# Banking Deregulation and The Rise in House Price Comovement *

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**Abstract**

This paper documents a steady increase in the average correlation of house price growth across US states over the 1976-2006 period and shows that this phenomenon can be explained in large part by the geographic integration of the banking market over this period. We theoretically derive an appropriate measure of banking integration across state pairs and document that the cross section of state pair correlations is strongly related to this measure of financial integration. We then use bilateral cross state banking deregulations to instrument banking integration of a state pair. Using our IV estimates, we find that financial integration of the US banking market explains about 25% of the rise of the average home price correlation over the period.

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# 1. Introduction

House prices in the US have become more and more correlated. Between 1976 and 1980, the average correlation 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, house price synchronization has continuously increased over the past three decades. This paper starts by documenting this fact.

We then establish a causal connection between this trend and the unification of the US banking market that took place over the same period. This is the main contribution of the paper. The integration of the US banking market was the result of deregulations that took place between the late 1970s and the mid 1990s (see for instance Kroszner and Strahan, 1999). The mechanism we have in mind is very simple: Once banks start operating simultaneously in several states, this will create commonality in lending in these states, which will synchronize house price movements. This mechanism rests on the assumption that bank lending affects house prices (Adelino, Schoar and Severino, 2012; Favara and Imbs, 2012; Loutskina and Strahan, 2012). To empirically establish causality between bank integration and house price comovement, we proceed in two steps.

First, we develop a simple statistical model that links bank integration with house price comovement. The objective of this model is to derive an empirically testable relationship between house price correlation and bank integration, as well as provide us with an integration measure. But more importantly, this model helps to clarify intuitions about the respective roles of aggregate and idiosyncratic bank shocks in shaping house price comovement. The model delivers two insights. First, most of the relationship between integration and comovement goes through idiosyncratic bank lending shocks. When banks have similar exposure to aggregate risk (because they all securitize, or because they all depend on the market for wholesale funding), their impact on comovement will be similar if they lend only in one state, or if they overlap on several states. When banks face idiosyncratic lending shocks, their overlap across states makes house prices comove. The second insight of the model is that integration does not affect comovement if banks remain small. If the banking market becomes integrated, but banks are small, the law of large number will smooth out the effect of their idiosyncratic shocks, and integration will have no effect.

Our second step consists in cross-sectional regressions. First, we provide evidence that interstate banking deregulations –which occurred in a staggered way between pairs of states– had a strong and immediate impact on cross-state banking flows (Michalski and Ors, 2012). Therefore, they provide good instruments for bank integration. We also show that these deregulations were immediately followed by a sharp increase in house price correlation (by about 6 percentage points), consistently with the mechanism we have in mind. Finally, we use banking deregulations as instruments for banking market integration, in a regression that seeks to explain house price correlation. We find a strong relationship between integration and house price correlations. Given the increase in integration that we observe between 1976 and 1995, our estimates suggest that the unification of the US banking market may explain as much as a quarter of the rise in correlation we document. In line with our mechanism, we find that bank overlap across states strongly increased over the period, and that almost all of this increase is driven by the top 20 banks in the country. Thus, idiosyncratic bank risk is a good candidate to explain house price comovement: Large banks became more and more likely to overlap several states, and subjected state-level lending fluctuations to their idiosyncratic shocks.

Last, we rule out an alternative story, namely that increased common shocks to banks might be the driving force behind the correlation trend. Indeed, if banks have become more and more synchronized over the period in their lending policy (for instance because of rising securitization or reliance of wholesale funding), house prices would inherit, somewhat mechanically, from this syncronicity. We rule out this channel by showing that average lending growth across banks has not become more volatile over the period.

This paper contributes to several literatures. First, we indirectly document that credit supply affect 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, Schoar and Severino, 2012; Loutskina and Strahan, 2012), or interstate branching deregulation (Favara and Imbs, 2012). We complement this literature through the use of an alternative instrument (interstate banking laws). While this paper seek to explain house price changes, we focus on the time series and cross-sectional properties of house price comovement.

Second, the paper 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. Because capital flows can move more freely across borders, asset prices are more sensitive to shifts in global investor demand than before. In line with this interpretation, this literature thus looks for cross-sectional relationships between asset price correlation and the intensity of capital flows between countries.[1] Within this literature, our paper provides analogous evidence for a new asset class (real estate), in a set of regions who experienced a drastic integration of capital markets (US states). Such integration occurred via the banking market and was driven primarily by state pair-level deregulations. These policy experiments in the context of otherwise relatively homogenous states, allow us to isolate the causal impact of capital circulation on asset price comovement. This paper also relates to the nascent literature on the real effects of financial integration: GDP growth volatility across US states (Morgan, Rime and Strahan, 2004) and GDP growth comovement across EU member states (Kalemli-Ozcan, Papaioannou and Peydro, 2013).

Last, a key feature of our paper is its emphasis on the role of idiosyncratic shocks to explain comovement. In a sense, our paper is connected to recent work by Gabaix (2011), which emphasizes the role of big firms to explain aggregate volatility. Our paper emphasizes

[1] Consistently with this, Quinn and Voth (2012) show that asset price correlation was also high in the beginning of the $20^{th}$ century, and that it decreased before WWII.

the role of big banks in the rise in house price correlation. Since average bank lending did not become more volatile, the rise of the aggregate shock is not a plausible candidate. Moreover, our model shows that integration only matters if big banks start lending across states. Consistently with this, we find that the unification of US banking happened through the constitution of mega banks overlapping different states. As we show theoretically and empirically, the rise of these large entities can explain the rise in house price comovement.

Section 2 describes the data and documents the strong increase in house price comovement over the past 3 decades. In passing, we also explain that aggregate shocks to banks have become, if anything, less volatile over the same period. Section 3 lays out a simple statistical model in order to derive the relationship between comovement and bank integration. This model also serves to define a proper measure of bank integration. It also shows that bank idiosyncratic risk is a key factor to understand the link between integration and comovement. We do also, in this Section, document the rise in bank integration in US data. Section 4 goes to the data and shows the causal impact of bank integration on house price correlation in the cross-section of state pairs.

# 2. Rising Correlation: Establishing the Fact

## 2.1. The Data

Our main dataset is the balanced panel of all state-pairs, followed annually over 1976-1994. It documents: cross-state house price correlation, labor income correlation, proximity in industry composition, and banking integration and concentration. To calculate these variables, we use three sources of data: house prices from OFHEO, bank geographic dispersion from the Call Reports, and state-level labor income from the BLS.

### 2.1.1. House Prices

First, we retrieve state-level, repeated-sales, house price indices from the OFHEO website. These data are available quarterly for all US states since 1976. We use these data to calculate quarterly price growth. In this paper, we work at the state level because the deregulations that we study were implemented between state-pairs. Also, state-level data have the advantage of being available as a fully balanced panel since 1976. Finally, Call Reports only allow us to consolidate bank activity at the state level. We have checked, however, that most of our results carry through using MSA-level house price data.

For each state pair, we use these data to calculate house price correlations. We make this calculation on a forward rolling basis: each year, for a given state-pair, we use the future house price growths of these two states for the coming 20 quarters, and use these two series to calculate a pairwise correlation. We also explore robustness using 12 quarters only. In Table 1, we report summary statistics for these two correlation measures, for each $50 \times 51/2 = 1275$ state pairs between 1976 and 2006. There is no big difference between the two correlation measures. The average and the median are .3, and the correlation is often positive. We will go back to the analysis of trends in Section 2.2.

### 2.1.2. Geographic Dispersion of Banks

To measure bank lending at the state level, we follow the conventions described in Morgan, Rime and Strahan (2004), which force us to restrict ouselves to the 1976-1994 period. We use Call Reports consolidated at the BHC level, from 1976-1994. Call reports are available quarterly and provide us, for each commercial bank: its ID number (rssd9001), its total assets (rcon2170), its state of location (rssd9200), and the bank holding company (BHC) it is affiliated to (rssd9348). We then collapse the asset data, each quarter, at the BHC-state level. For instance, if a BHC owns two commercial banks in Arizona (with assets of \$3bn and \$5bn), we say that its total assets in this state are \$8bn. If 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 valid approximation until the end of 1994, when the Riegle-Neal Act allowed BHCs to consolidate activities in several states into one commercial bank (Morgan, Rime and Strahan, 2004). We use these data to calculate measures of banking integration. We defer the definition of these measures to Section 3, as they will naturally emerge from our statistical model.

We restrict ourselves to 1976-1994 for two reasons. The first reason is the availability of state-level bank assets. As we just discussed, after 1994, the Riegel-Neal Act makes it more difficult to use Call Reports to calculate state-level lending of banks. An alternative would be to use FDIC data on deposits, that report, for each bank, the geographic dispersion of deposits. The problem is that these data are only available after 1993, which brings us to the second reason why we stop in 1994: In our data, we use, as instruments for bank integration, interstate banking laws that occurred between 1978 and 1994.

### 2.1.3. Fundamental Proximity Measures

Third, we retrieve quarterly data about state-level labor income and employment from the Bureau of Labor Statistics. The data source is called the Quarterly Census on Employment and Wages (QCEW), and provides us with quarterly total employment and wage bill by industry (2-digit SIC code) and county (FIPS code), starting in 1975. We aggregate the data at the state level to calculate quarterly series of labor income.

For each state pair, we use these data to calculate the 5-year forward rolling correlation in labor income growths. At each date, we take all observations on house price growths in both states of the next 20 quarters, and use them to calculate the correlation. For each state pair, we also compute a measure of distance in industry composition: For each state in the pair, we first calculate the vector of employment shares by industry, and then take the Euclidian distance between these two vectors. This number is large when the two states have very different industrial specialisation. Summary statistics for these variables are reported in Table 1. We see from this table that average income correlation is high (0.51), and that it is rarely negative.

