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Softening the Blow: U.S. State-Level Banking Deregulation and Sectoral Reallocation after the China Trade Shock

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Abstract

U.S. state-level banking deregulation during the 1980's mitigated the impact of the China trade shock (CTS) on local economies (states and commuting zones) a decade later, in the 1990s. Local economies, where local banking markets opened up earlier, were also effectively financially more integrated by the 1990's and saw smaller declines in house prices, wages, and income following the CTS. We explain this pattern in a theoretical model that emphasizes the stabilizing effect of financial integration on demand for housing and on housing prices: faced with an adverse shock to their region's terms-of-trade (i.e. the CTS), households in more open states can more easily access credit to smooth consumption. This stabilizes consumer demand for housing, keeps the relative price of housing up, stabilizes wages in the non-tradable sector and thus facilitates the sectoral reallocation of labor away from import-exposed manufacturing towards the housing sector. This in turn stabilizes income and consumption. We corroborate these predictions of our model in state- and commuting zone level data. Then, using granular bank-county-level data, we show that household consumption smoothing in response to the CTS was easier in financially open areas, because geographically diversified banks were more elastic in their lending response to household's increased demand for credit. Our findings highlight the importance of household access to finance in the adjustment to asymmetric terms-of-trade shocks in monetary unions.

Keywords: banking deregulation, China trade shock, sectoral reallocation, house prices, consumer access to finance

JEL Classification: F16, F41, G18, G21, J20

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1 Introduction

During the 1990's and early 2000's, growing import competition from China disrupted the U.S. manufacturing sector. This "China Syndrome" was first documented by Autor, Dorn and Hanson (2013) who show that U.S. labor market regions (commuting zones) with manufacturing industries that were particularly exposed to Chinese import competition also saw the biggest drops in manufacturing employment and wages.

The seminal paper by Autor et al. (2013) sparked a considerable body of follow-up empirical and theoretical work (e.g., Acemoglu et al. (2016); Autor et al. (2016); Pierce and Schott (2016); Caliendo et al. (2019)). This literature has drawn attention to the fact that net gains from international trade are very unequally distributed. While the benefits in the form of cheaper imports are widely dispersed across U.S. households (Amiti et al. (2017)), the costs, e.g. in terms of the displacement of workers, are geographically concentrated in the areas where industries directly competing with Chinese imports tend to cluster.

There is no consensus in the literature about what would be the best policy to even out the geographically heterogeneous negative effects of trade integration. One obvious way in which this could happen is via financial integration. Interestingly, no study so far has asked to what extent geographic differences in financial integration affected the response of U.S. regional economies to the China trade shock and the sectoral reallocation that followed it. In this paper, we attempt to provide an answer to this question.

The China trade shock constituted a major deterioration of the terms of trade of many local economies in the United States. At a theoretical level, one would expect that regions with easier access to finance would see a swifter sectoral reallocation after a such terms-of-trade shock. This could happen through various channels. Better access to finance may make it easier for directly exposed manufacturing firms to survive the China trade shock in the first place, thus attenuating the drop in manufacturing employment and wages. Better access to finance may also make it easier for displaced manufacturing workers to retrain or start businesses in other sectors. Last but not least, easier access to finance may allow consumers to smooth consumption, which props up local demand for non-tradable consumption, thus facilitating the reallocation from manufacturing to non-tradable industries.

To explore these hypotheses empirically, we exploit the fact that the United States experienced a period of significant deregulation of the banking industry during the 1980's. In particular, in the decade before the China trade shock, individual states opened their local banking markets by allowing banks from outside the state to enter (Jayaratne and Strahan, 1996; Morgan et al., 2004). Since states deregulated in different years (Kroszner and Strahan, 1999), there was considerable variation at the state level in the number of years that had elapsed since banking liberalization until a local economy was hit by the China trade shock in the mid-1990's. By the time the China trade shock started to hit in the 1990's, banking deregulation at the state level was largely complete. However, as we have argued in Hoffmann and Stewen (2020), deregulation left a long shadow in the sense that differences in the *de facto* level of integration of state banking markets continued to persist for more than a decade, with states that opened their markets earlier also being more integrated *de facto*. We condition on these pre-determined differences in financial integration to ask if and how state banking systems that were more integrated with the rest of the country were able to help local economies deal with the fallout from the China trade shock.

Our results suggest that the fallout of the China trade shock on local economies was indeed attenuated by financial integration. To interpret our empirical findings, we propose a two-sector model with a tradable (manufacturing) and a non-tradable durable (housing) sector and in which regions differ in their access to finance. Based on this model, we argue that the patterns in the data support the view that access to finance primarily worked by stabilizing local consumer demand, thus keeping demand for housing and house prices up. This, in turn facilitated the reallocation of displaced workers from the manufacturing to the non-tradable sector.

We test this model using annual panel data for the U.S. states and commuting zones covering the period from 1991 to 2007. To do so, we expand the data set of Autor et al. (2013) to obtain state- and commuting zone-level import exposures at the annual frequency. Our estimation results confirm the predictions of the stylized model. Local differences in financial integration did *not* directly mitigate the impact of the China trade shock on manufacturing firms and manufacturing employment. Rather, by allowing households to smooth consumption through borrowing, better access to bank finance led to a stabilization of demand for non-tradable goods and housing. This kept prices in these sectors relatively high and allowed a swifter reallocation of workers from the import-exposed manufacturing sector to the housing sector. Consistent with this pattern and the predictions of the model, we find that—conditional on their exposure to the China trade shock—states and commuting zones that were financially more integrated saw higher mortgage lending growth.

Our empirical findings hold up controlling for a host of local characteristics that could have affected pre-1991 trends at the local level, such as house price growth, employment growth, the relative sizes of the tradable and non-tradable sectors, and the openness to trade. Controlling for these factors is important since state-level banking deregulation is known to have affected many of these state-level characteristics and we need to rule out the possibility that these outcomes—rather than the long shadow that banking deregulation left on local access to credit—modulated the response of local economies to the China trade shock.

We also control for a host of alternative channels through which local differences in financial integration could have affected the response of local economies to aggregate factors such as monetary policy, credit availability or capital inflows. Again our results are robust.

One concern about using U.S. banking deregulation to identify local differences in access to finance is that it varies only at the state level. We therefore also explore an alternative identification strategy that exploits differences in financial openness at the county-level and that allows us to put some key elements of our theory under the microscope. Specifically, in our model, reallocation after the China trade shock is swifter in financially open states because households have better access to credit, which allows them to smooth consumption and, in turn, stabilizes the demand for and the prices of non-tradable goods, notably of housing. Hence we would expect that i) the China trade shock actually amounts to a positive credit demand shock, ii) that banks are more elastic in their response to this shock in more financially open locations, and iii) and that house prices remained higher in counties where ii) is the case.

We examine these three elements of the mechanism using bank-county level data on mortgage refinancing demand from the Home Mortgage Disclosure Act (HMDA) data base. This data allows us to separate bank-level credit supply shocks from the local-specific demand shocks faced by banks using the methodology recently proposed by Amiti and Weinstein (2018) and adapted to bank-county level data in Hoffmann and Stewen (2020). Consistent with our theory, we find that county-level import exposure is positively associated with the demand for refinancing and for mortgage equity withdrawal faced by the banks in the county. Importantly, geographically more diversified banks that are active in several states are more willing to satisfy this demand. Hence, local and geographically diversified banks differ in their elasticity of credit supply, i.e. they expand their supply of credit differentially in response to a given demand shock. This finding explains, why—given their exposure to Chinese imports—households could generally borrow more easily in early-deregulated states, which have a stronger presence of geographically diversified banks.

Finally, we show that counties and commuting zones dominated by geographically diversified banks with relatively more elastic credit supply responses saw more stable housing prices in response to the China trade shock. To this end, we build on Gabaix and Koijen (2020) and construct a granular lending response—$\mathcal{GLR}$—that aggregates individual banks' responses to the county-level, correcting for the potential confounding effects that import exposure could have on local outcomes through other channels. In order to alleviate the concern that banks' market shares could themselves be endogenous, we follow Hoffmann and Stewen (2020) and construct an exogenous measure of banks' market shares that exploits the different deregulation histories of the home states of banks active in a specific county. In line with the mechanism in our theory, we find that $\mathcal{GLR}$ has a strong positive effect on county-level house prices.

Our paper directly relates to a growing body of literature—starting with Jayaratne and Strahan (1996)—that has used the quasi-experiment of state-level banking deregulation to study the effects of credit supply shock on economic outcomes. More recently Favara and Imbs (2015) have documented the impact of banking deregulation on mortgage credit supply and house prices. Hoffmann and Stewen (2020) show that house prices in states that liberalized early during the 1980's were more correlated with capital inflows into the U.S. after 1997. Bremus, Krause and Noth (2019) examine the role of idiosyncratic banking shocks on local mortgage credit supply in the United States. Mian, Sufi and Verner (2020) show that states that liberalized their banking markets earlier during the 1980's saw more pronounced boom-bust cycles in consumer lending during the late 1980's and early 1990's. Their results support the view that the effect of banking deregulation on credit supply was largely transmitted through an increase in household debt. Our analysis also relates to the recent study by Federico, Hassan and Rappoport (2020) who examine the impact of the China trade shock on bank credit supply, using Italian bank-firm level data.

Different from all of these papers which focus on credit supply, our analysis draws attention to the role that banking deregulation played in modulating a major shock to credit *demand*. Specifically, we argue that the pattern in the data is consistent with the view that the blow of the China trade shock got softened mainly because households in more financially integrated states could smooth consumption by increasing net borrowing. Hence, differently from earlier papers, we do not focus on the credit supply effect of financial liberalization itself. Rather, we ask how better access to finance of private households can stabilize consumer demand in the presence of large external shock to a region's terms-of-trade and – in so doing — can facilitate the sectoral reallocation of employment.

Our findings therefore also shed light on the role of households' access to finance in sharing the risks associated with asymmetric shocks among regions of a monetary union. It is well-documented that cross-border banking integration fosters better risk sharing (Demyanyk et al., 2007; Kalemli-Ozcan et al., 2009). The lack of genuine cross-border banking integration in the European Monetary Union (EMU) is often identified as a prime reason for why risk sharing among EMU countries is so low (Draghi, 2018; Hoffmann, Maslov, Sørensen and Stewen, 2019). Also, earlier literature has focused on the impact of improved firm access to finance (Demyanyk et al., 2007; Rice and Strahan, 2010; Hoffmann and Stewen, 2011), while our results show that retail (consumer) financial integration is equally important for risk sharing.

Finally, our results also complement previous research on the long-run impact of the China trade shock on the level and composition of employment in U.S. regional labor markets. Charles, Hurst and Notowidigdo (2016) have argued recently that the true employment effects of the China trade shock were masked by the concurrent rise in house prices prior to 2008. Charles et al. (2016) argue that the rise of the housing bubble in the late 1990's made it easier for households to temporarily maintain consumption (mainly through job creation in construction but possibly also through mortgage borrowing and equity withdrawal) even though their income and employment prospects had been permanently harmed by import competition from China. Our results here suggest that that the reallocation of workers towards construction and the increase in household debt during this period could, at least in part, be a direct causal consequence of the China trade shock rather than a coincidence.

The paper is organized as follows. We start, in section 2, with a brief history of state-level banking deregulation in the United States. In section 3, we take a first look at the data. Section 4 presents a model of how financial openness modulates the response of an economy to a terms-of-trade shock. Section 5 presents our data. Section 6 discusses the empirical framework and presents our empirical results at the state and commuting zone levels. Section 7 presents further bank-county level evidence on our mechanism. Section 8 concludes.

2 Background: state-level banking deregulation in the U.S.

In our analysis we make use of the quasi-experiment of the gradual abolition of geographical restrictions on banking in the United States during the 1980s and early 1990s. The staggered timing of this deregulation provides an ideal laboratory to explore empirically how these regulatory differences in openness to a bank entry affected the real economy. While the China trade shock only started to hit the U.S. from the mid–1990s onward (Autor et al., 2013), our argument builds on Hoffmann and Stewen (2020) who show that banking deregulation in the 1980s left a long shadow in the sense that states that opened their banking markets earlier during the 1980s still were financially more integrated with the rest of the U.S. than a decade later.

As discussed by Hoffmann and Stewen (2020), many of the restrictions barring the activity of out-of-state banks (as well as intra-state branching restrictions discussed below) dated back to the 19th century. More recently it was the Douglas Amendment to the Bank Holding Company Act of 1956 that gave states the authority to effectively prohibit out-of-state banks from acquiring banks in the state. All states implemented this prohibition which only gradually got diluted from the late 1970s onward. Beginning with Maine in 1978, state legislatures began to enact laws that allowed out-of-state bank holding companies (BHCs) to control banks in their state. These laws often authorized out-of-state acquisitions only on a reciprocal basis, i.e. “home” banks were only allowed to be acquired by banks headquartered in a state that also had allowed entry of “home” banks or by banks from a neighboring state. We will exploit this reciprocal nature of deregulation to construct our county-level measure of financial openness later in the paper.

At the federal level, in 1982 legislators amended the Bank Holding Company Act to allow failed banks to be acquired by any holding company, regardless of state laws. Furthermore, the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 forced all states to allow entry of out-of-state banks if they had not yet done so. As the last state, Hawaii allowed out-of-state entry in 1995.

Until the early 1990s, geographical barriers to bank entry were not only prevalent between states but also within them, with many states upholding restrictions on intrastate branching. Our focus in this paper is on how household-level access to finance helped stabilize local economies after the China trade shock. Given that the fallout from the shock was highly localized, we would expect that the removal of intrastate branching restrictions would have a similar effect on access to credit as interstate deregulation. Many states are big enough to allow for a meaningful geographic diversification of banks even within the state’s borders—provided there are no branching restrictions. Like interstate integration, we would expect this to make banks more willing to increase supply in response to highly local credit demand shocks. Based on these considerations, our main measure of state-level financial openess is

$$\textsc{di}^s = 1995 - \min\{\text{Year of Intrastate Branching, Year of Interstate Banking}\}. \qquad (1)$$

where s indexes the state. Hence, we count the number of years between the 'effective' date of liberalization of banking markets– interstate or intrastate liberalization, whichever is earlier—and 1995, the year when the IBBEA effectively removed all of these barriers. Building on Hoffmann and Stewen (2020) we then argue–and will show empirically–that the time elapsed since the liberalization of a state's banking markets mattered for households ability to borrow when faced with the China trade shock, a decade later.

