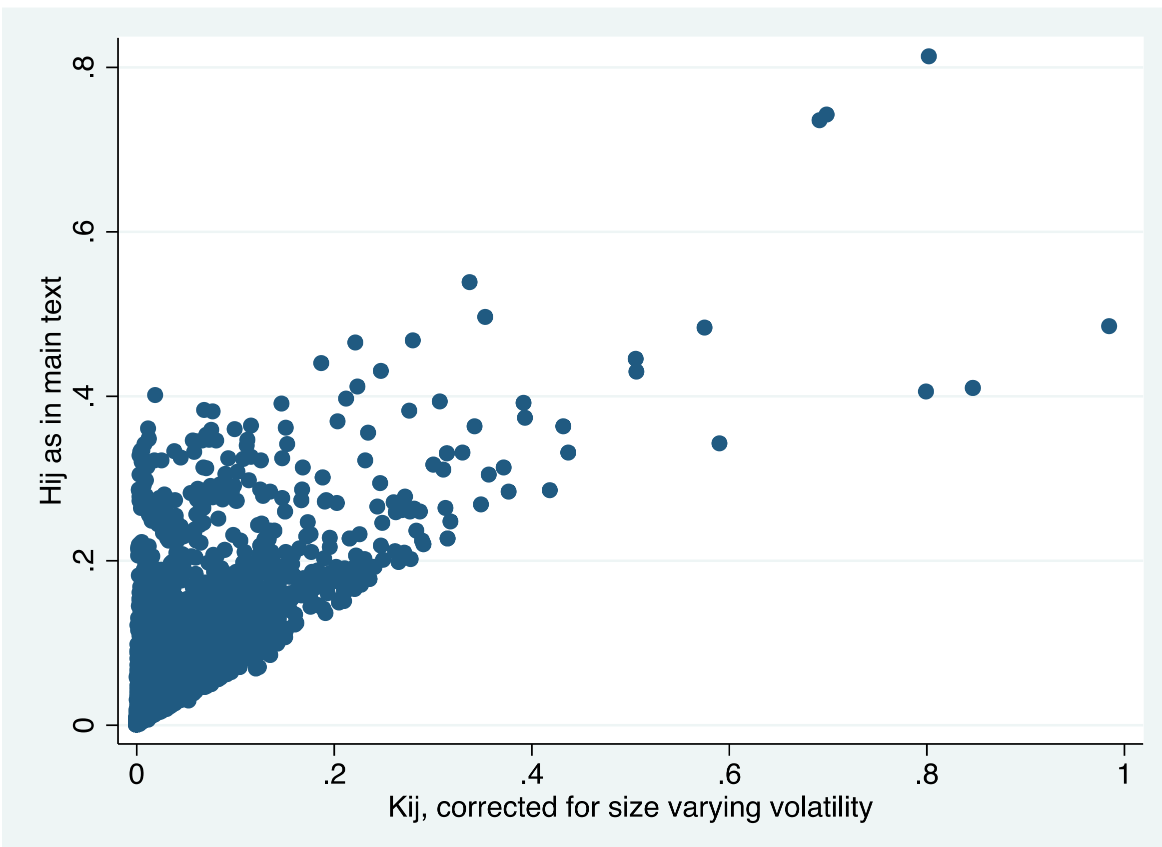

Table A.I: Bank Size and Bank Volatility - Regressions
Source: Call Reports. *Note*: We first split our sample into 4 subperiods. Within each of these periods, we focus on the balanced panel of banks that report loan figures in the Call Reports for each of the 20 quarters. Then, we calculate, for each bank, the log of total loans at the first quarter of the period, and the standard deviation of quarterly loan growth over the period. We then report the cross-sectional regression results, separately for each sub-period. t-stats are between parentheses. *** means "significant at 1%".

	Volatility of $\frac{\Delta L_t^k}{L_{t-1}^k}$			
	(1)	(2)	(3)	(4)
	1980-1984	1985-1989	1990-1994	1995-1999
$\log(\text{Loans}_0^k)$	-.3***	-.23***	-.18***	-.15***
	(-56)	(-43)	(-39)	(-31)
Constant	3.5***	3***	2.5***	2.2***
	(79)	(67)	(59)	(48)
Observations	4986	5099	5194	4172
R2	.39	.26	.23	.19

Table A.II: OLS and IV Estimation: Using Alternative Integration Measure K_{ij}

Source: OFHEO house price index and Call Reports. Note: This Table redoes the estimations presented in Table VI, except that it uses alternative measure of bank integration K_{ij} defined in equation (9). This alternative measure takes into account the fact that larger banks have lower volatility in our sample. Columns 1 and 3 use OLS; Columns 2 and 4 provide IV estimates. All columns include state-pair fixed effects and state-year fixed effects for each state in the pair. Because of the large number of fixed effects, we there is no procedure in Stata that calculates the s.e. exactly in IV regressions. Hence, standard errors are obtained through a bootstrap procedure: We make one draw from the sample, then estimate the first stage equation and construct the predictor of integration. Then, we regress correlation on this predictor, and retrieve the point estimate. We repeat the procedure 100 times, and take the empirical standard deviation of these estimates as our measure of the standard error of the estimate. We use this s.e. to construct the t statistics reported in parentheses. *, **, and *** mean statistically different from zero at 10, 5 and 1% levels of significance.