## 2.2. Rising Correlations

We now document the large increase in house price correlation across states since 1976, which is the motivating fact of the paper. In Figure 1, we plot the year-by-year distribution of correlations across state pairs. As can be seen, the average and the median correlation increase from about 10% in 1976 to 60% in 2006. In the same figure, we also report the evolution of the $25^{th}$ and $75^{th}$ percentiles of the distribution: These lines confirm that the full distribution shifts upwards over the period. Interestingly, we observe that the $25^{th}$ percentile is negative until the late 1980s: Until then, more than 25% of the state pairs had *negative* house price correlation. Finally, we take the time series of the average correlation, and regress it on a trend. We adjust for 5-year correlation in error terms using the Newey-West procedure. The fitted trend is equal to 0.021 with a t-stat of 5.3. On average, over 1976-2006, the average house correlation increased by about 2 percentage points every year.

In Figure 2, we focus on the 1976-1994 period, which is the period we use to run our regressions (see above discussion on why we stop in 1994). The upward trend is still strong and significant: Correlation goes up by 1.5 percentage point per year on average (statistically significant with Newey-West standard errors). The trend is a bit smaller because we exclude data from the 2000s. The full distribution moves upward. Thus, the broad pattern presented in Figure 1 remains unchanged when we exclude data from the bubble years.

This fact resists to numerous additional robustness checks. First, it is also present using 3-year, instead of 5-year, rolling correlation. Over 1976-1994, the average 3-year rolling correlation increases on average by 1.9 ppt per year. The fitted trend has a Newey-West adjusted t-stat of 4.4 (using a 3 year lag). Second, we also show that the fact is present at the city-level using MSA-level price indices from OFHEO. Because prices are only available for a few cities until 1980, we start the analysis in 1980. There we find that correlation trends upwards from 0.02 in 1980 to 0.15 in 1994 (and .22 in 2000). This is equivalent to an increase by 1 ppt by year; The fitted trend has a Newey-West adjusted t-stat of 14.1.

We do not use city-level in our analysis for three reasons. First, the panel is strongly unbalanced in the period we focus on. Prices are available for 19 cities in 1976, 147 in 1980, 221 in 1985, and 381 in 1994. Second, we cannot use the Call Reports to localize bank lending at the city level. Third, the reforms we use as IV occur at the state, not the city level.

# 3. Statistical Framework

## 3.1. Basic Framework and Intuitions

This Section develops a simple statistical framework to investigate the role of idiosyncratic bank shocks in shaping the comovement of home prices. Our framework, in the spirit of Gabaix (2011), contains aggregate and idiosyncratic bank shocks, and shows that they affect house price comovement in different ways.

We first model bank lending as the sum of bank-specific shock and an aggregate shock. Banks may operate in several states. $L_{i,t}^k$ is the lending of bank $k$ in state $i$.

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

where $\eta_{k,t}$ is the idiosyncratic bank shock. The variance matrix of idiosyncratic shocks is given by $\Sigma_\eta = \sigma_\eta^2 Id$. 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. It can be interpreted as a shock to the supply of wholesale funding , or as a shock to the demand of securitized loans. $\sigma_a$ is the volatility of $a_t$.

Our second assumption is that lending shocks affect house prices (Adelino, Schoar and Severino, 2012; Favara and Imbs, 2012). We posit that house price growth 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 the $\epsilon$'s are independent from the $\eta$'s and $a_t$. The variance matrix of the $\epsilon$'s 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 $k$: $L_{i,t} = \sum_k L_{i,t}^k$. $\mu$ is the elasticity of house prices to mortgage lending.

We combine (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 clarify the respective role of aggregate and idiosyncratic bank shocks. Let us start with the variance equation (3). The first term means that house prices are more volatile when price shocks are more volatile ($\sigma_\epsilon$ is bigger). The second term highlights the role of aggregate bank lending shocks on house prices. The third term captures the role of idiosyncratic bank shocks. The key lessons of equation (3) is that the structure of bank lending across states only affects house price volatility via the idiosyncratic shock. This happens because, in our model, all banks have the same exposure to aggregate shocks. Thus, whether there is one big bank or several small ones, does not affect aggregate lending exposure to the global shock. Banking market structure does, however, impact the way idiosyncratic shocks are transmitted to house prices. When the Herfindahl $H_{ii}$ coefficient is large, a few large banks dominate the market in state $i$. Their idiosyncratic shocks are not smoothed out, and impact aggregate lending.

The same intuitions help to interpret covariance equation (4), which has also three terms. The first term captures the fundamental comovement $\rho$ 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. 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 big lenders in both states, and when the overlap is concentrated in few banks. As was the case in the variance equation (3), bank overlap only affects comovement via idiosyncratic shock. In the absence of idiosyncratic shocks, whether banks overlap or not does not change covariance. This happens because all banks have the same exposure to the aggregate shock. To generate meaningful comovement, idiosyncratic risk has to be borne by few, large, overlapping banks.

## 3.2. Correlation and Bank Integration

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

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

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 $\sigma_a$ goes up, for given house price fundamental volatility $\sigma_\epsilon$. This first effect formalizes the intuition that a more volatile "common factor" to bank lending would lead to more house price comovement. As we have seen, however, in Section 5, $\sigma_a$ decreases over the period, which does not make it a good candidate to explain the rise in correlation.

The second term of (5) will be the focus of our empirical analysis: it captures the impact of idiosyncratic shocks (it disappears if $\sigma_\eta = 0$). Idiosyncratic shocks generate more comovement if bank overlap $H_{ij}$ is bigger, i.e. a few banks explain most of the common lending in the two states. This effect is muted as aggregate shock volatility increases, since $\sigma_a$ makes house price volatility go up. 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 lowers the correlation.

The integration measure $H_{ij}$ differs significantly from the bank integration measures previously used in the literature (see Morgan, Rime and Strahan, 2004 and Michalski and Ors, 2012 for instance). In contrast to these measures, $H_{ij}$ captures the extent to which banks that are big in $i$ are also big in $j$. It also captures the extent to which flows are due to large banks –like a Herfindahl index. Our framework shows that this is important since integration impacts comovement through idiosyncratic shocks only, and that idiosyncratic shocks only matter if the size distribution is very heterogenous.

In the next Section, we will estimate the reduced form (5), by regressing house price correlation on direct empirical measures of $H_{ij}$ and $\frac{H_{ii}+H_{jj}}{2}$. To address endogeneity concerns, we will use banking reforms to instrument these measures. Before proceeding, let us describe the empirical properties of the bank integration measure.

## 3.3. Bank Integration Measures in the Data

We now go to the data to calculate bank overlap and concentration measures $H_{ij}$ and $\frac{H_{ii}+H_{jj}}{2}$. We are able to do this using BHC-state level assets constructed in Section 2.1.2. At the last quarter of each year, for each state pair $(i, j)$, we are able to calculate $H_{ij}$ by aggregating across BHCs the products of state-level market shares of each BHC that overlaps on both states. This provides us with a single bank integration measure per state pair-year. We then apply the same procedure to calculate average bank concentration $\frac{H_{ii}+H_{jj}}{2}$. We report descriptive statistics in Table 1.

Bank integration, as we measure it, increases strongly over the 1976-1994 period. We show the evolution of bank integration over time in Figure 3. $H_{ij}$ is multiplied by about 4 between the beginning and the end of the period. The increase really starts around 1984, which corresponds to the timing of interstate banking laws that we use as instrument (see next Section). If we re-calculate bank integration $H_{ij}$ using the top 20 BHCs only, we obtain a very similar evolution, in particular after 1990. This is consistent with the idea that bank integration increased in two steps. At first, in the 1980s, small banks merged and begun to overlap a few states but remained small and regional: 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: most of the increase in bank integration is accounted for by the largest BHCs in the country.

# 4. Empirical Tests

In this Section, we show that bank integration causes house price comovement. To show this, we estimate equation (5). Since bank integration and house price comovement may share common unobserved determinants, we use state pair-level reforms that enhanced state pair-level bank integration, as instrument for integration. We first describe these reforms and provide clean evidence that they are good IVs. We then turn to OLS and IV estimates.

## 4.1. The Reforms that Increased Bank Overlap

To instrument $H_{ij}$, we use staggered interstate banking deregulations that took place across state pairs between 1978 and 1995. We rely on data compiled by Michalski and Ors (2012). Between late 1970s and 1995, various states allowed banks from other states to enter their 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.

There are good reasons to believe that these pairwise deregulations were exogenous to house price comovement. First, 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 minority. Second, the political economy of these reforms does not seem to have involved the mortgage market, but rather the struggle between small banks, who wanted the status-quo, and small firms, who wanted more banking competition (Kroszner and Strahan, 1999). Third, we will provide graphical evidence that both integration and house price correlation pick up right after cross state banking deregulations. Fourth, our regressions include various state pair controls designed to capture similarity between the two states: a state pair fixed effect, the rolling correlation between state labor incomes, and a measure of industrial composition proximity.

Looking at raw data, these reforms appear to have a strong impact on the level of bank integration. In Figure 4, we plot average integration $H_{ij}$ as a function of the number of years relative to the deregulation. For each date relative to the state pair's deregulation, we calculate the average $H_{ij}$ across all state pairs taken at this moment. As can be seen from the graph, the average $H_{ij}$ is flat before the reform (at around 0.003), and then starts to pick up right when the state pair deregulates. The change in trend is clear from the graph. Eight years after deregulation, integration is equal 0.012, approximately 5 times its pre reform level.

We then estimate the first stage regression econometrically. We run the following regression for state pair $(i,j)$ in year $t$:

$$H_{ijt}^{m} = \alpha_{ij} + POST_{ijt}^{m,1} + POST_{ijt}^{m,2} + \delta_t + controls_{ijt} + \nu_{ijt} \quad (6)$$

where $\alpha_{ij}$ is a state-pair fixed effect, designed to control for composition effects that arise from the fact that some states may deregulate before others. $\delta_t$ are year fixed effects that capture nationwide trends in bank integration potentially unrelated to the reforms. $controls_{ijt}$ are here to capture time-varying measures of state similarity that may correlate with the reform. We include: state specific trends, correlation between labor income growths, proximity in industry structure, and the logs of states $i$ and $j$'s total labor income. We cluster error terms $\nu_{ijt}$ at the state pair $(i,j)$ level.