3 A first look at the data

In Figure 1 we take a first look at the data. The figure plots average changes in manufacturing and real estate employment, wages and house prices against the state's exposure to import competition from China over the period from 1991 to 2007. Our measure of the degree of import competition—Chinese import exposure per worker—directly follows Autor et al. (2013) and we discuss the construction of this measure in more detail in the data section below. Based on our discussion of the history of state-level banking deregulation in the previous section, we classify states into two groups: early liberalizers are states that opened their banking markets for banks from other states before 1985. Conversely, states that opened their banking markets only after 1985 are classified as late liberalizers.

While our empirical analysis below will make use of state-, commuting zone-, and county-level data, the figure gives a preview of our main empirical results at the state level: higher exposure to import competition from China generally leads to larger drops in employment and wages in all states. The unconditional correlation between Chinese import exposure and labor market outcomes is significantly negative — this is the original results of Autor et al. (2013). However, importantly, depending on a state's financial openness the relative importance of price and wage adjustment is reversed. In the financially open states (early liberalizers), the negative link between Chinese import exposure and the manufacturing employment is much starker than for the late liberalizers. This seems to suggest that financial liberalization, if anything, did speed up the decline in manufacturing and seems to rule out the possibility that access to finance increased the resilience of manufacturing industries to Chinese import competition. At the same time, the link between Chinese import exposure and the real estate employment is reversed among the early-liberalizers, whereas it remains strongly negative among the late liberalizers. Turning to wages and prices, we see that average growth rate of wages and house prices is strongly negatively associated with the Chinese import exposure among the late liberalizers, while the relationship between import exposure and the growth rates of wages and house prices is insignificant or even positive for the early liberalizers. The same results also hold for the growth rates of state average income and consumption per capita.

These findings provide the benchmark for a stylized model that we present next. In the model, financially more open states experience a stronger adjustment in employment patterns following the terms-of-trade shock and relatively stable wages in both sectors. This happens because household's ability to borrow stabilizes demand for the non-tradable good—housing in the model—and thus keeps housing prices higher. This in turn keeps wages up in the non-tradable sector, providing a stronger incentive for the sectoral reallocation of labor from the import exposed tradable sector to the non-tradable sector. The bottom right graph of Figure 1 shows that prices of the probably most non-tradable good—housing—indeed remained higher in early-liberalized states and were also less affected by Chinese import competition, which is a key prediction of the theory that we now present.

4 Theoretical Framework

To guide our empirical analysis, in this section we present a simple model with two sectors: a manufacturing (tradable) and a local housing (non-tradable) sector. The model builds on and extends Monacelli (2009) and Ferrero (2015), and in particular emphasizes the role of consumers' demand and their access to finance in facilitating the reallocation of labor between sectors. In the model, the China trade shock amounts to a deterioration in the local economy's terms of trade which will decrease wages and employment in the manufacturing sector. Without access to finance, households will not be able to smooth consumption. This leads to a drop in the household demand for housing and thus lowers local housing prices. Since house prices drop in line with income, there is no reallocation of labor between sector. By contrast, if households can borrow to smooth consumption, household demand for housing is stabilized. This mitigates the negative impact of the terms-of-trade shock on house prices, keeping them relatively high. Higher housing prices speed up the reallocation of labor into the housing sector, which in turn stabilizes wages and output.

4.1 Environment

Our model describes a small open local economy l (region) in a large monetary union (the United States) consisting of many such regions (states or commuting zones). Regions differ in their access to finance due to different state-level deregulation histories. Each local economy consists of two sectors: a manufacturing sector (M) which produces a tradable good and a housing sector (H) which produces a housing stock. Labor is perfectly mobile across sectors within the region but immobile between different regions. Households consume services from the stock of housing and a basket of differentiated home-produced and imported tradable goods. Time is discrete and indexed by $t = 0, 1, 2...\infty$. Unless required for precision, we generally omit the location subscript l.

4.1.1 Firms and production

The total endogenous supply of labor in region l in period t is N_t, which may be employed in the manufacturing or housing sector. Labor is the only input factor used in production of the manufacturing good M ,

$$Y_{M,t} = A_M N_{M,t}^{\alpha}, \tag{2}$$

where A_M is a constant total factor productivity and $\alpha \in (0,1)$ is the output elasticity of labor in the manufacturing sector.

The stock of housing evolves according to

$$H_t = (1-\delta)H_{t-1} + Y_{H,t}, \tag{3}$$

where $\delta \in (0,1)$ is a depreciation rate of the housing stock and $Y_{H,t}$ is the production of new housing (construction and maintenance). The production of new housing depends on the amount of labor employed in the housing sector,

$$Y_{H,t} = A_H N_{H,t}^{\eta}, \tag{4}$$

where A_H is a constant total factor productivity and $\eta \in (0,1)$ is the output elasticity of labor in the housing sector. Since labor is perfectly mobile between both sectors but not across regions, the wages equalize within a region in each time period

$$W_t \equiv W_{M,t} = W_{H,t}. \tag{5}$$

4.1.2 Household preferences and constraints

The demand side of each regional economy is given by a representative household who maximizes expected utility defined over the stochastic sequences of consumption, X_t, and employment, N_t,

$$U_0 = \mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \beta^t \left(\frac{X_t^{1-\sigma}}{1-\sigma} - \frac{N_t^{1+\nu}}{1+\nu} \right) \right\}, \tag{6}$$

where $\mathbb{E}_t$ denotes the expectation operator conditional on the information set available at the beginning of the time period t. β is the intertemporal subjective discount factor, σ and ν are inverses of the intertemporal elasticities of substitution for consumption and labor supply respectively. The consumption bundle X_t is given by a CES-aggregation over the consumption of tradable goods C_t, and housing services which are proportional to the housing stock H_t:

$$X_t = \left[\gamma^{\frac{1}{\theta}} C_t^{\frac{\theta-1}{\theta}} + (1-\gamma)^{\frac{1}{\theta}} H_t^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \tag{7}$$

where $\gamma \in (0,1)$ is the expenditure share going to the tradable goods and θ is the intratemporal elasticity of substitution between tradable goods and housing services.

The consumption bundle of the tradable manufacturing goods, C_t, is composed of the home-produced manufacturing good $C_{M,t}$ and the composite good $C_{I,t}$ which is imported from the other regions or from abroad:

$$C_t = \left[\varphi^{\frac{1}{\vartheta}} C_{M,t}^{\frac{\vartheta-1}{\vartheta}} + (1-\varphi)^{\frac{1}{\vartheta}} C_{I,t}^{\frac{\vartheta-1}{\vartheta}}\right]^{\frac{\vartheta}{\vartheta-1}}, \tag{8}$$

where $\varphi \in (0,1)$ is the expenditure share going to the home-produced manufacturing good and ϑ is the intratemporal elasticity of substitution between home-produced and imported goods. The tradable price index is then given by

$$P_{C,t} = \left[\varphi P_{M,t}^{1-\vartheta} + (1-\varphi) P_{I,t}^{1-\vartheta}\right]^{\frac{1}{1-\vartheta}}, \tag{9}$$

where $P_{M,t}$ is the price index of domestic manufactured goods and $P_{I,t}$ is the price index of imported goods which we normalize to one. Hence, since $P_{M,t}$ defines the region's terms of trade, it is the source of an exogenous shock in our model. Specifically, we will think of a drop in $P_{M,t}$ as the direct consequence of import competition from China.

We will generally assume that households spend the bulk of their tradable expenditures on $C_{I,t}$,so that the share of expenditures φ going to the home-produced manufactured good, $C_{M,t}$, is relatively small. This captures the idea that the fallout from import exposure is locally concentrated: the local economy specializes in production of the manufacturing good $M = M(s)$, but good $M(s)$ accounts only for a small part of the consumption expenditures of households in region s. Hence a negative shock to the terms-of-trade $P_{M(s)}$ has a big negative impact on local incomes but it does not substantially lower households' cost of living.

With these assumptions, we can now write the household's period budget constraint expressed in terms of tradable goods

$$C_t + \frac{P_{H,t}}{P_{C,t}} H_t + \frac{B_{t-1}}{(1+\pi_{C,t})P_{C,t-1}} = \frac{W_t}{P_{C,t}} N_t + \frac{P_{H,t}}{P_{C,t}}(1-\delta)H_{t-1} + \frac{\Pi_t}{P_{C,t}} + \frac{B_t}{(1+i_t)P_{C,t}}, \tag{10}$$

where $\pi_{C,t}$ denotes inflation of the tradable price index, $\Pi_t = \Pi_{M,t} + \Pi_{H,t}$ are profits from ownership of firms in the manufacturing and housing sectors, B_t is the end-of-period t nominal one-period debt, and i_t is the nominal interest rate.

4.1.3 Financial openness

Households in different regions differ in their access to finance. Following Aguiar and Gopinath (2007) and Schmitt-Grohé and Uribe (2003), we capture such differences in reduced form by assuming that the interest rate at which the region can borrow is sensitive to the level of outstanding debt:

$$i_t = i^* + \omega\left[\exp\left(\frac{B_t}{Y_t} - b\right) - 1\right], \tag{11}$$

where i^* is an exogenous U.S.-wide interest rate and B_t/Y_t represents the ratio of debt to GDP and b—its steady-state level. Importantly, we assume regions to differ in the sensitivity parameter

$\omega = \omega(l) > 0$. While we do not attempt to provide a micro-foundation for such differences in ω here, we can more generally think of this parameter as the inverse of the credit supply elasticity of the region's banking system. In fact, as we discuss and illustrate empirically in section 7 below, the lending supply of the banking system in states that liberalized their banking system early is indeed more elastic than in states that liberalized later. Hence, for early (late) liberalizers, the regional interest rate spread over the U.S.-wide rate is quite insensitive (sensitive) to local credit demand B_t, suggesting a low (high) ω.

Equation (11) closes our model of a small open regional economy.

4.1.4 First order and equilibrium conditions

With labor mobility between sectors, profit maximization in each sector implies that

$$W = \alpha A_M P_{M,t} N_{M,t}^{\alpha-1}, \tag{12}$$

$$W = \eta A_H P_{H,t} N_{H,t}^{\eta-1}, \tag{13}$$

Decreasing marginal productivity of labor implies positive profits in both sectors, i.e.

$$\Pi_{M,t} = (1-\alpha) P_{M,t} Y_{M,t}, \tag{14}$$

$$\Pi_{H,t} = (1-\eta) P_{H,t} Y_{H,t}. \tag{15}$$

The equalization of marginal revenue products according to (12) and (13) implies that

$$\frac{P_{H,t}}{P_{M,t}} = \frac{\alpha A_M N_{H,t}^{1-\eta}}{\eta A_H N_{M,t}^{1-\alpha}}. \tag{16}$$

Hence, for a given relative productivity the sector with a higher output price will attract a higher share of labor in the economy. Equation (16) is central for understanding the role of house prices for sectoral reallocation in our model. If households cannot borrow following the China trade shock, i.e. after an exogenous decline in P_M, then demand for housing will collapse as well and house prices will decline in lockstep with P_M, leaving the sectoral allocation unchanged. If households have access to finance however, this will stabilize their demand for housing, keeping house prices up. The increase in the relative price of housing will increase the production of housing, leading to a reallocation of labor away from manufacturing.

The first order conditions implied by the maximization of (6) subject to the consumption bundle (7) and the budget constraint (10) are given by

$$\beta \mathbb{E}_t \left\{ \left(\frac{C_t}{C_{t+1}} \right)^{\frac{1}{\theta}} \left(\frac{X_{t+1}}{X_t} \right)^{\frac{1}{\theta}-\sigma} \right\} = \frac{\mathbb{E}_t \left\{ 1 + \pi_{C,t+1} \right\}}{(1+i_t)}, \tag{17}$$

$$\left(\frac{C_t}{\gamma X_t}\right)^{\frac{1}{\theta}} X_t^{\sigma} N_t^{\nu} = \frac{W_t}{P_{C,t}}, \tag{18}$$

$$\left(\frac{(1-\gamma)C_t}{\gamma H_t}\right)^{\frac{1}{\theta}} = \frac{P_{H,t}}{P_{C,t}}\left(1 - \frac{(1-\delta)\mathbb{E}_t\left\{1+\pi_{H,t+1}\right\}}{(1+i_t)}\right), \tag{19}$$

where $\pi_{H,t+1}$ denotes inflation of the house price index. The first condition is the standard bond Euler equation and the second condition is the familiar labor supply function. The third condition, (19), describes the household's choice between the consumption of the non-durable, tradable (manufacturing) good and the durable, non-tradable good, housing. It equates the relative marginal utility of tradable and housing consumption to the user cost of housing expresed here in terms of tradable consumption .

To understand how household access to finance stabilizes housing prices after a deterioration of the terms-of-trade, consider how a temporary drop in P_M plays out in financially closed and financially open regions. In both regions, the terms-of-trade shock reduces today's income and induces households to borrow in order to smooth consumption. In a financially closed region, this increased borrowing demand will increase the nominal interest rate i_t very strongly (according to equation (11)), forcing the households to accept a large drop in tradable consumption today. Since housing is durable, its stock cannot drop very much in the short run, so that the decline in tradable consumption induces a drop in the ratio C_t/H_t, thus increasing the relative marginal utility of tradable consumption relative to housing. According to equation (19), the user cost of housing has to drop as well, which, given future expected house prices, requires a drop in the relative price $P_H/P_{C,t}$. Consider the financially open region next. Here, the households will easily be able to smooth tradable consumption, since the nominal interest rate does not increase very much. As a consequence, the relative marginal utility of tradable consumption does not increase by much and the required drop in house prices is dampened.[1]

Finally, the demand structure for tradable goods given in equation (8) implies linear income expansion path for both home-produced and imported manufacturing goods. Hence, we can express the home-produced and imported consumption of manufactured goods, C_M and C_I, as a fraction of the tradable consumption bundle, C,

$$C_{M,t} = \varphi\left(\frac{P_{C,t}}{P_{M,t}}\right)^{\vartheta} C_t \tag{20}$$

$$C_{I,t} = (1-\varphi)\left(\frac{P_{C,t}}{P_{I,t}}\right)^{\vartheta} C_t. \tag{21}$$

[1]The difference between the financially open and closed economies would be quantitatively exacerbated in a model with a collateral constraint such as Monacelli (2009). For the financially closed economy, the drop in housing prices would tighten the collateral constraint, limiting the ability to borrow even further. We note, however, that the fundamental mechanisms here is independent of the presence of a collateral constraint.