	House Price Correlation			
	1976-2000		1976-1994	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
K_{ij}	1.3***	17***	3.4***	14***
	(3.4)	(4.6)	(4.1)	(4.5)
Industry Composition Difference	-.47	-3**	7.3***	5.6***
	(-.44)	(-2.4)	(5.5)	(4.1)
Income Correlation	.11***	.15***	.17***	.19***
	(4.8)	(6)	(6.3)	(6.9)
Observations	25725	25725	18375	18375
State-pair FE	Yes	Yes	Yes	Yes
State i × Year FE	Yes	Yes	Yes	Yes
State j × Year FE	Yes	Yes	Yes	Yes

B. Aggregate Bank Shocks and The Rise of House Price Correlation

This Appendix examines the explanatory power of increased bank lending comovement on the rise in house price comovement. This alternative explanation is not exclusive of ours, but, as we show here, it is not a plausible candidate. The reason is that, if anything, bank lending shocks tend to comove *less*, not more, over the past thirty years.

One potential explanation for the rise in house price correlation is that bank shocks have become more and more affected by common aggregate shocks than in the past. The rise in the reliance in wholesale funding, or on securitization of loans, may be evolutions that are making banks more and more subject to aggregate funding shocks. In this case, house prices may comove more, not because the same banks inject their own shocks to several state, but because banks have become more and more "alike".

In our model, this hypothesis amounts to saying that the contribution of the aggregate bank shock σ_a has increased, other parameters equal. To see this, it is useful to go back to equation (5):

$$\text{corr}\left(\frac{\Delta P_{i,t}}{P_{i,t}}, \frac{\Delta P_{j,t}}{P_{j,t}}\right) = \gamma_1(\sigma_a^2) + \gamma_2(\sigma_a^2)\ H_{ij} - \gamma_3(\sigma_a^2)\ \frac{H_{ii} + H_{jj}}{2}$$

where: $\gamma_1(x) = \frac{\rho + \frac{\mu^2}{\sigma_\epsilon^2}x}{1 + \frac{\mu^2}{\sigma_\epsilon^2}x}$, $\gamma_2(x) = \frac{\mu^2}{\sigma_\epsilon^2}\sigma_\eta^2 \frac{1}{1+\frac{\mu^2}{\sigma_\epsilon^2}x}$ and $\gamma_3(x) = \frac{\mu^2\sigma_\eta^2}{\sigma_\epsilon^2}\frac{\rho + \frac{\mu^2}{\sigma_\epsilon^2}x}{\left(1+\frac{\mu^2}{\sigma_\epsilon^2}x\right)^2}$. Aggregate risk ($\sigma_a$) thus affects price growth correlations through three distinct channels. The most obvious one – the "direct" channel – is captured by $\gamma_1(\sigma_a^2)$, and is independent of bank geographic interlocks and concentrations. When banks have more common volatility (σ_a), prices are subject to stronger common shocks and thus correlate more (γ_1 is increasing in σ_a). The two other channels involve more indirect interaction terms between market integration: Their impact can be ambiguous, so we focus on the first one, which is the most intuitive.

We go to the data and directly estimate the time series evolution of σ_a, which is observable. We start from the Call Report described in Section 3.2, and aggregate bank assets at the BHC-quarter level. For each BHC, we then calculate quarterly asset growth. Every quarter, we take the cross-sectional average of BHC asset growths, after removing outliers –observations for which asset growth was above 100%. This average bank asset growth is the common factor to bank lending. Finally, each quarter, we compute the 20-quarters forward rolling volatility of this factor. We report its evolution over 1976-2000 in Figure B.1. The volatility of average quarterly bank growth goes down from 1.8% in 1976 to 0.8% in 1996. If anything, the common factor to bank lending growth became *less* volatile over the period. This implies that the direct impact of aggregate risk does not have the power explain the rise in house price correlations over 1976-2000.

Figure B.1: The Volatility of Mean Bank Asset Growth

Source: Call Reports. *Note*: This figure plots the rolling standard deviation of average bank lending growth. For each BHC-quarter in the Call Reports, we first calculate quarterly asset growth. We then remove outliers (asset growth above 100%). We then calculate the cross-sectional equally-weighted average (across BHCs). Finally, the standard deviation is computed using a 5-years forward rolling window with quarterly data.