To be consistent with our definition of correlation (which is 5 year forward rolling), we use the 5 year forward rolling average of bank integration $H_{ij}$. This avoids situations where the correlation starts increasing before the reform –it is calculated over the next five years– while bank integration only increases when the reform is implemented. Since we have to use smoothly varying measures of correlation, we need to smooth the variations of bank integration too. Because we cannot use Call Report data after 1994, we thus need to restrict ourselves to the 1976-1991 period, which we do in estimating (7). Similarly, $POST_{ijt}^{1,m}$ is the 5 year forward rolling average of a dummy equal to 1 when one of the states of the pair has opened it banking market to the other. $POST_{ijt}^{2,m}$ is the 5 year forward rolling average of a dummy equal to 1 when both states have opened their markets.

We report estimates of (7) in Table 2. The first column only has time and state pair FEs, and no other controls. In this first specification, bilateral deregulation (the $POST_{ijt}^{2}$ dummy) is strongly significant at 0.0057 and a t-stat of 5.6. Hence, bank integration increases by 0.0057 between before and after the average reform. This is a large effect, approximately half the sample standard deviation of $H_{ij}$; This is consistent with graphical evidence. The coefficient is unaffected when we introduced the similarity controls (column 2): Income correlation is insignificant, while within pair increases in bank integration seem negatively related with increase in industry proximity. In column 3, we further add state-specific trends, which do not affect the point estimate of our regression. Column 4 breaks down the $POST^2_{ijt}$ dummy into 9 sub-periods from 6 years before until 3 years after deregulation (remember $H_{ijt}$ is a 5 year forward rolling average). Bank integration appears to be on a slightly increasing trend in the pre-reform period: $H_{ij}$ grows on average by 0.0005 by year. But, as shown in column 4, the trend accelerates sharply right deregulation (overlap increases on average by 0.002 per year). To help visualize the impact of the deregulation, we plot the coefficients, along with their standard deviations, in Figure 5. The estimates are strongly significant, suggesting that time to regulation provides us with a strong IV for bank integration. We defer IV strength tests to Section 4.4.

## 4.2. Banking Reforms and House Price Comovement

We now verify that interstate banking deregulations have been followed by an increase in house price comovement. Since we know that deregulations increased bank integration, and if we believe 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 bank geographic dispersion. It does not depend either on our formulation of the $H_{ij}$ measure. In a sense, the reduced form equation is more agnostic about the exact channel through which integration affects comovement.

We first look at the raw data in Figure 6. In this figure, we report, for each date relative to the deregulation (from 13 years before until 8 years after), the average house price correlation across state pairs. Remember that house price correlation is calculated over the future 20 quarters of data (5 years rolling forward). Given this slow adjustment, we observe from Figure 6 that correlation starts picking up 4 years prior to the reform and continuously increases until 2 years after the reform (where the correlation uses prices between +2 years and +6 years). From Figure 6, it appears quite convincingly that a significant increase in correlation (about 20 percentage points) is directly related to the reform.

We then test for this relationship econometrically. We use a specification close to equation (7):

$$\rho_{ijt} = \alpha_{ij} + POST^{1,m}_{ijt} + POST^{2,m}_{ijt} + \delta_t + controls_{ijt} + \nu_{ijt} \tag{7}$$

where $\rho_{ijt}$ is the 5 year rolling forward correlation of housing returns. Because the reaction of correlation to the reform has to be progressive, we use $POST^{1,m}_{ijt}$ and $POST^{2,m}_{ijt}$ variables. These averaged dummies allow the reform to impact correlations progressively between 4 years before and the date of the reform. They are adapted to the fact that the correlation is calculated over five years rolling and cannot react abruptly to the reform. Since these regressions do not require us to use the Call Reports, we use the full 1976-2000 period to estimate them –but check later that restricting ourselves to 1976-1994 does not materially affect the results.

Table 3 contains the estimates and is organized like Table 2. Column 1 only has time and state pair fixed effects: the reform is accompanied with a contemporary increase in correlation by 6.7 percentage points (t-stat of 3.1). This is significantly less than the 20 ppt increase found in Figure 6. Part of the discrepancy may be due to the fact that banking reforms do not explain the entirety of the rise in correlation. Columns 2 and 3 progressively add new controls (state proximity and income comovement, and state-specific trends). Consistently with intuition, income correlation is strongly correlated with house price comovement, but this control does not affect our main estimate. In column 4, we finally replace the $POST^{2,m}_{ijt}$ variables by dummies for each date relative to the reform to monitor the exact timing of the increase in correlation. Looking at column 4, it appears clearly that house price comovement remains small and insignificant until the reform, after which it increases in a statistically and economically significant way. We show these estimates graphically in Figure 7: Correlation is essentially flat until 4 years before the reforms, after which it starts increasing.

Table 4 provides additional robustness checks. Column 1 restricts the estimation period to

1976-1994. We do this for consistency with the OLS and IV regressions: In these regressions, $H_{ij}$, the dependent variable, is not available after 1994. The coefficient is slightly bigger at 8.1 ppt (t-stat of 3.4). Column 2 restricts the sample to state pairs that are between 8 years before and 4 years after deregulation. Such a narrowing of the observation window diminishes the pollution by unrelated events. After doing this, we find an even larger effect: 13.1 percentage points. Columns 3 and 4 restrict the estimation to state pairs where both states have deregulated simultaneously: the effect is now 5.9 ppt, and the dynamics are consistent with an effect of the deregulation. Column 5 uses the 3-year rolling correlation instead of 5-year. The effect is the same as in Table 3.

## 4.3. Instrumenting Bank Concentration

Before showing our final estimates, we also need to find an IV for the banking concentration $\frac{H_{ii}+H_{jj}}{2}$. Following the empirical banking literature, we use state branching laws. These deregulations, which happened between 1977 and 1991, allowed banks chartered in one state to branch more easily in the same state, either via the acquisition of existing branches (M&A) or via "de novo" branching, or both (see for instance Kroszner and Strahan, 1999, for more details). While numerous papers have shown that these laws have increased competition between banks, there is also evidence that they have led to consolidation and therefore to more market concentration (Jarayatne and Strahan, 1998). Hence, we expect these laws to predict increases in Herdindahl indices $\frac{H_{ii}+H_{jj}}{2}$.

We regress bank concentration on a branching index as our first stage regression, taking state pairs as our units of observation:

$$\frac{H_{iit}^m + H_{jjt}^m}{2} = \alpha_{ij} + \delta_t + BRANCHINDEX_{ijt}^m + controls_{ijt} + \nu_{ijt} \tag{8}$$

For state $i$, we define the branching index as being equal to 1 when the state allows either de novo or M&A branching, and equal to 2 when when both are allowed. For the pair $(i, j)$, we then calculate the average branching index across the two states. Finally, both for the average Herfindahl $\frac{H_{ii}+H_{jj}}{2}$ and the average branching index, we take 5 year forward rolling averages. As before, we do this to be consistent with the OLS and IV regressions, where correlations are calculated on a 5 year rolling basis.

We report the estimate in Table 5. Consistently with the literature, we find that branching laws led to an increase in market concentration. When the index goes from 0 to 2 in both states, the Herfindahl increases by 0.017, which corresponds to about one third of the standard deviation, and 17% of the mean. In aggregate terms, our estimates thus suggest that branching laws increased banking concentration by about 17% on average. This estimate is unaffected when we add similarity and income comovement controls. It becomes twice as large as we control for state-specific trends.

## 4.4. 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:

$$\rho_{ijt} = \alpha_{ij} + a.H^m_{ijt} + b.\frac{H^m_{iit} + H^m_{jjt}}{2} + \delta_t + controls_{ijt} + \nu_{ijt} \tag{9}$$

where $H^m_{ijt}$ is the 5 year forward rolling average of $H_{ijt}$. For data reliability reasons, we cannot use information beyond 1994, so we need stop our sample in 1991. We take rolling averages of integration and concentration to match the progressive reaction of our correlation measure, as previously discussed. We instrument bank integration $H^m_{ijt}$ with the two variables $POST^{1,m}_{ijt}$ and $POST^{2,m}_{ijt}$ –as previously discussed these instruments are also forward rolling averages. As for $H^m_{ijt}$, we take rolling averages of these dummies to reflect the fact that the correlation measure reacts progressively to the instrument, as in equation (7). We instrument $\frac{H^m_{iit}+H^m_{jjt}}{2}$ with the forward rolling average of the bank branching index described in the previous Section.

Regression results are gathered in Table 6. Columns 1-4 are plain OLS estimates, which progressively include all controls. Including state pair fixed effects do not change our estimate; Controlling for fundamental income comovement, industry composition similarity and state trends attenuate our estimate somewhat, but the attenuation is not statistically significant. Columns 5-6 present the IV estimates. Column 5 uses the POST dummies and the branching index as instruments. Column 6 takes advantage of the slow reaction of $H_{ijt}$ to the reform documented above, and uses one dummy per number of years since deregulation, as in Table 2, column 4. In both cases, the IVs are strong, and the coefficient is around 10, 2 to 3 times larger than the OLS estimate.

Given our estimates, the rise of bank integration can explain nearly a quarter of the overall increase in house price comovement between 1976 and 1994. From Figure 3, we see that bank overlap $H_{ijt}$ raises from 0.0015 to 0.006 over this period. Given a coefficient estimate of 10, our cross-section estimates can thus explain an increase in correlation of $0.45 \times 10 = 4.5$ percentage points over this period, compared to an overall increase in correlation by about 19 ppt. As shown in Figure 3, the emergence of the 20 largest banks in the country explain about 80% of this evolution, most of it happening in the 1990s.