Definition

A competitive equilibrium in region l is a set of allocations $\{X_t, C_t, C_{M,t}, C_{I,t}, H_t, N_t, N_{M,t}, N_{H,t}, B_t\}$ and a system of prices $\{W_t, P_{H,t}, r_t\}$ such that, given the exogenous prices of home-produced and imported manufacturing goods, $P_{M,t}$ and $P_{I,t}$: i) $\{X_t, C_t, C_{M,t}, C_{I,t}, H_t, N_t, B_t\}$ solve the household's optimality conditions (17), (18), (19), (20), and (21) subject to the budget constraint (10), the consumption bundles (7), (8), and the interest rate (11), ii) $\{N_{M,t}, N_{H,t}\}$ solve the optimality conditions in the manufacturing and housing production, (12) and (13), iii) and the labor market clears, i.e. $N_{M,t} + N_{H,t} = N_t$.

4.2 Empirical predictions of the model

The benchmark parameterization of our model is based on the parameter values used in Monacelli (2009) and Ferrero (2015). The household's discount factor is set $\beta = 0.98$. The coefficient of relative risk aversion σ and the inverse of labor supply elasticity ν are both set equal to one. The intratemporal elasticity of substitution between consumption of tradable goods and housing services θ is set equal to one. The share of tradable goods in the consumption aggregate index is set $\gamma = 0.8$. The elasticity of substitution between home-produced and imported tradable goods ϑ equals 2. The share of home-produced manufacturing good in the tradable consumption basket is set $\varphi = 0.3$. The elasticities of labor in the manufacturing and housing sectors are set $\alpha = 0.35$ and $\eta = 0.65$, respectively. Finally, we choose an annual depreciation rate of the housing stock $\delta = 0.04$.

In our exposition we focus on two polar cases. Region E (which we associate with early liberalizers) is assumed to be financially more integrated ($\omega_E = 0.01$) so that households can borrow at the union-wide interest rate $i_{E,t} \approx i^*$. By contrast, region L (which we associate with late liberalizers) is assumed to be financially less integrated ($\omega_L = 1$), and the local interest rate is sensitive to the level of outstanding debt. Otherwise, regions E and L are identical. Further we assume that households in both regions start with a zero debt, i.e. $B_0 = 0$, such that the monetary union interest rate in steady-state is $i^* = 1/\beta - 1$.

We introduce uncertainty in this economy and assume that the logarithmic price of home-produced tradable good follows a first-order autoregressive process,

$$lnP_{M,t} = \rho lnP_{M,t-1} + \varepsilon_t, \tag{22}$$

where ε_t is an exogenous shock to the current price level in the manufacturing sector (e.g. due to import competition), $\rho \in (0, 1)$ captures the persistence of the shocks, and the initial price level of home-produced manufacturing good, $P_{M,0}$, is normalized to one.

Suppose now that in the first time period the whole monetary union is hit by a persistent import competition shock ($\rho = 0.97$) such that the price of home-produced tradable good, $P_{M,1}$, falls (e.g., $\varepsilon_1 = -0.1$).[2] However, the price of imported tradable goods remains the same, i.e. $P_{I,t} = 1$.[3] Figure 2 shows the impact of this terms-of-trade shock on the key variables in our model in regions E and L: the real wage, the relative price of housing services, employment in the manufacturing and housing sectors, real consumption, and real household debt. Consider first the late deregulation region L. After the terms-of-trade shock, production of the manufacturing goods drops in line with manufacturing wages. Since households essentially cannot borrow, they have to reduce consumption, which also affects demand for the locally produced non-tradable consumption good, housing. The drop in the price of housing has two effects: on the one hand, it lowers wages in the housing sector, limiting the incentive to reallocate labor from manufacturing to housing production. On the other hand, since housing is a stock variable there will also be a negative wealth effect from the drop in the price of housing that exacerbates the drop in consumption.[4]

Now consider the early deregulation region E. Since credit supply in region E is relatively more elastic, households start to borrow in order to smooth their consumption after the terms-of-trade shock, inducing the economy to run a current account deficit. In particular, borrowing also allows households to uphold demand for housing services, stabilizing the price of housing. This makes housing production relatively more attractive than manufacturing, keeping up the marginal revenue product of labor in the housing sector. Since wages have to equalize between two sectors, the optimality condition in production (16) implies that labor starts to be reallocated from the manufacturing to the housing sector.

Hence, the main prediction of our model is that, for a given decline in the price of domestically manufactured goods (terms-of-trade shock), the negative impact on the price of housing and thus on consumption and wages is mitigated in the financially more open economy. Since housing production is relatively more attractive in the financially integrated region, it should also see a stronger reallocation of labor away from the import-exposed manufacturing sector towards housing sector along with the relatively more stable wages. The key mechanism through which financial integration affects real outcomes in our model is its stabilizing impact on consumer demand. This is in contrast with much of the earlier literature that has emphasized how firm-level access to finance helped in cushioning external shocks. In the remainder of the paper we seek to confront the predictions of our model with the data.

[2]For expositional simplicity, we assume here that both regions have the same degree of exposure to this shock. Clearly, our empirical analysis will allow the import exposure to differ along the lines of Autor et al. (2013).

[3]This formulation allows us to properly model a terms-of-trade shock, in which an exogenous shock to the current price level in the domestic tradable sector does not necessarily affect tradable prices in the rest of the world.

[4]Qualitatively, our results would also hold in a model in which the non-traded good is not a stock variable such as housing. The wealth effect does however increase the magnitude of the effects discussed here.

5 Data and Measurements

Our industry-level data comes from the County Business Patterns (CBP) provided by the U.S. Census Bureau. The CBP provides subnational economic statistics on U.S. business establishments at the state and county levels. The data is arranged by the Standard Industrial Classification (SIC) System from 1990 to 1997 and the North American Industry Classification System (NAICS) from 1998 to 2007, which we call sectors hereinafter.[5] We use information on the number of establishments, employment, and annual payroll (which is defined as a sum of wages and salaries paid during one year to all employees) at the 2-digit SIC-level. Furthermore, for each sector we calculate average wage per employee as annual payroll divided by the total number of employees in that sector. We follow Autor et al. (2013) and aggregate our county-level data to the commuting-zone level using the crosswalk files from Autor and Dorn (2013) to map counties to the commuting zones and the commuting zones to the states.

Data on GDP, personal income, consumption expenditures, population, and price indexes come from the Regional Economic Accounts provided by the U.S. Bureau of Economic Analysis (BEA). We use Consumer Price Index (CPI) to deflate personal income, consumption expenditures, annual payroll and average wages with a base year of 2009. Finally, data on house price indexes at the state- and county-level are taken from the Federal Housing Finance Agency (FHFA).[6]

Our indicator of the terms-of-trade shock to local economies is the measure of Chinese import exposure constructed by Autor et al. (2013). For each industry, Chinese imports to the U.S. are apportioned to each local economy according to its share of national employment in that industry. Since our analysis makes use of an annual panel data, we extend the import exposure measure by Autor et al. (2013) to the annual frequency, using annual trade flow data for 2-digit SIC industries for the U.S. from 1991 to 2007.[7] Furthermore, similar to this study, we use information on local industry employment structure (both at the state and commuting-zone levels) for the same time period from the CBP data. Then, Chinese import exposure per worker (ΔIE_t^l) in location (state or commuting-zone) l in year t is the employment-weighted average of year-to-year changes in U.S. imports from China relative to total U.S. employment in industry i ($\frac{\Delta IM_{ucit}}{L_{uit-1}}$) across all industries in location l:

$$\Delta\text{IE}_{ut}^l = \sum_i \frac{L_{it-1}^l}{L_{t-1}^l} \cdot \frac{\Delta IM_{ucit}}{L_{uit-1}}. \tag{23}$$

Since aggregate U.S. imports from China in industry i could be correlated with U.S. demand, we follow Autor et al. (2013) and identify the supply-driven component of Chinese import expo-

[5] The SIC is a United States government system for classifying industries, which was replaced by the NAICS starting in 1998. We applied the concordances between the both systems published by the U.S. Census Bureau to make the data consistent. For further information about the SIC and the NAICS see: https://www.census.gov/eos/www/naics/.

[6] https://www.fhfa.gov/DataTools/Downloads

[7] The trade flow data at the 4-digit SIC industry level is taken from the online Data Appendix of Autor et al. (2013).

sure from

$$\Delta \text{IE}^l_{ot} = \sum_i \frac{L^l_{it-1}}{L_{it-1}} \cdot \frac{\Delta IM_{ocit}}{L_{uit-1}}, \tag{24}$$

where ΔIM_{ocjt} is a change in Chinese exports to eight other high-income countries.[8] Unless otherwise noted, equation (24) is the main measure of Chinese import exposure that we use in the empirical analysis in this paper.

As discussed in section 2, our empirical analysis exploits the fact that the U.S. experienced a period of significant deregulation of the banking industry since the 1970s until the early 1990s (Kroszner and Strahan, 1999). Since states deregulated in different years, there was a considerable heterogeneity at the state level in the degree of financial liberalization when the local economy was hit by the China trade shock in the beginning of the 1990s. We compute our deregulation index (1) based on information provided in Table 1 by Kroszner and Strahan (1999). It equals the number of years that have passed until 1995 since a state adopted either intrastate branching and interstate banking deregulation laws.[9] Hence, more financially integrated states are associated with a larger financial deregulation index, since these states began deregulating their banking sector further in the past.[10]

Table 1 reports summary statistics of the key state-level variables used in our analysis. It also splits the whole sample into two groups of states that deregulated their banking sector before and after 1985. For each variable and groups of states we calculate the population weighted cross-state mean, the standard deviation, the minimum and the maximum value. Note that early and late deregulation states are similar in terms of the average total employment growth over the 1991-2007 period. However, early deregulation states experienced a stronger decline in the manufacturing employment, and at the same time, a faster growth in the real estate employment, average wage, consumption, mortgage loans, and house prices compared to the late deregulation states, which is consistent with the predictions of our theoretical model. Note also that early and late deregulation states are very similar in terms of their Chinese import exposure.

6 Empirical Framework and identification

We conduct our analysis at two levels of aggregation. First, at the state-level, which gives us an annual panel of 48 U.S. states (excluding Alaska and Hawaii) for the period from 1991 to 2007. Secondly, we follow Autor et al. (2013) and conduct our analysis also at the commuting zone level. This has the advantage of considerable finer geographical granularity since there are 722 commuting zones.

[8] These countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland

[9] With the exception of Iowa, all states had deregulated both interstate banking and intrastate branching laws by 1995. Iowa liberalized intrastate branching only in 1997.

[10] Our measurement of state financial openness is consistent with the deregulation measures used in Hoffmann and Stewen (2020) and Mian et al. (2020). In fact, our main results are robust to using these alternative measures of financial openness.

At each level of aggregation, we estimate panel equations of the following general form:

$$\Delta Y_t^l = \beta_1 \Delta\text{IE}_t^l + \beta_2 \Delta\text{IE}_t^l \times \text{DI}^{s(l)} + \beta_3 \boldsymbol{X}_t^l + \alpha^l + \tau_t + \epsilon_t^l, \tag{25}$$

where l indexes the state or commuting zone. The dependent variable ΔY_t^l stands for a range of local outcomes, including labor market variables (wages and employment in the tradable and non-tradable sectors), non-tradable prices (in particular housing prices), but also other local outcomes such as income, consumption and unemployment. ΔIE_t^l is our location-specific measure of a change in Chinese import exposure per worker, and $\text{DI}^{s(l)}$ is our measure of state financial openness, i.e. the number of years elapsed until 1995 that state s, in which commuting zone l is located, has been open.[11] The vector $\boldsymbol{X}_t^l$ contains a rich set of controls that vary by location and year, such as population growth and the share government expenditures in total GDP. It also includes various interactions of ΔIE_t^l with the pre-sample location characteristics and interactions between $\text{DI}^{s(l)}$ and aggregate macro variables that we discuss below. Finally, α^l and τ_t represent location and year fixed effects respectively. Note that, since $\text{DI}^{s(l)}$ varies by location only, its first order effect in regression (25) is absorbed by the location fixed-effect. All our regressions are weighted using a state's or commuting zone's share of national population in 1990 and we report robust standards errors clustered by state throughout.

Regression (25) is a differences-in-differences (DiD) specification. This specification will correctly identify the 'causal' effect of how financial openness modulates the China trade shock, *i)*, if ΔIE_t^l does not affect outcomes through other state characteristics that are correlated with DI and, *ii)*, if ΔIE_t^l is uncorrelated with local demand for imports or with aggregate shocks that could themselves be modulated through financial openness.

To address the first concern, our vector of control variables includes a range of interactions of ΔIE_t^l with other pre-sample state-level characteristics that could correlate cross-sectionally with $\text{DI}^{s(l)}$, such as the growth rates of tradable and non-tradable GDP, employment, wages, and the house price growth in the decade before 1991. Specifically, a broad literature has documented the impact of banking deregulation in the 1980's on economic growth and the correlation of business cycles (Morgan, Rime and Strahan, 2004), trade (Michalski and Ors, 2012), the relative size of tradable and non-tradable sectors, and the growth rate of consumer credit (Mian et al., 2020) as well as firm creation. We summarize these pre-sample state-level characteristics in the vector $\textbf{PRE}^s$.

To address the second challenge, we include interactions of $\text{DI}^{s(l)}$ with a range of aggregate variables, such as the stance of monetary policy, U.S. capital inflows, measures of credit availability and demand for housing from Hoffmann and Stewen (2020), which is discussed in more detail in the appendix. We collect these aggregate common factors in the vector $\mathbf{F}_t$. Including the interactions $\text{DI}^{s(l)} \times \mathbf{F}_t$ controls for a possible correlation of $\Delta\text{IE}_t^l \times \text{DI}^{s(l)}$ with aggregate, U.S.-wide shocks that occurred during our sample period.

[11] Clearly, when the regression is run at the state-level, $s(l) = l$ for state l.

6.1 State-level results

This subsection presents results for regression ((25)) estimated at the state level. All regressions presented here are based on annual data for 48 states (excluding Alaska and Hawaii) and are estimated by OLS, using ΔIE^s_{ot} as our measure of import exposure. All regressions feature state- and year-fixed effects.

A key prediction of our model is that household access to finance stabilizes consumption and keeps house prices up. This in turn leads to higher wages and income, and finally a reallocation towards the housing sector. Tables 2 to 7 show that this mechanism is borne out in state-level data. In all tables, column (1) shows the results for the set of baseline controls. Columns (2) and (3) respectively, add the controls for the interactions of ΔIE with the set of state-level pre-sample characteristics, $\textbf{PRE}^s$, and the interaction between DI and a range of aggregate factors, $\mathbf{F}_t$. As discussed in the beginning of the section, the first set of controls captures the effect of the China shock on the local economy through other vectors of transmission, while $\text{DI}^{s(l)} \times \mathbf{F}_t$ allows for an impact of the aggregate economy to vary depending on the state's financial openness. Finally, column (4) considers all controls together.

Table 2 starts with the results for house prices. As expected, house prices are adversely affected by the China trade shock, i.e. the coefficient on the stand-alone term ΔIE is negative and statistically significant throughout. However, the adverse impact of the shock is substantially mitigated in financially more integrated states. The coefficient on the interaction $\Delta\text{IE}^l_t \times \text{DI}^{s(l)}$ is significantly positive and stable across specifications. This dampening effect is economically sizeable: The coefficient estimate of around 0.06 implies that for a state with an average level of import exposure (around 0.02,see Table 1) annual house price growth was 0.12 percent higher for each year that the state liberalized earlier. From Table 1, the difference in the number of years since liberalization between the early and late deregulation groups is around 13 years. This implies that the average early-deregulation state would have experienced an annual growth rate in house prices that was 1.56 percent higher than a state that liberalized late. Over the 16 years of our sample period (1991-2007), this amounts to an almost 25 percent difference in the level of house prices.[12]

Table3 presents the results for state-level consumption growth. Again, all four specifications suggest that financial liberalization considerably dampens the impact of the China trade shock. The coefficient on the stand-alone term ΔIE of around -0.3 would imply that a state with average levels of import exposure would experience a drop in annual consumption growth by around 0.6 percentage points. The coefficient on the interaction term $\Delta\text{IE} \times \text{DI}$ of around 0.01 suggests that for such a state, liberalizing 10 years earlier would have increased annual consumption growth by more than 0.2 percentage points, thus reducing the original impact of the China trade shock on consumption growth by around a third.

[12]It is instructive to compare these numbers with the effects that the China trade shock may have had on house prices without banking liberalization: the stand-alone coefficient on ΔIE is around -2.5, which suggests that at average levels of import exposure a state would have seen a lower house price growth by up to five percent per year if the state had not liberalized at all by 1995.

Table 4 turns to the results for wage growth. Again our estimated coefficient of interest is significant and stable across specifications. With an average level of $0.15 - 0.18$ it implies that liberalizing ten years earlier would have increased annual wage growth by between 0.3 and 0.4 percentage points per year for a state with average levels of import exposure. This compares with a drop of annual wage growth by around half a percentage point that would have experienced by this state (based on the stand-alone coefficient on ΔIE of around -0.25) had it not liberalized. Again, this suggests that financial liberalization considerably softened the blow of the China trade shock on local economies.

In Table 5, we also estimate the model (25) with the growth rate of state personal income per capita obtained from the NIPA tables. Personal income is a broader definition of income than wages since it also includes incomes of local business owners and therefore allows us to capture the wider impact of the China trade shock on the local economy. Also, the CBP employment data contain both full-time and part-time employees, which could affect the precision with which average wages are measured. Again, all specifications suggest that financial openness considerably mitigated the impact of the China trade shock on local economies. The stand-alone coefficient on ΔIE of around -0.5 would imply that a state with average import exposure would have seen one percentage point lower annual income growth over our sample period. However, the range of estimates of our coefficient on the interaction DI $\times$ ΔIE implies that that liberalizing ten years earlier would have dampened this decline by between 0.4 and 0.6 percentage points.

Table 6 explores the implications for state-level employment growth. Panel A shows the results for total employment, panels B and C for manufacturing and real estate employment respectively. The estimated coefficients for total employment growth on the stand-alone ΔIE-term are in line with the findings in Autor et al. (2013) suggesting a significant negative impact of the Chinese import exposure not only on the number of employees in the manufacturing sector, but across all sectors. The point estimates on the interaction term ΔIE $\times$ DI are positive but generally not significant. Early liberalization did not generally increase total employment growth.

Instead it affected the sectoral composition of the economy. Turning to manufacturing employment (Panel B), we continue to find small and insignificant coefficients on ΔIE $\times$ DI, while the stand-alone coefficients on ΔIE are all significantly negative. For employment growth in the real estate sector (Panel C), however, financial openness significantly mitigates the fallout from the China trade shock, with the interaction term positive and significant throughout. This suggests that financial openness favored the reallocation of labor towards the housing sector following the China trade shock.

We conclude this subsection by estimating the effect of Chinese import competition on state-level unemployment rates (Table 7).[13] While our model does not feature an explicit labor market friction, we can think of lower unemployment as an indirect indicator that local labor markets are able to reallocate workers to other sectors of the economy. Indeed our results suggest that financial openness dampened the adverse effect of the China shock on state-level unemployment.

[13]The data on unemployment rate at the state level are from the Bureau of Labor Statistics.

At average levels of import exposure, a state would have experienced an increase in the unemployment rate by around $0.25 - 0.5$ percentage points. According to our estimates, liberalizing ten years earlier would have dampened this increase in unemployment by around 0.15 percentage points.

6.2 Results at commuting-zone level

Tables 8 through 11 provide robustness analysis of our findings at the commuting zone (CZ) level. Our sample includes 722 CZs which covers the entire mainland of the United States (both metropolitan and rural areas). Using CZs' local labor markets as sub-economies in our analysis has several advantages. First, it provides a larger sample. Second, CZs are logical geographic units for defining local labor markets and they differ in their exposure to import competition as a result of regional variation in industry specialization (Autor et al., 2013). Thus, moving to the CZ-level also allows us to use a much more geographically granular version of the import exposure measure in our estimations.[14]

Table 8 provides estimation results for the growth rate of housing prices in the CZs, which are calculated as population weighted averages of house price indexes in the related counties. The results are very similar to the estimated coefficients reported in Table 2 at the state level.

Tables 9 and 10 show CZ-level results for the growth rates of average wage and personal income respectively. It is evident that the average wage and personal income have been significantly less affected by Chinese import competition in the CZs associated with the early deregulation states, again in line with the predictions of the model and with our previous state-level results.

Table 11 reports estimation results for total employment (Panel A) and employment in the manufacturing and real estate sectors (Panels B and C respectively). The results confirm that the Chinese imports exposure has caused a significantly negative effect on total employment growth also at the CZ-level. This negative effect has been mitigated primarily through higher employment growth in the real estate sector in those CZs, where banking markets were more integrated, i.e. the estimated coefficient on the interaction term $\text{DI} \times \Delta\text{IE}$ in Panel C is positive. The results in Table (11) are generally somewhat less conclusively significant than the corresponding results for employment at the state-level. However, we note that all of the specifications in the table contain CZ-fixed and time effects in addition to the highly demanding set of controls from the state-level data, while the treatment (banking deregulation) necessarily remains at the state-level. Nonetheless, the estimated coefficients are almost identical to the ones obtained from the state-level regressions and remain remarkably stable across specifications.

The commuter-zone level results clearly corroborate our earlier state-level findings: the China trade shock has caused a significantly negative impact on local labor markets and non-tradable prices; however, financially more integrated regions were able to withstand the "China Syndrome"

[14] See section 5 above for details. Unfortunately, we cannot explore the impact of the China trade shock and deregulation on consumption at the CZ level, since time series on consumption are not available at the county-level.

better. Household access to finance stabilized local private demand and in particular housing prices, which in turn facilitated the reallocation of labor away from manufacturing towards the housing sector.

6.3 Dynamic responses

In this section, we address the question of how persistent the trade shock effects are and we look at the dynamic responses of local outcomes after the China trade shock. For this purpose, we apply a local linear projection method first suggested by Jordà (2005). The cumulative growth in a local outcome ΔY^l from year t to year $t+h$ is regressed on Chinese import exposure in year t:

$$\Delta Y^l_{t,t+h} = \beta_h \Delta \text{IE}^l_t + \alpha^l + \tau_t + \epsilon^l_{t+h}, \tag{26}$$

where α^l and τ_t represent location and year fixed effects respectively. Then we collect the estimated coefficients of β_h for different forecasting horizons h and plot them for two samples of early and late deregulation states.

Figure 3 shows the estimation results for our state-level data. It is evident that the Chinese import exposure has a significant and persistent negative effect on the growth rate of the manufacturing employment in both samples of early and late deregulation states. The growth rate of real estate employment tends to increase in early deregulation states and to decrease in late deregulation states during the first years after the China trade shock. However, the effect on the growth rate of the real estate employment is not persistent, i.e. the coefficients become statistically insignificant three years after the shock. Furthermore, the China trade shock has a significant and persistently negative impact on the growth rates of average wage, personal income, consumption, and house prices in the sample of late deregulation states, but not in the sample of early deregulation states. These findings are consistent with the predictions of our theoretical model: financially more integrated states should see a swifter reallocation of labor from the import exposed manufacturing sector into the non-tradable sector, and smaller declines in wages, consumption, and non-tradable prices following the terms-of-trade shock.

7 Evidence from bank-county level data

Our empirical results so far lend support to the mechanism highlighted in the theoretical model: banking systems in financially more open states could accommodate the increased borrowing demand of households. This stabilized local demand, kept non-tradable (and in particular: housing) prices high and faciliated the reallocation of workers to the non-tradable sector. However, so far we have not shown that households actually started to borrow more following the China trade shock—as our interpretation of the shock as a credit demand shock would require. Also, our stylized model does not spell out *why* banks in states that liberalized earlier should have a more elastic response to households' increased credit demand. We address these two points in this section. First, we show that higher import exposure did indeed lead to higher credit demand and, secondly, that geographically diversified banks were more elastic in their lending supply response to these local credit demand shocks. Since early-liberalized states had a stronger presence of geographically diversified banks, these findings help understand our state-level results. We illustrate these points using highly disaggregated bank-county level data on mortgage refinancing from the home mortgage disclosure act (HMDA) data base. Using these granular data will also allow us to overcome potential remaining challenges to identification that we cannot directly address at the state or commuting zone levels.

The HMDA data base collects all mortgage applications by private households in the United States handled by financial institutions that exceed a low, annually adjusted threshold in mortgage assets. It contains detailed information about the geographical location of the property, whether the application was successful (i.e. the mortgage loan was granted) and the loan size. Importantly, the HMDA records also provide information about the purpose of the mortgage loans, i.e. whether it was granted for the purchases of a new property or whether the mortgage constitutes a refinancing or mortgage equity withdrawal by the household. In our analysis, we focus on refinancing demand and mortgage equity withdrawals because these are the types of mortgage lending that actually allow households to smooth consumption in the face of adverse shocks to earnings. By contrast, borrowing for the purchase of a new home is usually not driven by consumption smoothing motives.

The HMDA also provides information about the financial institution that processed the loan, such as its regulatory ID number, the institution type (commercial bank, credit or savings union, mortgage company), total assets as well as the institution's home state. This allows us to identify whether a bank is locally headquartered or from another state. Furthermore, the data also allow us to measure the geographical diversification of an institution's mortgage portfolio. We aggregate the HMDA data to obtain the annual growth rates of mortgage lending by institution and county for the period 1995-2007. Our analysis includes all counties in one of the 722 commuting zones defined by Autor et al. (2013).

Our interest is in identifying how banks react to the location- (i.e. county-) specific component of credit demand of which we conjecture that it is a function of the local economy's exposure to Chinese import competition. We therefore need to disentangle the supply component of bank lending from the local credit demand component. To this end, following Amiti and Weinstein (2018); Hoffmann and Stewen (2020) we consider the following decomposition of the growth rate of mortgage lending by institution ("bank") b in county c:[15]

$$\frac{L_t^{b,c} - L_{t-1}^{b,c}}{L_{t-1}^{b,c}} = \beta_t^b + \gamma_t^c + \nu_t^{b,c} \tag{27}$$

[15] At a later stage of our analysis, we will distinguish further between banks that were affected by banking deregulation in a state and other financial institutions (such as mortgage companies) that were not. Whenever this distinction does not matter, however, we refer to all financial institutions as "banks" for brevity.

Here, β_t^b is a bank-time-specific effect and γ_t^c is a county-time effect and $\nu_t^{b,c}$ a residual that we assume is i.i.d across institutions and counties as well as over time. The county-time effect γ_t^c is free of bank-specific supply factors and we can therefore think of it as the demand component of mortgage lending in county c that is common to all banks that are active in the county. Conversely, since β_t^b varies only by bank, it reflects the bank-specific supply component that affects all counties in which bank b is active.