# 5. Ruling out an Alternative Hypothesis: Stronger Common Shocks to Banks

One potential explanation for the rise in house price correlation might be that banks are more strongly subject to common shocks than in the past. For instance, the amount that banks can lend in a given year may become more and more sensitive to how much can be absorbed by demand for securitized mortgages. Demand shocks on the securitization market –partly driven by GSE decisions– may make bank lending comove more. Another cause of a rise in common banking shocks could be an increasing reliance on wholesale funding –for instance from money market mutual funds, which is more integrated a market than demand deposits– to expand loan production. Under this story, bank lending would become more and more sensitive to supply shocks on the bank funding market. This would also generate commonality in bank lending and therefore comovement in house prices. To clarify the exact link between common banking shocks and housing returns correlations, it is useful to go back to equation 5, which writes:

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

where:

$$\begin{cases} \gamma_1(x) & = & \frac{\rho + \frac{\mu^2}{\sigma_\epsilon^2} x}{1 + \frac{\mu^2}{\sigma_\epsilon^2} x} \\ \gamma_2(x) & = & \frac{\mu^2}{\sigma_\epsilon^2} \sigma_\eta^2 \frac{1}{1 + \frac{\mu^2}{\sigma_\epsilon^2} x} \\ \gamma_3(x) & = & \frac{\mu^2 \sigma_\eta^2}{\sigma_\epsilon^2} \frac{\rho + \frac{\mu^2}{\sigma_\epsilon^2} x}{\left(1 + \frac{\mu^2}{\sigma_\epsilon^2} x\right)^2} \end{cases}$$

Aggregate risk ($\sigma_a$) thus affects price growth correlations through three distinct channels. The most obvious one, the "direct" channel, which we have just discussed, is captured by $\gamma_1(\sigma_a^2)$, and is independent of bank geographic interlocks and concentrations. When banks have more common volatility ($\sigma_a$), prices are subject to stronger common shocks and thus correlate more ($\gamma_1$ is increasing in $\sigma_a$).

The second channel comes from an interaction between aggregate shocks and geographic dispersion. When aggregate shocks are small, the geographic propagation of idiosyncratic shocks plays a relatively more important role in explaining variation of prices and thus correlation induced through this channel is higher: $\gamma_2$ ($\gamma_2$ is decreasing in $\sigma_a$).

Last, the interaction between state-level concentration and aggregate risk has an ambiguous impact on correlations: $\rho > 1/2$ is a necessary and sufficient condition for $\gamma_3$ to be decreasing in $\sigma_a$ (for all $\sigma_a$).

Looking at the data, we actually find that aggregate risk became smaller over time. This implies that the direct impact of aggregate risk (channel 1), cannot explain by itself the rise in house returns correlations. Specifically, we compute the volatility of average bank lending. We first aggregate assets at the BHC-quarter level. For each BHC, we then calculate quarterly asset growth. At each date, we then take the cross-sectional average of BHC asset growth, after removing observations for which asset growth was above 100%. This average bank asset growth is a quarterly time series. We interpret it as the common factor to bank lending. Finally, at each quarter, we calculate the 20-quarter forward rolling volatility of this factor. We report its evolution over 1976-2000 in Figure 8. The volatility of average quarterly bank growth goes down from 1.2% to 0.8%. If anything, the common factor to bank growth became *less* volatile over the full period, and in particular over 1976-1994, the period that we focus on in our cross-sectional analysis. The evidence from Figure 8 thus suggests that stronger exposure to common aggregate shocks is not a good candidate to explain by itself the rise in house price correlation over 1976-1994.

Interestingly, the decline in aggregate risk does interact in theory with the geographic propagation channel we have put forth in this paper: ($\gamma_2$ increases when $\sigma_a$ decreases. Assuming that the other paramaters do not trend, this leads to a testable prediction: when running year-by-year estimations of our baseline regression,

$$\rho_{ij}^t = \alpha_{ijt} + \beta_{1t} H_{ij}^t + \beta_{2t}((H_{ii}^t + H_{jj}^t)/2) + \lambda_t X_{ij}^t + \epsilon_{ij}^t,$$

the coefficient on $H_{ij}$ should be increasing over time. Figure 9 provides suggestive evidence that this is the case. This figure plots the estimates (and the corresponding confidence interval) for the beta coefficients in the reduced-form regression, run year-by-year. All in all, aggregate risk can not *directly* drive the increase in correlations that we observe but might *amplify* the geographic propagation channel that we focus on.

# 6. Conclusion

This paper shows that the unification of the US banking market in the 1980s-1990s has led to synchronization of house prices across US regions. We thus provide evidence that freeing capital flow movement –at least through the banking system– can lead to significant contagion across regions. In doing so, we highlight the importance of idiosyncratic risk in shaping the relationship between bank integration and asset price 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, Rime and Strahan, 2004; Loustkina and Strahan, 2012), with a few large banks sloxly becoming the national key-players. This suggests that these deregulations can be further used as exogenous experiments to test macroeconomic models regarding the economic effects of capital markets integration.

# 7. References

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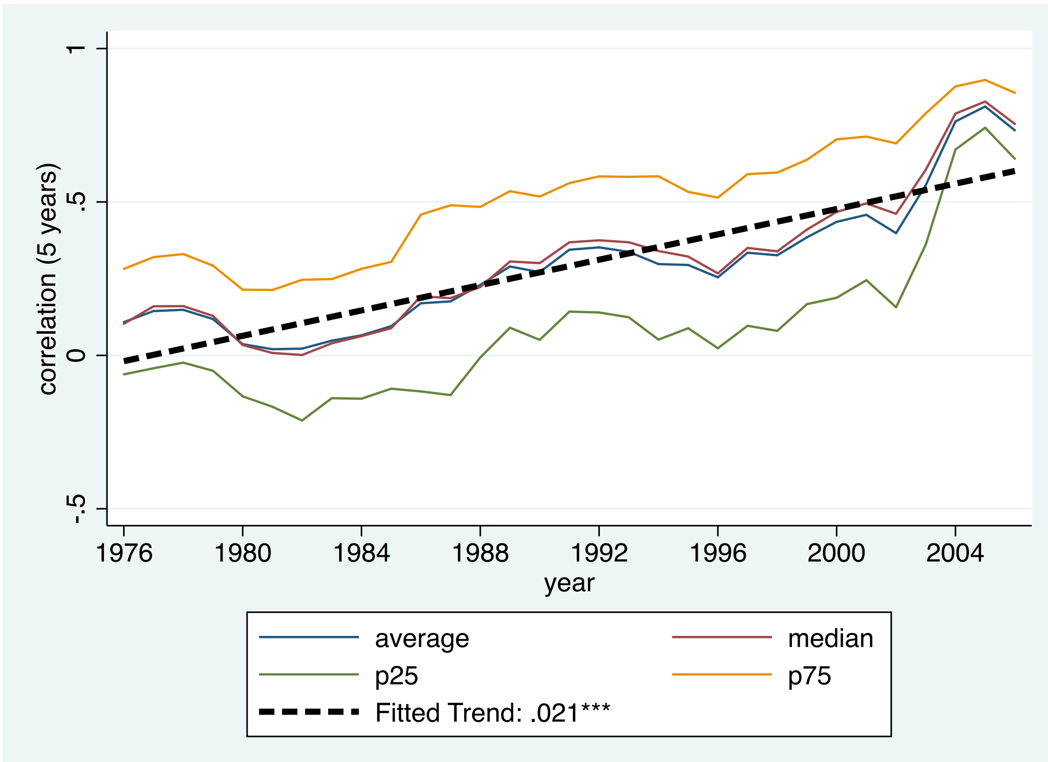
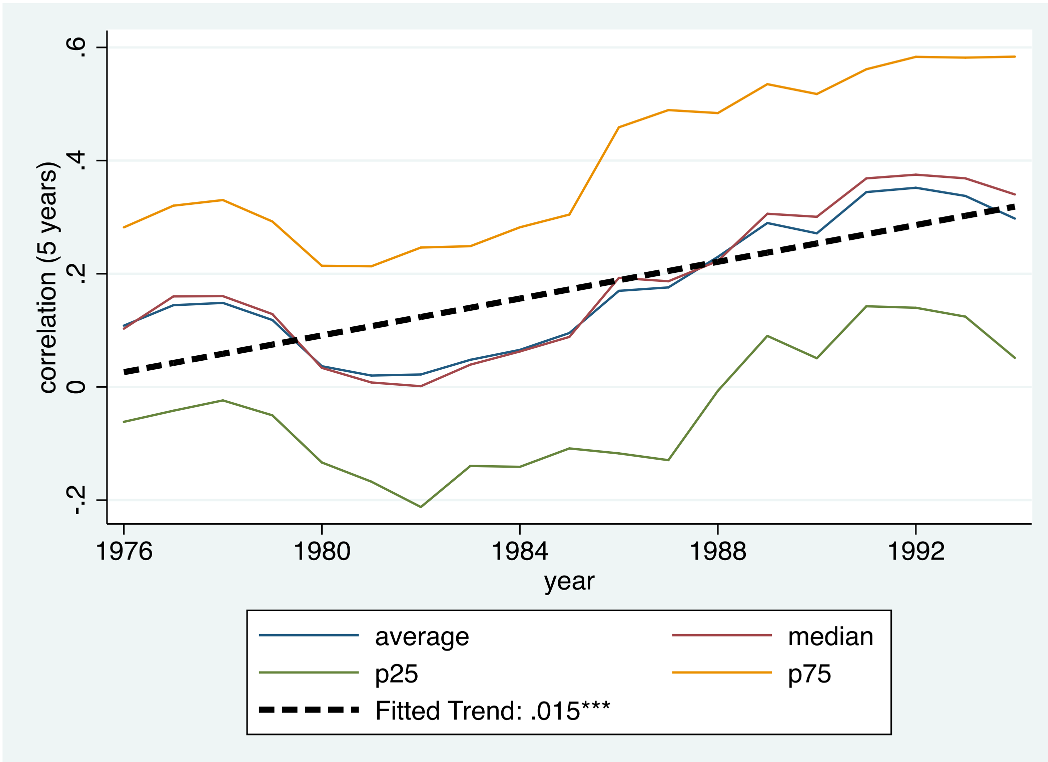
## 8. Tables and Figures

Figure 1: Pairwise correlation of real estate price growth across U.S. States: 1976-2006.