To obtain economically meaningful bank-specific supply and local-specific demand factors, we build on Hoffmann and Stewen (2020) who adapt the method proposed by Amiti and Weinstein (2018) for matched bank-firm data to our setting here. The method proposed by Amiti and Weinstein (2018) offers two key advantages that are relevant in our context here.

First, the method yields estimates of β_t^b and γ_t^c that are consistent with aggregation. It therefore explicitly takes account of the granular structure of the banking sector which is characterized by a few relatively large banks dominating many local markets.[16]

To illustrate how the restrictions imposed by aggregation help identify β_t^b and γ_t^c , we follow the exposition in Hoffmann and Stewen (2020). Assume there are B banks and C counties and let

$$\boldsymbol{\omega}_{t-1}^c = \left[\omega_{t-1}^{1,c}, ..., \omega_{t-1,}^{b,c}, ..., \omega_{t-1}^{B,c}\right]'$$

denote the vector of market shares of all banks in county c at time $t-1$ and

$$\boldsymbol{\phi}_{t-1}^b = \left[\phi_{t-1}^{b,1}, ...\phi_{t-1,}^{b,c}..., \phi_{t-1}^{b,C}\right]'$$

the vector of shares of each county in bank b's country-wide mortgage portfolio. Stack the bank-time and county-time effects into the vectors $\boldsymbol{\beta}_t$ and $\boldsymbol{\gamma}_t$ respectively and let $\boldsymbol{\Lambda}_t$ be the $B \times C$ matrix of bank-county-level growth rates with $\boldsymbol{\Lambda}_t^{b:}$ its b-th row and $\boldsymbol{\Lambda}_t^{:c}$ its c-th column. Then, the growth rate of bank b's mortgage lending can be written as

$$\frac{L_t^b - L_{t-1}^b}{L_{t-1}^b} = \boldsymbol{\Lambda}_t^{b:}\boldsymbol{\phi}_{t-1}^b = \beta_t^b + \boldsymbol{\phi}_{t-1}^{b\prime}\boldsymbol{\gamma}_t \tag{28}$$

and the growth rate of lending for each county c is

$$\frac{L_t^c - L_{t-1}^c}{L_{t-1}^c} = \boldsymbol{\omega}_{t-1}^{c\prime}\boldsymbol{\Lambda}_t^{:c} = \gamma_t^c + \boldsymbol{\omega}_{t-1}^{c\prime}\boldsymbol{\beta}_t \tag{29}$$

where we have used that the elements of $\boldsymbol{\phi}_{t-1}^b$ and $\boldsymbol{\omega}_{t-1}^c$ sum to one and where the i.i.d.-ness of $\nu_t^{b,c}$ ensures that $\sum_{b=1}^B \omega^{b,c}\nu_t^{b,c}$ and $\sum_{c=1}^C \phi^{b,c}\nu_t^{b,c}$ go to zero for sufficiently large B and C. Amiti and Weinstein (2018) show that the two sets of moment conditions (28) and (29) uniquely identify (up to normalization) the vectors $\boldsymbol{\beta}_t$ and $\boldsymbol{\gamma}_t$. Hence, there is only one solution to the decomposition

[16] Bremus et al. (2018) and show that shocks to big banks have a disproportionate effect on macroeconomic outcomes at the international level.

(27) that satisfies the condition that the (market or portfolio share) weighted sums of bank and county effects sum to county- and bank-wide aggregates respectively.

The second advantage of the method by Amiti and Weinstein (2018) is that it allows to deal with the creation of new lending relationships between banks and counties.[17] This is important in our setting, because both intra-state branching as well as interstate deregulation during the 1980s and early 1990s led to the entry of many new banks into local (county-level) banking markets and this process continued well after the *de iure* liberalization of state-level markets had been completed. To obtain credible estimates of the supply and demand components of local credit, it is therefore important to explicitly allow for the adjustment in banks' lending supply along the extensive margin.

7.1 Estimating banks' responses to county-level credit demand

Based on the decomposition (27), we can write the demand component of a bank's lending in a county as

$$\mathrm{LR}_t^{b,c} = \frac{L_t^{b,c} - L_{t-1}^{b,c}}{L_{t-1}^{b,c}} - \beta_t^b = \gamma_t^c + \nu_t^{b,c}$$

We can think of $\mathrm{LR}_t^{b,c}$ as the endogenous response of the bank's lending to local credit demand, *given* the bank's lending supply curve. Our conjecture is that more geographically diversified banks have more elastic lending supply so that they respond more strongly to variations in local credit demand. The reason for this conjecture is that geographically more diversified banks have a higher risk-taking capacity which makes them more willing to satisfy local credit demand.[18] Figure 4 illustrates this effect: the two banks are faced with the same credit demand shock, but since the integrated bank has a more elastic supply curve, its lending supply responds more strongly to the increase in demand.

Based on these considerations, we therefore estimate the following specification at the bank-county level:

$$\mathrm{LR}_t^{b,c} = \alpha \times \Delta\mathrm{IE}_t^{\mathcal{CZ}(c)} + \delta \times \Delta\mathrm{IE}_t^{\mathcal{CZ}(c)} \times \mathrm{DIV}_{t-1}^b + \mathrm{CONTROLS} \tag{30}$$

where $\Delta\mathrm{IE}_t^{\mathcal{CZ}(c)}$ is import exposure affecting the commuting zone to which county c belongs and here acts as the stand-in for the local credit demand shock and DIV_t^b captures the geographical diversification of the bank. The vector CONTROLS includes a range of bank-, county- and state-

[17] Amiti and Weinstein show that the weighted-least squares estimate of the decomposition (27) with weights $L_{t-1}^{b,c}$ satisfies the moment conditions (28) and (29) if and only if there is no new lending along the extensive margin, i.e. if banks only lend to counties to which they already had a lending relationship. In the general case when there is new lending along the extensive margin, the moment conditions have to be solved explicitly for β_t and γ_t, which requires the solution of a $(B + C - 2)$-dimensional system of linear equations for each period t. This is the approach we follow in our analysis here.

[18] In a simple model in which banks face a value at risk constraint (see e.g. Shin (2012) and Hoffmann and Stewen (2020), The maximum leverage the bank can take in this model will be inversely related to the risk of its portfolio—and thus positively related to its geographic diversification). In this setting it can easily be shown that banks with lower notional portfolio risk will increase lending more in response to a positive credit demand shock.

year fixed effects as well as the standalone term of DIV_t^b. Our conjecture is that the estimates of both α and δ are positive. A positive value of α would imply that higher import exposure would lead to higher loan demand, vindicating our claim that the China trade shock was indeed a loan demand shock. Furthermore, a positive value of δ would imply that geographically more diversified banks actually were more elastic in their credit supply, satisfying demand to a larger extent than local banks. Finally, twe include the standalone term for DIV_{t-1}^b in the set of controls.

To measure the geographical diversification of a bank's portfolio, we construct

$$\text{DIV}_{t-1}^b = \frac{1}{\sqrt{\sum_{l \in \mathcal{L}(b)} \left(\phi_{t-1}^{b,l}\right)^2}} \tag{31}$$

where $\mathcal{L}(b)$ is the set of locations in which bank b is active and where the $\phi_{t-1}^{b,l}$ reflects the share of location l in the bank's mortgage portfolio from the previous section. Hence DIV_t^b corresponds to the inverse square root of the Herfindahl index of the bank's credit portfolio. If the bank's returns are independently and identically distributed across locations l, the denominator of DIV_t^b is directly proportional to the standard deviation of the bank's portfolio return.[19] The empirical question we face is at which level of aggregation this assumption about the independence of location-specific shocks is actually satisfied. Our data is sufficiently granular to allow us to compute DIV_t^b at the county-level. However, as discussed in Hoffmann and Stewen (2020), this could be misleading if the shocks affecting individual counties are correlated within a commuting zone or even within the state. For robustness, we therefore report results for the bank-county-level regression using versions of DIV_t^b computed at the county, commuting zone, and state levels.

Table 12 shows the results for the bank-county level regression (30) for the "treatment group" of financial institutions that were affected by the deregulation of the 1980s and 1990s, i.e. commercial banks. Columns (1) shows the regression with import exposure alone. Columns (2)-(4) for the specifications with the interaction between import exposures and DIV_{t-1}^b computed at the county, commuting zone and state levels. Column (5) shows the results of a specification where a bank's geographic diversification is calculated based on the the history of deregulation of its home state and the states in which is active. We discuss the construction of this diversification measure in detail in the next subsection. All regressions control for bank-county fixed effects as well as for state-year effects. Standard errors are clustered at the state-level.

In all regressions the coefficient α is positive and significant. This supports the view that higher import exposure is indeed associated with a higher demand for refinancing or mortgage equity withdrawal: exposure to Chinese import competition acts like a positive credit demand shock. Turning to the coefficient δ on the interaction term between import exposure and bank-level diversification, we again find significantly positive coefficients throughout. Hence, geographically more diversified banks are indeed more elastic in their response to local credit demand,

[19] Note that the functional form of DIV_t^b (as a ratio) would be naturally arise as the marginal risk taking capacity of a bank in a model in which the bank faces a value at risk constraint (see Hoffmann and Stewen (2020)).

consistent with our hypothesis.

In Table 13, we report the same regressions, but now on a placebo sample of mortgage companies that were not affected by the state-level banking deregulation of the 1980s. The business model of mortgage companies is to originate and distribute mortgage loans. Hence, these institutions do not generally hold originated loans on their books for extended periods which would suggest that their lending supply should not be affected by their geographic diversification. This is exactly what we find the data: in the placebo the estimate of the coefficient δ on the interaction term $\Delta\text{IE}_t^{\mathcal{CZ}(c)} \times \text{DIV}_t^b$ is much closer to zero than for the treatment group and generally insignificant. Hence, financial institutions in the placebo sample do not generally differ in the elasticity of their lending supply. Consistent with our interpretation of import competition as a loan demand shock, however, we continue to find the coefficient α on the standalone term $\Delta\text{IE}_t^{\mathcal{CZ}(c)}$ to be positive and significant.

7.2 Aggregate implications

We have shown that import competition from China constituted a positive credit demand shock and geographically diversified banks were more elastic in their response to this shock. In this subsection we illustrate that easier credit provision in response to the shock stabilized local economies by attenuating the fall in house prices and that it was banking deregulation that made credit provision more elastic in the first place. To this end, we estimate the regression

$$\Delta hpi_t^c = a \times \text{LR}_t^c + b \times \Delta\text{IE}_t^{\mathcal{CZ}(c)} + \text{CONTROLS} \tag{32}$$

where Δhpi_t^c is the county-level growth rate of house prices. The first term on the right hand side, $\text{LR}_t^c = \sum_b \omega_{t-1}^{b,c} \text{LR}_t^{b,c}$, is the county-level lending response, aggregated over all banks in county c and we expect the associated coefficient to be positive. The second term captures the presumably negative impact of the China trade shock on local outcomes through all other channels. Even though LR_t^c is free of bank-level lending supply shocks it is still likely to be correlated with a range of local housing demand shocks. To isolate the component of the lending response that is explained by the China trade shock, we build on our bank-county level results in the previous subsection. Following the approach of Gabaix and Koijen (2020) we construct an optimal granular instrumental variable as the difference between a market share weighted and a precision weighted average of idiosyncratic shocks to bank's lending response as follows:

$$\mathcal{GLR}_t^c = \sum_{b \in \mathcal{T}_{t-1}(c)} \Gamma_{t-1}^{b,c} \times \widetilde{\text{LR}}_t^{b,c}, \tag{33}$$

where $\mathcal{T}_{t-1}(c)$ is the set of (treated) banks—those affected by deregulation—active in county c at the end of period $t-1$, $\Gamma_{t-1}^{b,c}$ denotes a set of "granular"weights with $\sum_{b\in\mathcal{T}(c)} \Gamma_{t-1}^{b,c} = 0$ to be discussed shortly and $\widetilde{\text{LR}}_t^{b,c}$ denotes the bank-specific (idiosyncratic) component of the lending response to the China trade shock. We refer to $\mathcal{GLR}_t^c$ as the granular lending response.

As we have shown in the previous subsection, banks differ in their lending responses because more diversified banks have more elastic lending supply, so that we can write the idiosyncratic part of a bank's lending response to the China trade shock as

$$\widetilde{\text{LR}}_t^{b,c} = \Delta\text{IE}_t^{\mathcal{CZ}(c)} \times \text{DIV}_{t-1}^b \tag{34}$$

so that

$$\mathcal{GLR}_t^c = \underbrace{\left(\sum_{b \in \mathcal{T}_{t-1}(c)} \Gamma_{t-1}^{b,c} \times \text{DIV}_{t-1}^b \right)}_{\mathcal{G}_{t-1}^c} \times \Delta\text{IE}_t^{\mathcal{CZ}(c)}, \tag{35}$$

The granularity term in parentheses, $\mathcal{G}_{t-1}^c$, modulates the response of aggregate county-level lending to the import exposure shock. The question is how to choose the granular weights $\Gamma_{t-1}^{b,c}$. Gabaix and Koijen (2020) show that the optimal granular instrument—in the sense that it leads to an efficient IV estimator—is given by the difference between a market share weighted and a precision weighted average of idiosyncratic shocks. In our setting, this implies for the granular weights that

$$\Gamma_{t-1}^{b,c} = \left(\omega_{t-1}^{b,c} - \pi_{t-1}^{b,c} \right) \tag{36}$$

where the weights $\omega_{t-1}^{b,c}$ reflect a bank's market share of in the county whereas $\pi_{t-1}^{b,c}$ is a a set of precision weights that correct for bank-specific differences in the variability of lending. Following Gabaix and Koijen (2020) we construct the precision weights as

$$\pi_{t-1}^{b,c} = \frac{1/var\left(\widetilde{\text{LR}}_t^b\right)}{\sum_{b \in \mathcal{T}(c)} 1/var\left(\widetilde{\text{LR}}_t^b\right)} = \frac{1/\left(\text{DIV}_{t-1}^b\right)^2}{\sum_{b \in \mathcal{T}(c)} 1/\left(\text{DIV}_{t-1}^b\right)^2} \tag{37}$$

where the second equality follows directly from (34). The precision weights assign a low weight to banks with very volatile lending responses. In the stylized model of Figure 4, all banks face the same local demand shocks, so differences in the volatility of $\widetilde{\text{LR}}^b$ are just a function of differences in the elasticity of lending supply curves which are parametrized by DIV_{t-1}^b. Then, choosing the weights $\Gamma_{t-1}^{b,c}$ according to (36) above gives particular importance to the idiosyncratic lending response of banks that have a high share in the local market and that are, at the same time, also highly geographically diversified.

This raises the issue of how to measure the components of $\Gamma_{t-1}^{b,c}$, i.e. banks' market share $\omega_{t-1}^{b,c}$ and their geographical diversification. A limitation of using de facto market shares is that their cross-county variation could itself be the outcome of differences in the structure of local credit demand. For example, if geographically diversified banks systematically are more accommodative of growing local credit demand, then over time they might have a systematically higher market share than local banks. This in turn would also affect the geographical diversification of banks active in these counties and thus also the precision weights $\pi_t^{b,c}$.

To deal with this potential endogeneity, we build on and extend a procedure suggested by Hoffmann and Stewen (2020) and construct *de iure* measure of $\omega_{t-1}^{b,c}$ and DIV_t^b based on the regulatory history of the bank's home state and of the states in which it is active. The measure makes explicit use of the fact that the liberalization of a state's banking market in most cases amounted to a liberalization on a reciprocal basis. Specifically, we adapt the market share measure of Hoffmann and Stewen (2020) to our setting here as follows:[20]

$$\omega_{t-1}^{b,c} = \frac{min\left\{\text{INTER}^{s(c)}, \text{INTER}^{s(b)}\right\} \times \mathbf{1}_{\{s(c)\neq s(b)\}} + \mathbf{1}_{\{s(c)=s(b)\}} \times \text{INTRA}^{s(c)}}{\sum_{b\in\mathcal{B}_{t-1}(c)} \left\{min\left\{\text{INTER}^{s(c)}, \text{INTER}^{s(b)}\right\} \times \mathbf{1}_{\{s(c)\neq s(b)\}} + \mathbf{1}_{\{s(c)=s(b)\}} \times \text{INTRA}^{s(c)}\right\}} \tag{38}$$

where $s(c)$ denotes the state to which county c belongs and $s(b)$ denotes the home state of bank b and where the variables INTER (INTRA) denote the number of years (until 1995) that have passed since the interstate (intrastate branching) liberalization of the state's banking market. $\mathcal{B}_{t-1}(c)$ is the set of all banks (financial institutions) active in county c at time $t-1$. To the extent that interstate liberalization happens on a reciprocal basis, the first term in the numerator, , $min\left\{\text{INTER}^{s(c)}, \text{INTER}^{s(b)}\right\}$, is the number of years that the state $s(c)$ in which bank b is active has been open for banks from bank b's home state, $s(b)$: for banks from outside the state, i.e. for which the indicator functions are $\mathbf{1}_{\{s(l)\neq s(b)\}} = 1$ and $\mathbf{1}_{\{s(l)=s(b)\}} = 0$, this number takes the value $\text{INTER}^{s(c)}$ if the home state of the bank liberalized earlier than state $s(c)$. For out-of-state banks from states that liberalized later, it takes the value $\text{INTER}^{s(b)}$. For local banks for which state $s(c)$ is the home state ($\mathbf{1}_{\{s(c)\neq s(b)\}} = 0$, $\mathbf{1}_{\{s(c)=s(b)\}} = 1$) it takes on the value $\text{INTRA}^{s(c)}$.

The numerator therefore varies for each bank in state $s(c)$ as a function of the bank's home state. The denominator just sums this bank-specific number across all (treated) banks active in county c which ensures that $\sum_{b\in\mathcal{B}_{t-1}(c)} \omega_{t-1}^{b,c} = 1$.

Hoffmann and Stewen (2020) suggest to interpret the weights $\omega_{t-1}^{b,c}$ constructed according to (38) as the hypothetical market share that bank b should have in county c if banks' started to enter the target market c at the earliest possible date and then grow their lending at a rate that is equal across all banks. For each bank, this 'as-if' share only depends on its own home state, the regulation of the state to which the target market belongs as well as on the regulation of the home states of the other banks that are active in c. Our identifying assumption is that this as-if measure of $\omega_{t-1}^{b,c}$ is uncorrelated with local demand conditions.

Based on the same assumptions, we can now also construct a de iure measure of the share of county c in bank b's portfolio, $\phi_{t-1}^{b,c}$, that we then use to construct a de iure bank-level diversification measure according to (31) above.[21] Specifically, for each bank we can look at the set of counties in which the bank is active at the end of period $t-1$,denoted by $\mathcal{C}_{t-1}(b)$ and ask for how many years (until 1995) the bank has legally been allowed to enter a given county. Again, the

[20] These mutual reciprocal liberalizations were initially often limited to states in the region and later expanded to the national level. We do not attempt to account for the complexity of these regional agreements here.

[21] This is the measure we have also used on column (5) of Table 12.

answer to this question is given by the numerator of (38), so that the notional share of county c in the bank's portfolio is

$$\phi_{t-1}^{b,c} = \frac{min\left\{\text{INTER}^{s(c)}, \text{INTER}^{s(b)}\right\} \times \mathbf{1}_{\{s(c)\neq s(b)\}} + \mathbf{1}_{\{s(c)=s(b)\}} \times \text{INTRA}^{s(c)}}{\sum_{c\in\mathcal{C}_{t-1}(b)} \left\{min\left\{\text{INTER}^{s(c)}, \text{INTER}^{s(b)}\right\} \times \mathbf{1}_{\{s(c)\neq s(b)\}} + \mathbf{1}_{\{s(c)=s(b)\}} \times \text{INTRA}^{s(c)}\right\}} \tag{39}$$

where the summation in the denominator again ensures $\sum_c \phi_{t-1}^{b,c} = 1$ and—different from (38) above—now runs across counties c for a given bank b.

Having constructed $\mathcal{GLR}_t^c$ we now use it as an instrument for the county-level lending response LR_t^c in the county-level house price regression (32). Table 14 provides the results for the first and second stages. In the vector of controls we include lagged population and GDP growth. We also include the interaction between a county fixed effect and the granular term $\mathcal{G}_{t-1}^c$ to control for the possibility that other shocks than import exposure affect local house price outcomes. The results of the first stage of reveal that $\mathcal{GLR}_t^c$ is a powerful instrument for LR_t^c,with the extant F-statistics exceeding the critical threshold of 10 (see Stock and Yogo (2005)) by a wide margin. The second stage reveals a significant and positive coefficient on $\widehat{\text{LR}}_t^c$ while the coefficient on ΔIE_t^c is very significantly negative. These results buttress the fundamental mechanism underlying our theoretical model: higher import exposure led to higher borrowing demand by households. In financially more open counties, the banking system reacted more elastically to this credit demand. This lending response stabilized demand for housing and thus house prices.

8 Conclusion

This paper has studied how financial integration allowed regional economies to cope with the fallout from the China trade shock. Our empirical analysis exploits the wave of state-level banking deregulation that swept through the United States during the 1980's. States that opened their banking markets for out-of-state banks earlier, had a stronger presence of geographically diversified banks — and therefore more elastic credit supply responses to local loan demand shocks — by the early 1990's, when the China trade shock started to deteriorate the terms-of-trade of many local economies across the United States. To guide our analysis, we propose a stylized model of local economies in which financial openness is key in modulating the response to an exogenous shock to the terms of trade. In financially more open economies, households can borrow more easily in response to the negative shocks to wages and employment. This allows them to smooth consumption stabilizing the demand for non-tradable goods. Because non-tradable prices (and in particular house prices) do not decline as much as would be the case without access to credit, wages in the non-tradable sector do not decline as strongly and the reallocation between the import-exposed tradable and the non-tradable sectors takes place more swiftly.

Consistent with the model predictions, we find that house prices remained relatively stable in financially more open states while household borrowing and debt increased more in states with ample credit supply. Higher local house prices then favored a swifter reallocation of labor between the import exposed manufacturing and the housing sector, stabilizing average wages, income and employment in the non-tradable sector.

Our findings shed new light on how financial integration affects the response of economies to external shocks. Much of the earlier literature has emphasized the role that banking deregulation across U.S. federal states played for credit supply, in particular for firms. By contrast, our results illustrate how banking integration helped accommodate a major credit demand shock by consumers and how the stabilization of consumer demand (through consumption smoothing) accelerated the necessary sectoral reallocation of labor. At a general level, our results highlight the importance of integrated markets for retail (consumer) finance in dealing with asymmetric terms-of-trade shocks in monetary unions.

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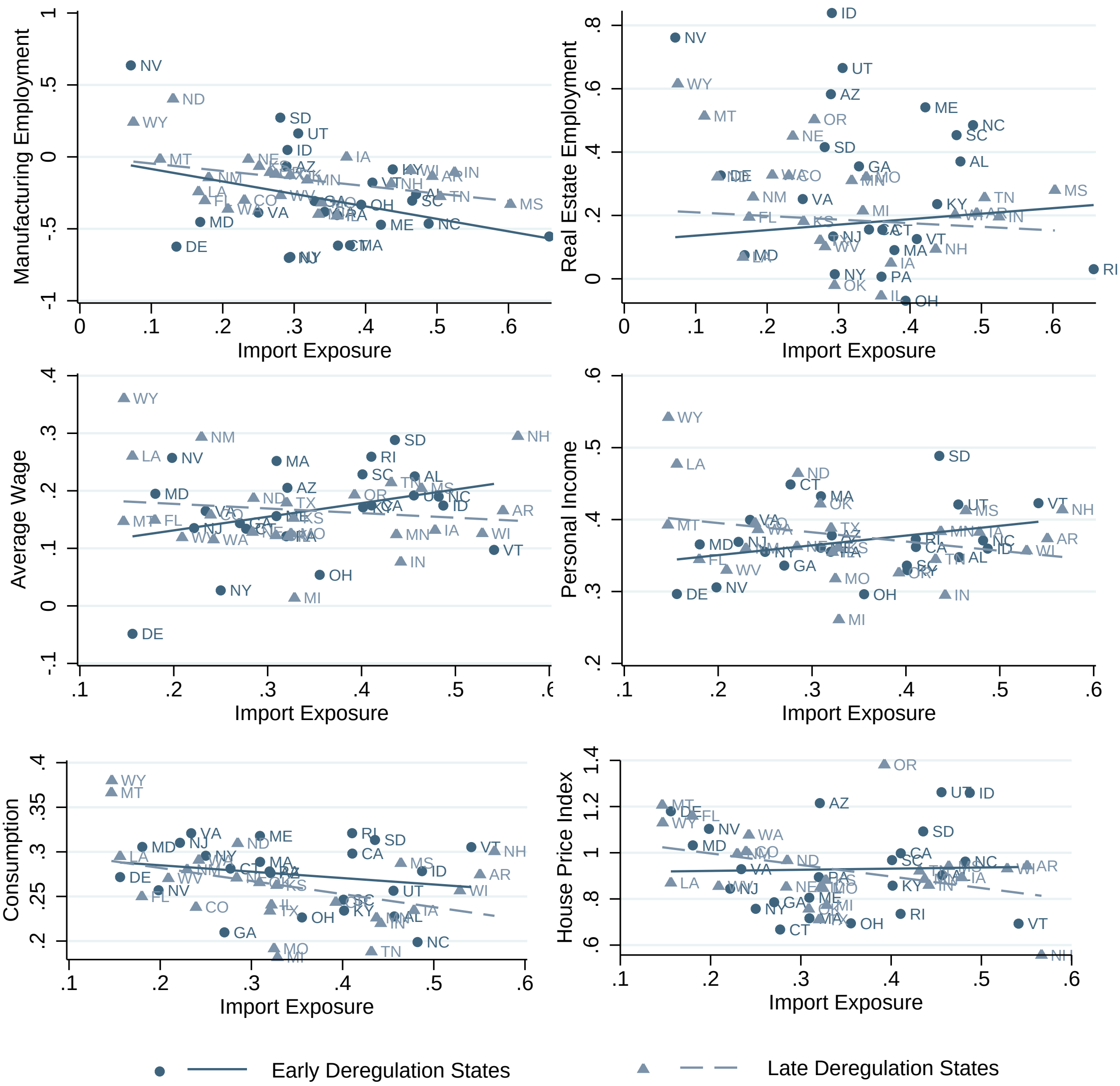
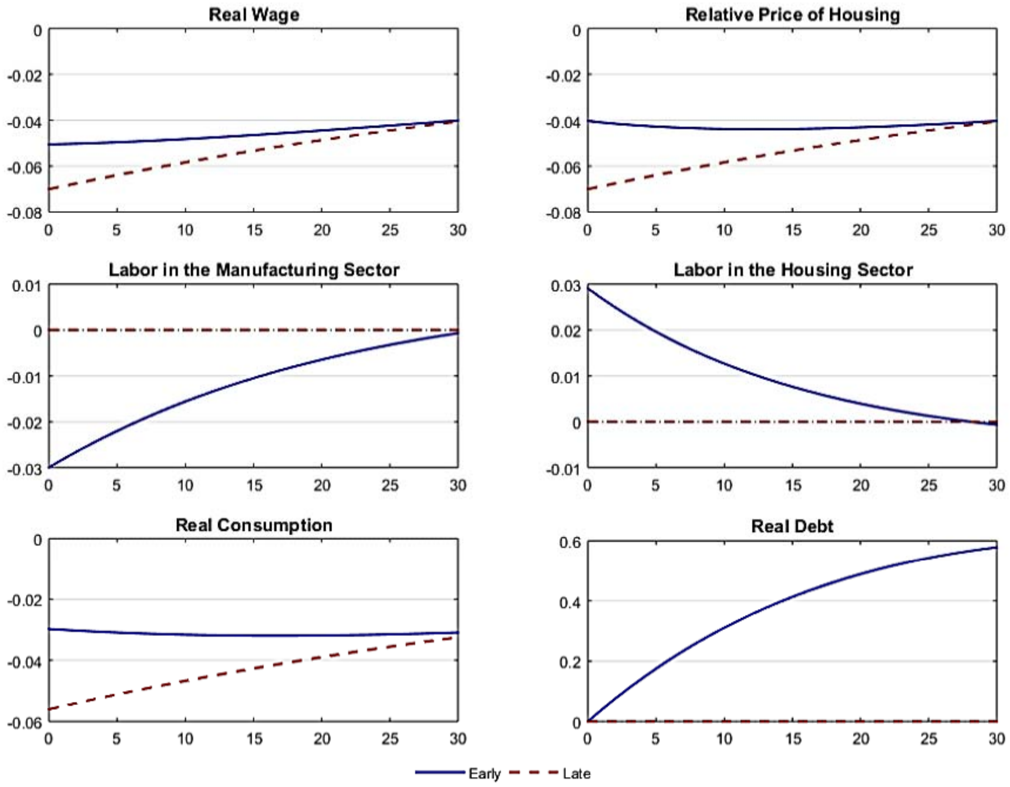
Figures and Tables