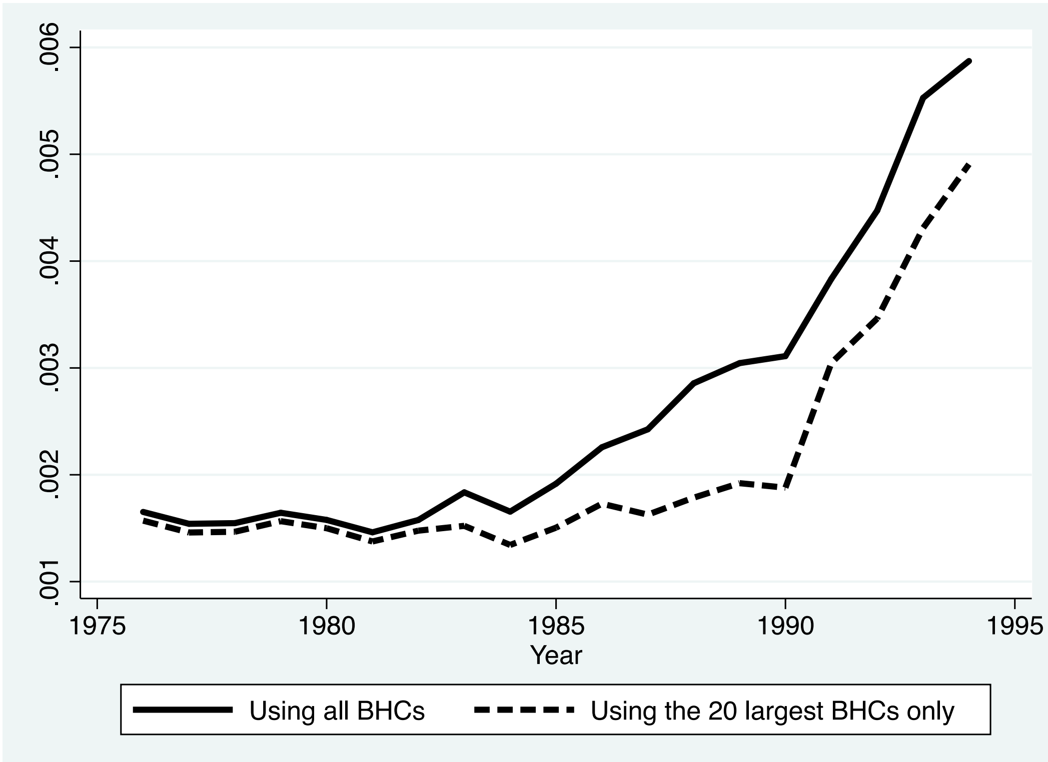

*Source*: OFHEO real estate price index. *Note*: This figure plots the mean, median, $25^{th}$ and $75^{th}$ percentiles of the distribution of pairwise correlations of real estate price growth across U.S. States for the 1976-2006 period. Correlation is computed using a 5-years forward rolling window with quarterly data.

Figure 2: Pairwise correlation of real estate price growth across U.S. States: 1976-2000.



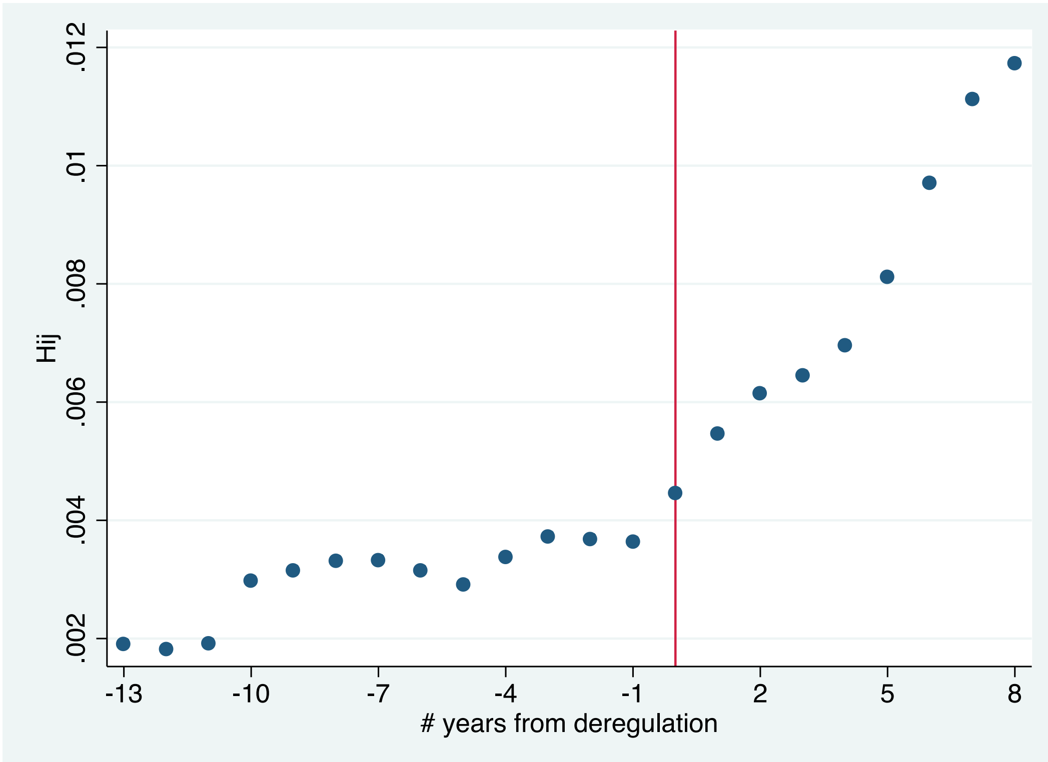

*Source*: OFHEO real estate price index. *Note*: This figure plots the mean, median, $25^{\text{th}}$ and $75^{\text{th}}$ percentiles of the distribution of the pairwise correlation of real estate price growth across U.S. States for the 1976-2000 period. Correlation is computed using a 5-years forward rolling window with quarterly data.

Figure 3: The Evolution of Bank Integration $H_{ij}$



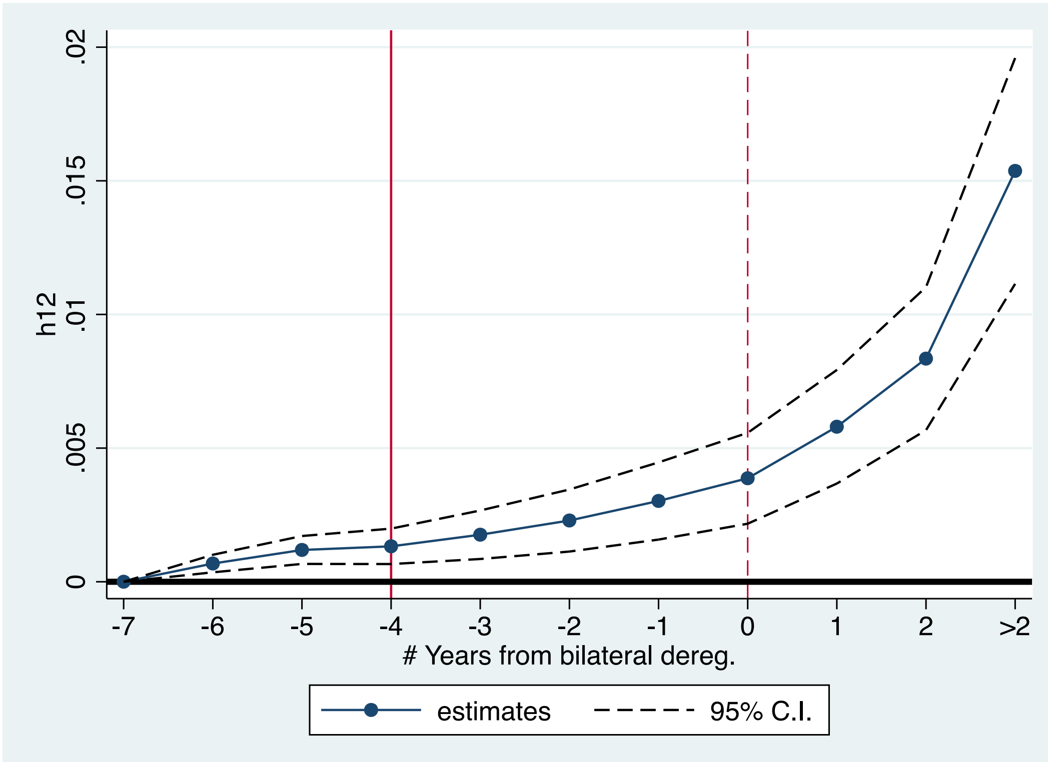

*Source*: Call Reports. *Note*: This figure plots the average, across state pairs, of the bank integration measure $H_{ij}$, for each year between 1976 and 1994. The definition of $H_{ij}$ is provided in Section 3. The thick line represent bank integration calculated using all the BHCs, and the dashed line only uses the 20 largest BHCs in the US.

Figure 4: Banking Integration and Interstate Banking Deregulation: Raw Data




*Source*: Call Reports. *Note*: This figure plots the average Co-Herfindhal of banking assets across pairs of U.S. states as a function of the distance to deregulation of interstate banking in the state-pair. The sample is restricted to the set of U.S. state-pairs where both states deregulate in the same year. The co-Herfindhal $H_{ij}$ is defined in Section 3.