Figure 1: Long-Run Effects of Chinese Imports Exposure



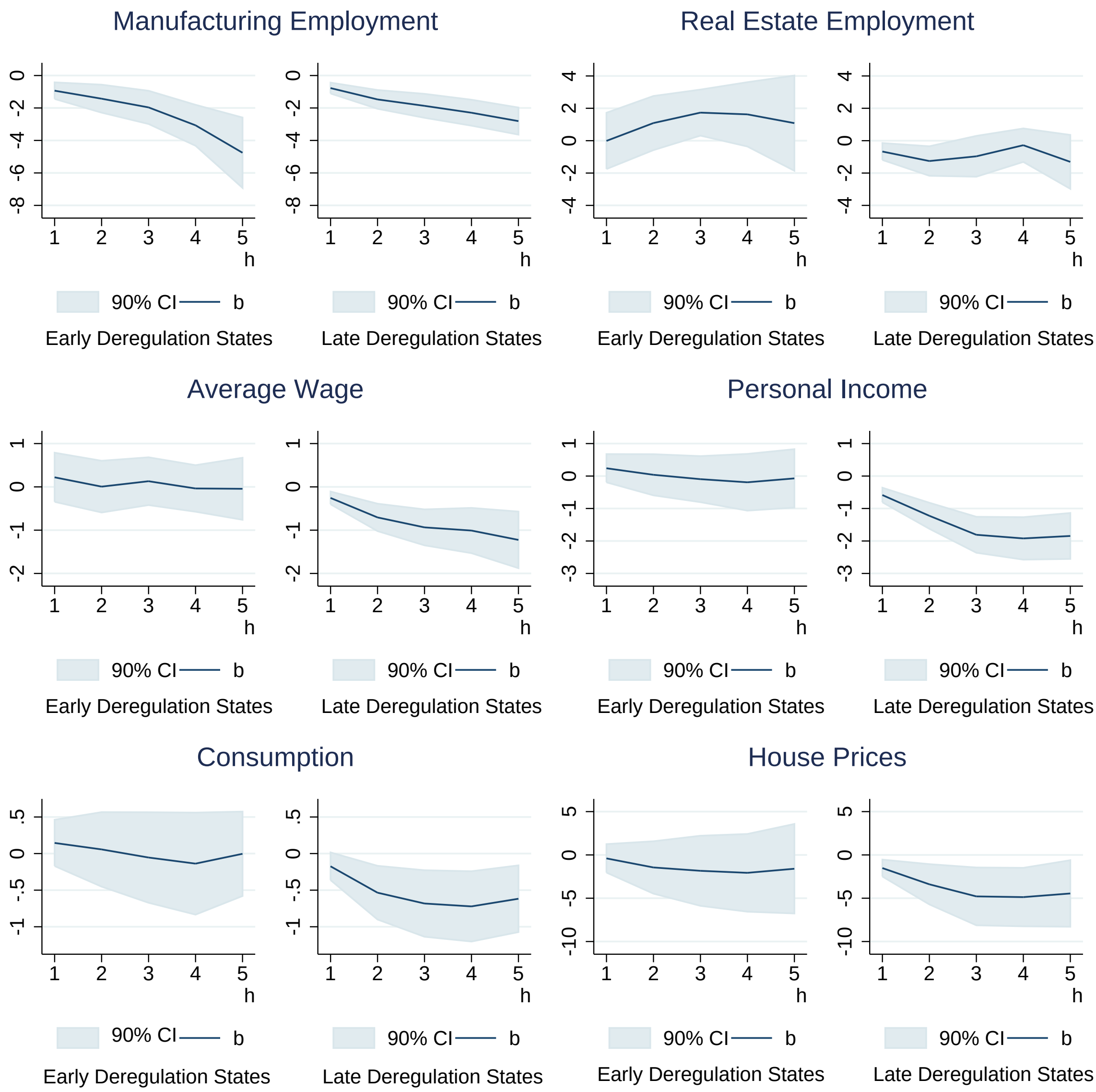
Notes: The figure shows the long-run relationship between Chinese import exposure and the central variables of interest for two samples of 23 early deregulation states and 25 late deregulation states (excl. Alaska and Hawaii) during the period from 1991 to 2007. States that deregulated their banking sector before (after) 1985 are classified as early (late) deregulation states. The vertical axes measure the log change of the corresponding dependent variable. The horizontal axes measure the change in import exposure per worker. All regressions are weighted by start of the period state share of national population.

Figure 2: Model Predictions - Benchmark Parameterization



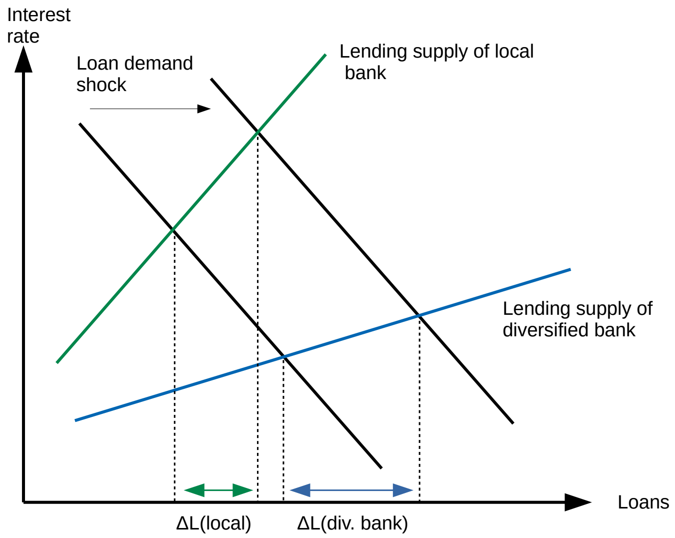
Notes: this figure depicts the logarithmic changes in the endogenous variables from the steady-state levels after a trade-of-term shock ($\varepsilon_1 = -0.1$) for early ($\omega_E = 0.01$) and late ($\omega_L = 1$) deregulation states. The benchmark parametrization of the model: $\alpha = 0.35$, $\eta = 0.65$, $\beta = 0.98$, $\sigma = 1$, $\nu = 1$, $\theta = 1$, $\vartheta = 2$, $\gamma = 0.8$, $\varphi = 0.3$, $\rho = 0.97$, $\delta = 0.04$.

Figure 3: Dynamic Responses after China Trade Shock



Notes: The figure shows dynamic effects of Chinese import exposure on the central variables of interest estimated using the regression model (26). The sample includes 23 early deregulation states and 25 late deregulation states (excl. Alaska and Hawaii) during the period from 1991 to 2007. States that deregulated their banking sector before (after) 1985 are classified as early (late) deregulation states. All regressions include state and year fixed effects and are weighted by state share of national population in 1990. Robust standard errors are clustered by state.

Figure 4: Lending responses of geographically diversified and local banks



Notes: The figure illustrates the differential lending responses of geographically diversified and local banks (i.e. those with locally concentrated portfolios) to local credit demand shocks. The lower notional portfolio risk of the diversified bank leads to a more elastic lending supply. Therefore, it increases its lending more for a given local demand shock.

Table 1: Summary Statistics

	All States (1)				Early Deregulation States (2)				Late Deregulation States (3)			
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Change in Import Exposure per Worker	.022	.018	-.034	.072	.023	.018	-.034	.071	.022	.018	-.026	.069
Instrument for Change in Import Exposure	.017	.016	-.019	.059	.017	.016	-.019	.059	.016	.015	-.016	.054
Deregulation Index	16.06	9.28	4	32	22.39	8.43	11	32	8.62	1.25	4	10
Log Change in Employment in All Sectors	.015	.020	-.048	.078	.015	.020	-.039	.078	.015	.021	-.048	.062
Log Change in Employment in Manufacturing	-.029	.043	-.365	.112	-.033	.044	-.365	.082	-.025	.041	-.170	.112
Log Change in Employment in Real Estate	.009	.070	-.342	.244	.011	.066	-.290	.244	.007	.074	-.342	.192
Log Change in Average Wage in All Sectors	.016	.021	-.058	.107	.017	.023	-.058	.089	.015	.018	-.045	.107
Log Change in Personal Income per Capita	.023	.019	-.035	.097	.024	.019	-.019	.082	.022	.020	-.035	.097
Log Change in Total Consumption per Capita	.026	.013	-.003	.089	.027	.012	.000	.059	.024	.014	-.003	.089
Log Change in House Price Index	.068	.050	-.108	.253	.075	.057	-.108	.253	.060	.038	-.062	.218
Unemployment Rate	.049	.010	.023	.081	.049	.010	.023	.069	.049	.011	.025	.081

Notes: This table reports means (population weighted), standard deviations, minimum and maximum values of the main variables used in the present study. The sample includes 48 states (excluding Alaska and Hawaii) and 17 years from 1991 to 2007. States that deregulated their banking sector before (after) 1985 are classified as early (late) deregulation states. The change in import exposure per worker and the instrument are calculated using equations (23) and (24) in the main text. Deregulation index equals number of years since the first year of deregulation. Data on employment and wages are from the CBP. Data on personal income and consumption are from the BEA. Data on house price indexes are from the FHFA. Data on unemployment rate are from the BLS.

Table 2: House prices, import exposure and banking deregulation (state-level results)

Dependent Variable: House Price Index	(1)	(2)	(3)	(4)
ΔIE	-2.1445***	-3.1155***	-2.4646***	-2.9590***
	(0.5642)	(0.6378)	(0.7346)	(0.7958)
ΔIE $\times$ DI	0.0561***	0.0377***	0.0815***	0.0682***
	(0.0110)	(0.0128)	(0.0218)	(0.0217)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.19	0.20	0.23	0.23

Notes: This table reports OLS estimates of the regression model (25). The sample includes 48 states (excluding Alaska and Hawaii) and 17 years from 1991 to 2007. Dependent variable is a logarithmic change in house price index. The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include state and year fixed effects and are weighted by state share of national population in 1990. Robust standard errors in parentheses are clustered by state. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 3: Consumption growth, import exposure and banking deregulation (state-level results)

Dependent Variable: Consumption per Capita	(1)	(2)	(3)	(4)
ΔIE	-0.2622**	-0.3319***	-0.2469*	-0.3107**
	(0.1106)	(0.1233)	(0.1235)	(0.1494)
ΔIE $\times$ DI	0.0116***	0.0108***	0.0087*	0.0076*
	(0.0020)	(0.0030)	(0.0043)	(0.0044)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.67	0.67	0.67	0.67

Notes: This table reports OLS estimates of the regression model (25). The sample includes 48 states (excluding Alaska and Hawaii) and 11 years from 1997 to 2007. Dependent variable is a logarithmic change in total consumption per capita. The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include state and year fixed effects and are weighted by state share of national population in 1990. Robust standard errors in parentheses are clustered by state. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 4: Wage growth, import exposure and banking deregulation (state-level results)

Dependent Variable: Average Wage	(1)	(2)	(3)	(4)
ΔIE	-0.2555**	-0.2180	-0.3968**	-0.3791
	(0.1169)	(0.1408)	(0.1569)	(0.2264)
ΔIE $\times$ DI	0.0170***	0.0141***	0.0189*	0.0149**
	(0.0058)	(0.0039)	(0.0103)	(0.0065)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.52	0.53	0.56	0.57

Notes: This table reports OLS estimates of the regression model (25). The sample includes 48 states (excluding Alaska and Hawaii) and 17 years from 1991 to 2007. Dependent variable is a logarithmic change in average wage. The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include state and year fixed effects and are weighted by state share of national population in 1990. Robust standard errors in parentheses are clustered by state. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 5: Personal income growth, import exposure and banking deregulation (state-level results)

Dependent Variable: Personal Income per Capita	(1)	(2)	(3)	(4)
ΔIE	-0.5115***	-0.5222***	-0.6351***	-0.5772***
	(0.1394)	(0.1406)	(0.1857)	(0.2081)
ΔIE $\times$ DI	0.0192***	0.0173***	0.0265**	0.0243***
	(0.0046)	(0.0038)	(0.0103)	(0.0074)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.57	0.58	0.56	0.58

Notes: This table reports OLS estimates of the regression model (25). The sample includes 48 states (excluding Alaska and Hawaii) and 17 years from 1991 to 2007. Dependent variable is a logarithmic change in personal income per capita. The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include state and year fixed effects and are weighted by state share of national population in 1990. Robust standard errors in parentheses are clustered by state. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 6: Sectoral employment, import exposure and banking deregulation (state-level results)