Figure 5: Banking Integration and Interstate Banking Deregulation: Regression Results

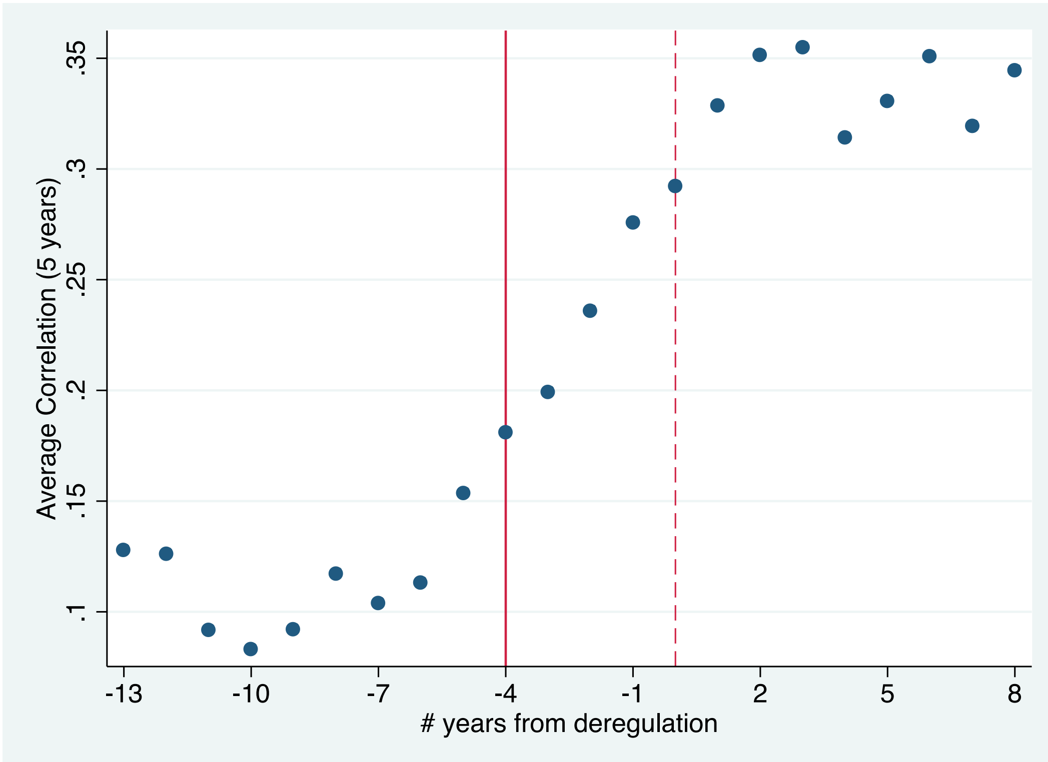



*Source*: Call Reports. *Note*: This figure plots the coefficient estimates (and the corresponding confidence interval) for the $\delta_k$ coefficients in the reduced-form regression:

$$H_{ij}^t = \sum_{k=-6}^{2} \delta_k \mathbb{I}_{t=T_{ij}+k} + \delta_{>2}\mathbb{I}_{t>T_{ij}+2} + \alpha_{ij} + \gamma_t + \kappa_i \times t + \kappa_j \times t + \lambda \mathbb{I}_{t>\tau_{ij}} + \beta X_{ij}^t + \epsilon_{ij}^t$$

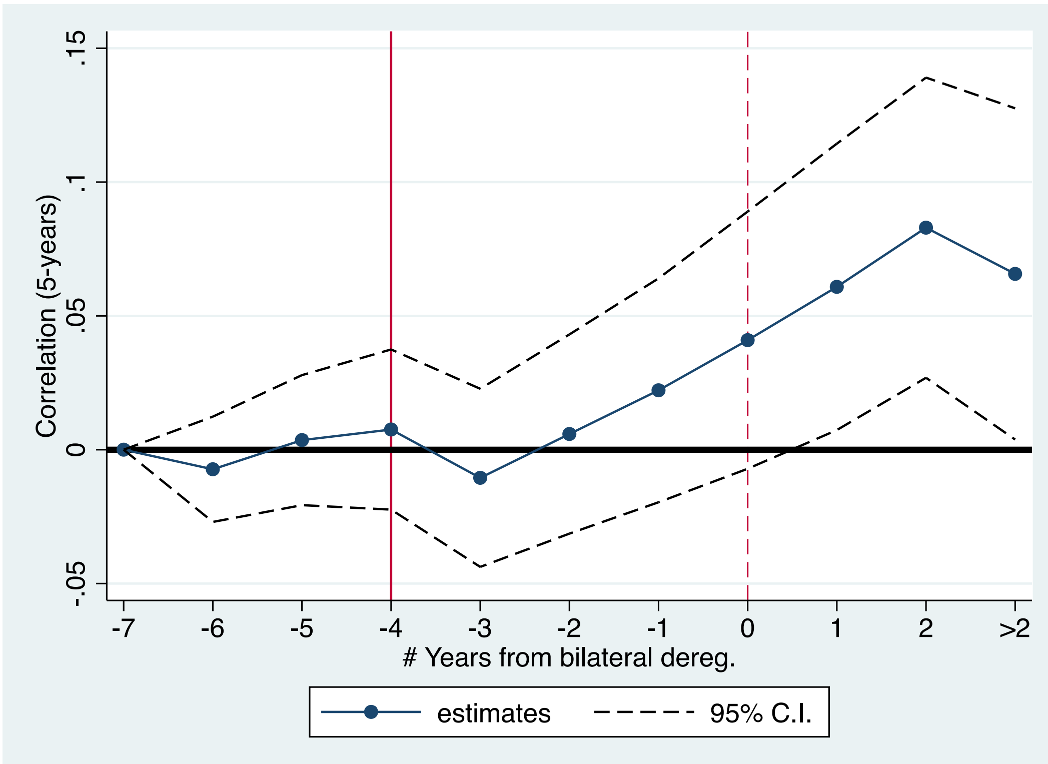
where $H_{ij}^t$ is the co-Herfindhal of banking assets in state-pair $ij$ as defined in Section 2.1 average over a 5-years forward rolling window, $T_{ij}$ is the year of bilateral deregulation of interstate banking for state-pair $ij$, X contains Log(Income 1), Log(Income 2), Differences in industry composition and $\rho_w$ as defined in Table 1 and $\tau_{ij}$ is the year of the first interstate banking deregulation in state-pair $ij$.

Figure 6: Real Estate Price Correlation and Interstate Banking Deregulation: Raw Data




*Source*: OFHEO real estate price index. *Note*: This figure plots the average housing return correlation across pairs of U.S. states ($\rho^t_{ij}$) as a function of the time distance to deregulation of interstate banking in the state-pair. The sample is restricted to the set of U.S. state-pairs where both states deregulate in the same year.

Figure 7: Real Estate Price Correlation and Interstate Banking Deregulation: Regression Results

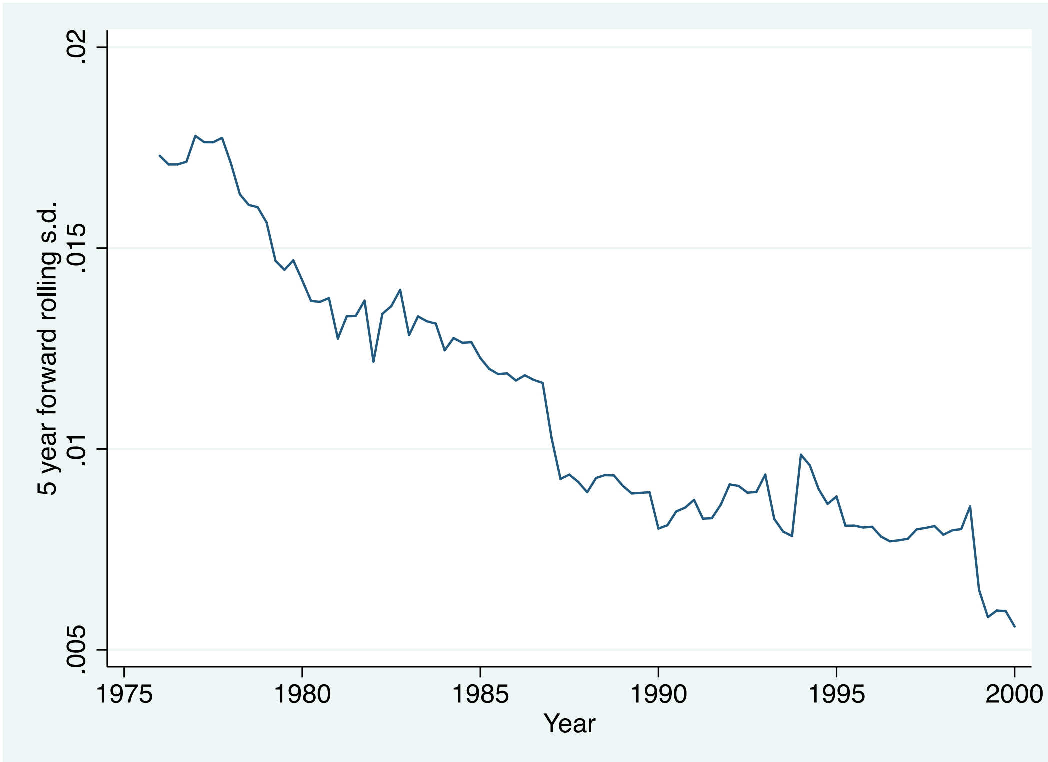



*Source*: OFHEO real estate price index. *Note*: This figure plots the coefficient estimates (and the corresponding confidence interval) for the $\delta_k$ coefficients in the reduced-form regression:

$$\rho_{ij}^t = \sum_{k=-6}^{2} \delta_k \mathbb{I}_{t=T_{ij}+k} + \delta_{>2}\mathbb{I}_{t>T_{ij}+2} + \alpha_{ij} + \gamma_t + \kappa_i \times t + \kappa_j \times t + \lambda \mathbb{I}_{t>\tau_{ij}} + \beta X_{ij}^t + \epsilon_{ij}^t$$

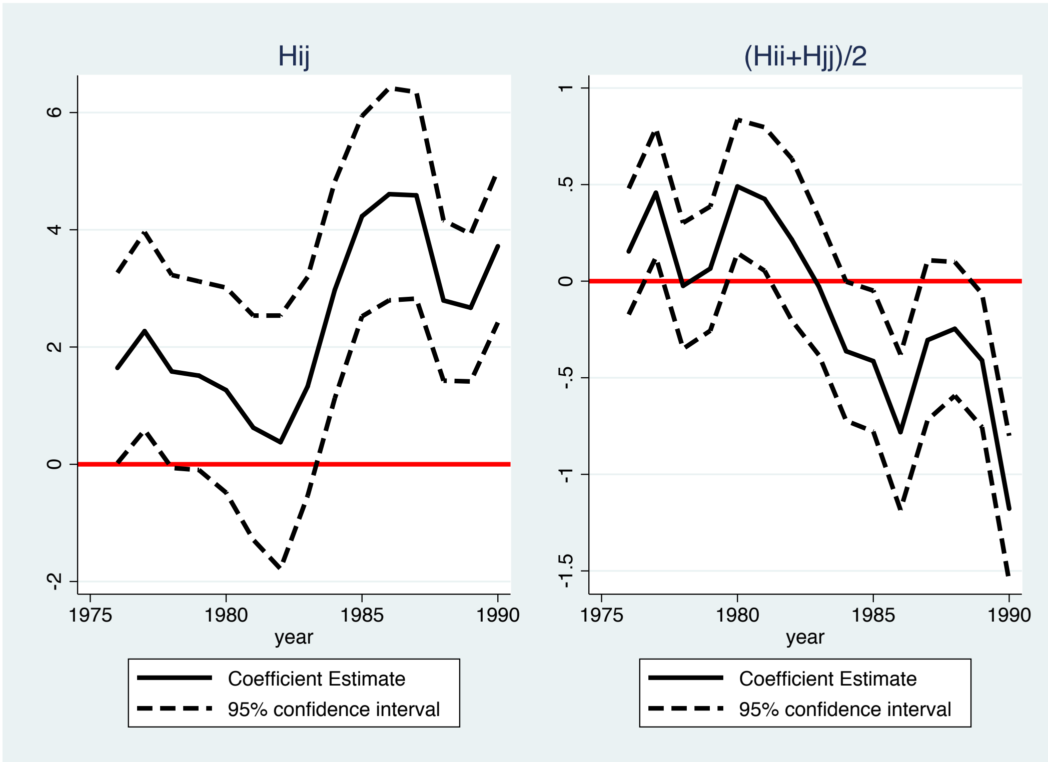
where $\rho_{ij}^t$ is the five-years forward correlation of real estate price growth in state-pair $ij$, $T_{ij}$ is the year of bilateral deregulation of interstate banking for state-pair $ij$, X contains Log(Income 1), Log(Income 2), Differences in industry composition and $\rho_w$ as defined in Table 1 and $\tau_{ij}$ is the year of the first interstate banking deregulation in state-pair $ij$.

Figure 8: 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.

Figure 9: Real Estate Price Correlation and Interstate Banking Deregulation: Year-by-year Regression Results




*Source*: OFHEO real estate price index. *Note*: This figure plots the coefficient estimates (and the corresponding confidence interval) for the beta coefficients in the reduced-form regression, run year-by-year:

$$\rho_{ij}^t = \alpha_{ijt} + \beta_{1t}H_{ij}^t + \beta_{2t}((H_{ii}^t + H_{jj}^t)/2) + \lambda_t X_{ij}^t + \epsilon_{ij}^t$$

,
where $\rho_{ij}^t$ is the five-years forward correlation of real estate price growth in state-pair $ij$, X contains Log(Income 1), Log(Income 2), Differences in industry composition and $\rho_w$ as defined in Table 1 and $\tau_{ij}$ is the year of the first interstate banking deregulation in state-pair $ij$.

Table 1: **Descriptive Statistics**

| variable | mean | median | min | max | sd | p25 | p75 | Obs. |
|---|---|---|---|---|---|---|---|---|
| $\rho$ | 0.29 | 0.29 | -0.83 | 0.99 | 0.36 | 0.02 | 0.59 | 39225 |
| $\rho_3$ | 0.28 | 0.30 | -0.94 | 1.00 | 0.39 | -0.01 | 0.59 | 39325 |
| $\rho_w$ | 0.51 | 0.54 | -0.63 | 0.97 | 0.25 | 0.35 | 0.69 | 39325 |
| Log(Income 1) | 10.95 | 10.96 | 8.40 | 14.15 | 1.16 | 10.04 | 11.86 | 34026 |
| Log(Income 2) | 11.03 | 11.01 | 8.40 | 14.15 | 1.13 | 10.19 | 11.82 | 34026 |
| Differences in industry composition | 0.02 | 0.01 | 0.00 | 0.19 | 0.02 | 0.00 | 0.02 | 34026 |
| $H_{ij}$ | 0.00 | 0.00 | 0.00 | 0.22 | 0.01 | 0.00 | 0.00 | 18726 |
| $\frac{H_{ii}+H_{jj}}{2}$ | 0.10 | 0.09 | 0.01 | 0.32 | 0.05 | 0.06 | 0.14 | 18726 |

*Source:* OFHEO real estate price index and BLS. *Note:* $\rho$ is the pairwise correlation of real estate price growth across U.S. states computed over a 5 years forward rolling windows with quarterly data. $\rho_3$ uses a 3-years forward rolling window. $\rho_w$ is the pairwise correlation of personal income growth across U.S. states computed over a 5 years rolling windows with quarterly data. Log(Income 1) (resp. Log(Income 2)) is the log of personal income in state 1 (resp. 2). Differences in industry composition is the sum of squares of the pairwise difference in the labor share of major industries across U.S. states. $H_{ij}$ and $\frac{H_{ii}+H_{jj}}{2}$ are the co-Herfindhal and average Herfindhal of banking assets for the state-pair, as defined in Section 4.1. Income 1, Income 2, Differences in industry composition, $H_{ij}$ and $\frac{H_{ii}+H_{jj}}{2}$ are averaged over a 5 years forward rolling window.

Table 2: **Banking Deregulation and Banking Integration: First-stage**

| | Banking assets Co-Herfindhal: $H_{ij}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| After Unilateral Deregulation | .00037 | .00029 | .0019*** | .0027*** |
| | (1.1) | (.72) | (2.8) | (3.9) |
| After Bilateral Deregulation | .0057*** | .0058*** | .006*** | |
| | (5.6) | (5.5) | (5.7) | |
| 6 years before bilateral deregulation | | | | .00068*** |
| | | | | (4.1) |
| 5 years before bilateral deregulation | | | | .0012*** |
| | | | | (4.5) |
| 4 years before bilateral deregulation | | | | .0013*** |
| | | | | (3.9) |
| 3 years before bilateral deregulation | | | | .0018*** |
| | | | | (3.8) |
| 2 years before bilateral deregulation | | | | .0023*** |
| | | | | (3.9) |
| 1 years before bilateral deregulation | | | | .003*** |
| | | | | (4.1) |
| year of bilateral deregulation | | | | .0039*** |
| | | | | (4.5) |
| 1 years after bilateral deregulation | | | | .0058*** |
| | | | | (5.3) |
| 2 years after bilateral deregulation | | | | .0083*** |
| | | | | (6.1) |
| $\geq$ 3 years after bilateral deregulation | | | | .015*** |
| | | | | (7.1) |
| Log(personal income 1) | | .0038** | -.0032 | -.0024 |
| | | (2.1) | (-1.4) | (-1.1) |
| Log(personal income 2) | | .0093** | -.0042** | -.004** |
| | | (2.2) | (-2.1) | (-2.1) |
| Differences in industry composition | | .069*** | .14* | .11 |
| | | (3.2) | (1.8) | (1.5) |
| Income correlation | | -.000048 | -.00075** | -.00056* |
| | | (-.14) | (-2.4) | (-1.9) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| State-Pair Fixed Effects | Yes | Yes | Yes | Yes |
| State-Spec. trends | No | No | Yes | Yes |
| Observations | 18,726 | 18,726 | 18,726 | 18,726 |
| Adj. R-Square | .78 | .78 | .8 | .81 |

*Note:* The dependent variable is the bank integration measure $H_{ijt}$, averaged over a 5 year forward rolling window. After Unilateral Deregulation is a dummy equal to 1 in the years following deregulation of interstate banking by at least 1 state in the state-pair. After Bilateral Deregulation is a dummy equal to 1 in the years following deregulation of interstate banking by both states in the state-pair. Both variables are averaged over a 5-years forward rolling window. k years before (resp. after) bilateral deregulation is a dummy variable equal to 1 when both states in the state-pair deregulate interstate banking with the other state in year t+k (resp. t-k). Other variables are defined in Table 1. All specifications include state and year fixed effects. Column (3) and (4) allow for state-specific trends. Standard errors are clustered at the state-pair level. ***, ** and * means significant at the 1, 5 and 10% confidence level.

Table 3: **Banking Deregulation and House Price Correlation: Reduced Form**

| | State-pair price growth correlation: $\rho$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| After Unilateral Deregulation | -.033* | -.03 | -.022 | -.019 |
| | (-1.7) | (-1.5) | (-1.1) | (-.92) |
| After Bilateral Deregulation | .066*** | .067*** | .072*** | |
| | (3.1) | (3.2) | (3.4) | |
| 6 years before bilateral deregulation | | | | -.0073 |
| | | | | (-.73) |
| 5 years before bilateral deregulation | | | | .0036 |
| | | | | (.29) |
| 4 years before bilateral deregulation | | | | .0075 |
| | | | | (.49) |
| 3 years before bilateral deregulation | | | | -.011 |
| | | | | (-.62) |
| 2 years before bilateral deregulation | | | | .0059 |
| | | | | (.31) |
| 1 years before bilateral deregulation | | | | .022 |
| | | | | (1) |
| year of bilateral deregulation | | | | .041* |
| | | | | (1.7) |
| 1 years after bilateral deregulation | | | | .061** |
| | | | | (2.2) |
| 2 years after bilateral deregulation | | | | .083*** |
| | | | | (2.9) |
| $\geq$ 3 years after bilateral deregulation | | | | .067** |
| | | | | (2.1) |
| Log(personal income 1) | | .15*** | .3*** | .29*** |
| | | (2.8) | (2.8) | (2.7) |
| Log(personal income 2) | | .11** | .26** | .25** |
| | | (2.4) | (2.2) | (2.1) |
| Differences in industry composition | | .38 | -.048 | -.06 |
| | | (.57) | (-.063) | (-.079) |
| Income correlation | | .06*** | .065*** | .066*** |
| | | (4.2) | (4.6) | (4.6) |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| State-Pair Fixed Effects | Yes | Yes | Yes | Yes |
| State-Spec. trends | No | No | Yes | Yes |
| Observations | 31,476 | 31,476 | 31,476 | 31,476 |
| Adj. R-Square | .35 | .35 | .39 | .39 |

*Note:* The dependent variable is the pairwise correlation of real estate price growth across U.S. states computed over a 5 years rolling windows with quarterly data. After Unilateral Deregulation is a dummy equal to 1 in the years following deregulation of interstate banking by at least 1 state in the state-pair. After Bilateral Deregulation is a dummy equal to 1 in the years following deregulation of interstate banking by both states in the state-pair. Both variables are averaged over a 5-years forward rolling window. k years before (resp. after) bilateral deregulation is a dummy variable equal to 1 when both states in the state-pair deregulate interstate banking with the other state in year t+k (resp. t-k). Other variables are defined in Table 1. All specifications include state and year fixed effects. Column (3) and (4) allow for state-specific trends. Standard errors are clustered at the state-pair level. ***, ** and * means significant at the 1, 5 and 10% confidence level.

Table 4: **Banking Deregulation and Correlation: Robustness Checks**

| | State-pair price growth correlation: $\rho$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| After Unilateral Deregulation | -.024 | -.056** | | | -.045*** |
| | (-1.1) | (-2.4) | | | (-2.7) |
| After Bilateral Deregulation | .081*** | .13*** | .059*** | | .068*** |
| | (3.4) | (5.3) | (3) | | (3.8) |
| 6 years before bilateral deregulation | | | | -.0043 | |
| | | | | (-.35) | |
| 5 years before bilateral deregulation | | | | .015 | |
| | | | | (1) | |
| 4 years before bilateral deregulation | | | | .025 | |
| | | | | (1.4) | |
| 3 years before bilateral deregulation | | | | .0049 | |
| | | | | (.25) | |
| 2 years before bilateral deregulation | | | | .0087 | |
| | | | | (.42) | |
| 1 years before bilateral deregulation | | | | .027 | |
| | | | | (1.2) | |
| year of bilateral deregulation | | | | .042* | |
| | | | | (1.7) | |
| 1 years after bilateral deregulation | | | | .064** | |
| | | | | (2.3) | |
| 2 years after bilateral deregulation | | | | .084*** | |
| | | | | (2.9) | |
| $\geq$ 3 years after bilateral deregulation | | | | .073*** | |
| | | | | (2.25) | |
| Log(personal income 1) | .26** | .03 | .7*** | .69*** | .15 |
| | (2.2) | (.19) | (4.5) | (4.5) | (1.5) |
| Log(personal income 2) | .28** | .26 | .37** | .36** | -.014 |
| | (2.3) | (1.5) | (2.2) | (2.2) | (-.12) |
| Differences in industry composition | 3.1*** | -1.1 | -.42 | -.42 | -.2 |
| | (3.2) | (-.82) | (-.44) | (-.44) | (-.3) |
| Income correlation | .073*** | .094*** | .039** | .04** | .0013 |
| | (4.5) | (5.5) | (2.2) | (2.3) | (.13) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| State-Pair Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| State-Spec. trends | Yes | Yes | Yes | Yes | Yes |
| Observations | 23,826 | 18,705 | 20,186 | 20,186 | 31,476 |
| Adj. R-Square | .41 | .47 | .4 | .4 | .3 |

*Note:* The dependent variable is the pairwise correlation of real estate price growth across U.S. states computed with quarterly data over (1) a 5 years rolling windows (column 1 to 4) and (2) a 3 years rolling windows (column 5). Column 1 estimates the main regression over the 1976-1994 period. Column 2 restricts the observations to a window of 8 years before the first deregulation of interstate banking within the state-pair and 4 years after both states have deregulated interstate banking. Column 3 and 4 use the sample of state pairs where both states simultaneously allow interstate banking within the pair. After Unilateral Deregulation is a dummy equal to 1 in the years following deregulation of interstate banking by at least 1 state in the state-pair. After Bilateral Deregulation is a dummy equal to 1 in the years following deregulation of interstate banking by both states in the state-pair. Both variables are averaged over a 5-years forward rolling window. k years before (resp. after) bilateral deregulation is a dummy variable equal to 1 when both states in the state-pair deregulate interstate banking with the other state in year t+k (resp. t-k). Other variables are defined in Table 1. All specifications include state and year fixed effects, as well as state-specific trends. Standard errors are clustered at the state-pair level. ***, ** and * means significant at the 1, 5 and 10% confidence level.

Table 5: **Banking Deregulation and Banking Concentration: First-stage**

| | Banking assets Herfindhal: $\frac{H_{ii}+H_{jj}}{2}$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Branching Index | .0086*** | .0094*** | .015*** |
| | (3.4) | (3.9) | (6.8) |
| Log(personal income 1) | | -.0044 | -.02*** |
| | | (-.68) | (-2.9) |
| Log(personal income 2) | | -.053*** | -.075*** |
| | | (-7) | (-8.6) |
| Differences in industry composition | | -.34*** | .14*** |
| | | (-3.5) | (5.9) |
| Income correlation | | .004*** | -.0017** |
| | | (3.4) | (-2.5) |
| Year Fixed Effects | Yes | Yes | Yes |
| State-Pair Fixed Effects | Yes | Yes | Yes |
| State-Spec. trends | No | No | Yes |
| Observations | 18,726 | 18,726 | 18,726 |
| Adj. R-Square | .92 | .92 | .98 |

*Note:* The dependent variable is the average herfindhal of banking assets in the state-pair as defined in Section 4.1. For state $i$, the branching index is equal to 1 if the state permits either de novo or M&A branching; It is equal to 2 if it permits both. We then take the average of this index across the two states of the pair. Finally, for consistency with the OLS regression, which include the 5-year rolling corrleation, we use here the 5 year forward rolling averages of $\frac{H_{ii}+H_{jj}}{2}$ and of the branching index. k years before (resp. after) bilateral deregulation is a dummy variable equal to 1 when both states in the state-pair deregulate interstate banking with the other state in year t+k (resp. t-k). Other variables are defined in Table 1. All specifications include state and year fixed effects. Column (3) and (4) allow for state-specific trends. Standard errors are clustered at the state-pair level. ***, ** and * means significant at the 1, 5 and 10% confidence level.

Table 6: **Correlation and Banking Integration: OLS and IV estimation**

| | State-pair price growth correlation: $\rho$ | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | | | IV | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $H_{ij}$ | 3.1*** | 3.5*** | 2.8*** | 2.2*** | 11*** | 8.9*** |
| | (5.6) | (3.2) | (2.9) | (3) | (3.5) | (4.2) |
| $\frac{H_{ii}+H_{jj}}{2}$ | -.51*** | .034 | .31 | -1.8*** | -3.2 | -4.1** |
| | (-5.5) | (.13) | (1.2) | (-5.3) | (-1.6) | (-2.3) |
| Log(personal income 1) | | | .3*** | -.091 | -.1 | -.12 |
| | | | (4.5) | (-.69) | (-.77) | (-.92) |
| Log(personal income 2) | | | .27*** | .14 | .06 | -.0054 |
| | | | (3.5) | (1) | (.31) | (-.029) |
| Differences in industry composition | | | 7.1*** | 7.7*** | 6.5*** | 6.9*** |
| | | | (8.1) | (6.7) | (4.6) | (5.4) |
| Income correlation | | | .12*** | .11*** | .11*** | .11*** |
| | | | (6.3) | (5.9) | (6.1) | (6.1) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| State-Pair Fixed Effects | No | Yes | Yes | Yes | Yes | Yes |
| State-Spec. trends | No | No | No | Yes | Yes | Yes |
| Observations | 18,726 | 18,726 | 18,726 | 18,726 | 18,726 | 18,726 |
| Adj. R-Square | | .33 | .35 | .41 | - | - |
| Cragg-Donald F-stat. | | | | | 179 | 59 |

*Note:* The dependent variable is the co-herfindhal of banking assets in the state-pair as defined in Section 4.1. All variables are defined in Table 1. Column 1 to 4 present OLS results and column 5 and 6 present IV results. Column 5 uses After Unilateral Deregulation, After Bilateral Deregulation and the Branching Index as instruments for $H_{ij}$ and $\frac{H_{ii}+H_{jj}}{2}$. Column 6 uses After Unilateral Deregulation, the k years before (resp. after) bilateral deregulation dummies used in Table 2 and the Branching Index as instruments for $H_{ij}$ and $\frac{H_{ii}+H_{jj}}{2}$. All specifications include state and year fixed effects. Column 4, 5 and 6 allow for state-specific trends. Standard errors are clustered at the state-pair level. ***, ** and * means significant at the 1, 5 and 10% confidence level.