Dependent Variable: Employment	(1)	(2)	(3)	(4)
Panel A. All Sectors				
ΔIE	-0.3760***	-0.5254***	-0.4575**	-0.6230***
	(0.1339)	(0.1360)	(0.1905)	(0.2287)
ΔIE $\times$ DI	0.0083*	0.0033	0.0119	0.0075
	(0.0045)	(0.0047)	(0.0104)	(0.0084)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.72	0.72	0.72	0.73
Panel B. Manufacturing				
ΔIE	-0.8006***	-0.6669***	-1.1026***	-1.0917***
	(0.2070)	(0.2387)	(0.3466)	(0.3911)
ΔIE $\times$ DI	-0.0010	-0.0007	0.0148	0.0162
	(0.0031)	(0.0047)	(0.0139)	(0.0147)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.71	0.71	0.72	0.72
Panel C. Real Estate				
ΔIE	-1.4000**	-1.5421**	-1.9523**	-2.3714**
	(0.5605)	(0.7432)	(0.8278)	(1.0351)
ΔIE $\times$ DI	0.0307***	0.0332**	0.0539**	0.0404*
	(0.0106)	(0.0138)	(0.0255)	(0.0214)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.58	0.59	0.59	0.59

Notes: This table reports OLS estimates of the regression model (25). The sample includes 48 states (excluding Alaska and Hawaii) and 17 years from 1991 to 2007. Dependent variable is a logarithmic change in number of employees in all sectors (Panel A), the manufacturing sector (Panel B), and the real estate sector (Panel C). The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include state and year fixed effects and are weighted by state share of national population in 1990. Robust standard errors in parentheses are clustered by state. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 7: Unemployment, import exposure and banking deregulation (state-level results)

Dependent Variable: Unemployment Rate	(1)	(2)	(3)	(4)
ΔIE	0.1152***	0.1182***	0.2155***	0.2099***
	(0.0382)	(0.0423)	(0.0589)	(0.0588)
ΔIE $\times$ DI	-0.0024***	-0.0026*	-0.0083***	-0.0077***
	(0.0008)	(0.0014)	(0.0019)	(0.0021)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.62	0.63	0.62	0.62

Notes: This table reports OLS estimates of the regression model (25). The sample includes 48 states (excluding Alaska and Hawaii) and 17 years from 1991 to 2007. Dependent variable is a change in unemployment rate. The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include state and year fixed effects and are weighted by state share of national population in 1990. Robust standard errors in parentheses are clustered by state. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 8: House prices, import exposure and banking deregulation (commuting zone-level results)

Dependent Variable: House Price Index	(1)	(2)	(3)	(4)
ΔIE	-1.1466***	-1.7355***	-0.8528***	-1.4086***
	(0.1789)	(0.2563)	(0.1938)	(0.3369)
ΔIE $\times$ DI	0.0509***	0.0249***	0.0318**	0.0074
	(0.0141)	(0.0074)	(0.0150)	(0.0068)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.40	0.41	0.47	0.48

Notes: This table reports OLS estimates of the regression model (25). The sample includes 722 commuting zones and 17 years from 1991 to 2007. Dependent variable is a logarithmic change in house price index. The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include commuting zone and year fixed effects and are weighted by commuting zone share of national population in 1990. Robust standard errors in parentheses are clustered by commuting zone. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 9: Wage growth, import exposure and banking deregulation (commuting zone-level results)

Dependent Variable: Average Wage	(1)	(2)	(3)	(4)
ΔIE	-0.1641***	-0.1551	-0.1899***	-0.1720
	(0.0404)	(0.1087)	(0.0716)	(0.1747)
ΔIE $\times$ DI	0.0091***	0.0072***	0.0103*	0.0078**
	(0.0035)	(0.0021)	(0.0055)	(0.0032)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.21	0.21	0.23	0.23

Notes: This table reports OLS estimates of the regression model (25). The sample includes 722 commuting zones and 17 years from 1991 to 2007. Dependent variable is a logarithmic change in average wage. The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include commuting zone and year fixed effects and are weighted by commuting zone share of national population in 1990. Robust standard errors in parentheses are clustered by commuting zone. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 10: Personal income growth, import exposure and banking deregulation (commuting zone-level results)

Dependent Variable: Personal Income per Capita	(1)	(2)	(3)	(4)
ΔIE	-0.2827***	-0.3633***	-0.3040***	-0.3885***
	(0.0515)	(0.0813)	(0.0695)	(0.1160)
ΔIE $\times$ DI	0.0117***	0.0093***	0.0127***	0.0097***
	(0.0027)	(0.0024)	(0.0043)	(0.0030)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 $\times$ ΔIE	No	Yes	No	Yes
Aggregate $\times$ DI	No	No	Yes	Yes
Adjusted R^2	0.20	0.20	0.21	0.22

Notes: This table reports OLS estimates of the regression model (25). The sample includes 722 commuting zones and 17 years from 1991 to 2007. Dependent variable is a logarithmic change in personal income per capita. The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include commuting zone and year fixed effects and are weighted by commuting zone share of national population in 1990. Robust standard errors in parentheses are clustered by commuting zone. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 11: Sectoral employment, import exposure and banking deregulation (commuting zone-level results)

Dependent Variable: Employment	(1)	(2)	(3)	(4)
Panel A. All Sectors				
ΔIE	-0.1916***	-0.2728***	-0.1935*	-0.2950*
	(0.0550)	(0.0783)	(0.1004)	(0.1530)
ΔIE × DI	0.0060**	0.0024	0.0067	0.0039
	(0.0030)	(0.0025)	(0.0055)	(0.0039)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 × ΔIE	No	Yes	No	Yes
Aggregate × DI	No	No	Yes	Yes
Adjusted R^2	0.37	0.37	0.37	0.38
Panel B. Manufacturing				
ΔIE	-0.5600***	-0.3866**	-0.7770***	-0.7158***
	(0.1016)	(0.1629)	(0.1734)	(0.2717)
ΔIE × DI	-0.0007	0.0031	0.0126	0.0169*
	(0.0035)	(0.0051)	(0.0092)	(0.0089)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 × ΔIE	No	Yes	No	Yes
Aggregate × DI	No	No	Yes	Yes
Adjusted R^2	0.27	0.27	0.31	0.30
Panel C. Real Estate				
ΔIE	-0.5590***	-0.7945***	-0.7227**	-1.0496**
	(0.1932)	(0.2936)	(0.3065)	(0.4389)
ΔIE × DI	0.0186*	0.0175	0.0281*	0.0187
	(0.0096)	(0.0127)	(0.0167)	(0.0170)
Baseline	Yes	Yes	Yes	Yes
Pre-1991 × ΔIE	No	Yes	No	Yes
Aggregate × DI	No	No	Yes	Yes
Adjusted R^2	0.08	0.08	0.08	0.08

Notes: This table reports OLS estimates of the regression model (25). The sample includes 722 commuting zones and 17 years from 1991 to 2007. Dependent variable is a logarithmic change in number of employees in all sectors (Panel A), the manufacturing sector (Panel B), and the real estate sector (Panel C). The change in import exposure per worker is calculated using equation (24) in the main text. Deregulation index equals number of years since the first year of deregulation. All regressions include commuting zone and year fixed effects and are weighted by commuting zone share of national population in 1990. Robust standard errors in parentheses are clustered by commuting zone. *,**,*** indicate statistical significance at the 10%, 5%, 1% level respectively.

Table 12: Bank-County lending responses of commercial banks to the China shock

	Dependent variable: $\text{LR}_t^{b,c}$				
	(1)	(2)	(3)	(4)	(5)
		Diversification measure			
		county	CZ	state	de iure
$\Delta\text{IE}_t^{\mathcal{CZ}(c)}$	0.715	0.866^{*}	0.858^{*}	1.018^{**}	0.983^{*}
	(0.443)	(0.452)	(0.440)	(0.473)	(0.532)
$\text{DIV}_{t-1}^{b} \times \Delta\text{IE}_t^{\mathcal{CZ}(c)}$		0.236^{***}	0.307^{***}	1.124^{***}	0.002^{***}
		(0.052)	(0.069)	(0.242)	(0.001)
DIV_{t-1}^{b}		-0.166^{***}	-0.102	-0.729^{***}	-0.004^{***}
		(0.063)	(0.151)	(0.214)	(0.001)
Observations	409,038	405,381	405,381	405,381	383,686
R^2	0.202	0.201	0.201	0.201	0.202

Notes: The table reports bank-county level regressions of the form $\text{LR}_t^{b,c} = \alpha \times \Delta\text{IE}_t^c + \delta \times \Delta\text{IE}_t^c \times \text{DIV}_{t-1}^b + \text{CONTROLS}$ for different measures of bank-level diversification as indicated in the headings of columns (2)-(5) and for a sample of commercial banks over the period 1995-2007. The vector of controls contains bank-county and state-year fixed effects and (except in column (1)) the stand-alone term DIV_{t-1}^b. To make the coefficient α comparable across specifications (1) and (2)-(5) as the county-level average effect, DIV_{t-1}^b is cross-sectionally demeaned. Standard errors in parentheses are clustered at the state level and 1,2,3 asterisks denote significance at the 10, 5 and 1 percent levels respectively.

Table 13: Lending responses to the China shock in a placebo sample of mortgage companies

	Dependent variable: $\text{LR}_t^{b,c}$			
	(1)	(2)	(3)	(4)
		Diversification measure		
		county	CZ	state
$\Delta\text{IE}_t^{\mathcal{CZ}(c)}$	1.503**	1.521**	1.515**	1.515**
	(0.603)	(0.600)	(0.606)	(0.609)
$\text{DIV}_{t-1}^{b} \times \Delta\text{IE}_t^{\mathcal{CZ}(c)}$		0.026	−0.071	0.209
		(0.106)	(0.193)	(0.420)
DIV_{t-1}^{b}		−0.103**	−0.005	−0.187
		(0.043)	(0.064)	(0.240)
Observations	958,809	957,029	957,029	957,029
R^2	0.632	0.632	0.632	0.632

Notes: The table reports institution-county level regressions of form $\text{LR}_t^{b,c} = \alpha \times \Delta\text{IE}_t^c + \delta \times \Delta\text{IE}_t^c \times \text{DIV}_{t-1}^b + \text{CONTROLS}$ for different measures of bank-level diversification as indicated in the headings of columns (2)-(4) and for a sample of mortgage companies over the period 1995-2007. The vector of controls contains bank-county and state-year fixed effects and (except in column (1)) the stand-alone term DIV_{t-1}^b. To make the coefficient α comparable across specifications (1) and (2)-(4) as the county-level average effect, DIV_{t-1}^b is cross-sectionally demeaned. Standard errors in parentheses are clustered at the state level and 1,2,3 asterisks denote significance at the 10, 5 and 1 percent levels respectively.

Table 14: County level instrumental variable regression for house prices

Dep. variable	(1) 1st stage LR_t^c	(2) 2nd stage Δhpi_t^c
$\widehat{\text{LR}_t^c}$		0.015^{***}
		(0.005)
$\mathcal{GLR}_t^c$	0.001^{***}	
	(0.0002)	
$\Delta\text{IE}_t^{\mathcal{CZ}(c)}$	-0.006	-0.019^{***}
	(0.097)	(0.004)
population growth lagged	-1.443^{**}	0.292^{***}
	(0.623)	(0.099)
income growth lagged	-0.173	0.102^{***}
	(0.263)	(0.016)
Observations	29,093	29,093
R^2	0.194	-0.032
F-stat on excluded instruments	27.2	
	(p-val: 0)	

Notes: The table reports the first and second stages of the county-level IV regression for house price growth, (32)

$$\Delta hpi_t^c = a \times \text{LR}_t^c + b \times \Delta\text{IE}_t^{\mathcal{CZ}(c)} + \text{CONTROLS}$$

with LR_t^c instrumented by the granular lending response $\mathcal{GLR}_t^c$. The granular lending response is constructed with the granular weights $\Gamma_{t-1}^{b,c} = \omega_{t-1}^{b,c} - \pi_{t-1}^{b,c}$, with $\omega_{t-1}^{b,c,}$ given by the de iure market shares (38) and with DIV_{t-1}^{b} and $\pi_{t-1}^{b,c}$ calculated based on the de iure portfolio shares (39). The sample comprises counties in the 722 commuter zones over the period 1995-2007. The vector of controls contains year fixed effects and and interaction of state-fixed effects with the granular term $\mathcal{G}_{t-1}^c$ in equation (35). Standard errors in parentheses are clustered at the commuter zone level and 1,2,3 asterisks denote significance at the 10, 5 and 1 percent levels respectively.

Appendix

A1 Data

In our empirical analysis we use the following control variables provided by Hoffmann and Stewen (2020).

Indicators of monetary policy and credit availability: The *short-term real interest rate* is constructed as U.S. (effective) Federal Funds minus U.S.-wide inflation. Data on Federal Funds are from the Board of Governors of the Federal Reserve System, Historical Data. U.S. inflation is computed using data on Personal Consumption Expenditures from the BEA. The measure of *monetary policy looseness* is constructed as the deviation of the monetary policy rate from the interest rate implied by a Taylor rule. The monetary policy rate is the U.S. (effective) Federal Funds rate from the Board of Governors of the Federal Reserve System. The Taylor rule used is: 0.02 + 1.5 (p - 0.02) + 0.5 · output gap, where p is U.S.- wide inflation and the output gap is measured by detrending an index for real GDP (constructed using the cumulation of official quarterly real GDP growth rates) with the HP-filter. *Real long-term interest rates* are measured as the 10-year constant maturity Treasury bond rate minus expectations of the average annual rate of CPI inflation over the next 10 years from the Survey of Professional Forecasters (only available from 1992), in percent per annum. Finally, we use two measures from surveys on credit credit conditions. The first is *Net Percentage of Domestic Banks Reporting Increased Willingness to Make Consumer Installment Loans* from the Senior Loan Officer Opinion Survey on Bank Lending Practices of the Board of Governors of the Federal Reserve System (US), retrieved from FRED, Federal Reserve Bank of St. Louis. A positive value for this variable therefore indicates a loosening of credit conditions. The second measure, *"Good time to buy"*, the University of Michigan Survey of Consumers that reflects consumers' opinion towards the house buying conditions. *Financial Distress* is measured as Corporate Bond Yield Spread between AAA- and BAA-rated corporate bonds.

Pre-91 state-level characteristics: *GDP of tradable sector* is measured by manufacturing sector GDP at state level from the BEA regional accounts. *GDP of non-tradable sector* is measured by retail trade sector GDP at state level from the BEA regional accounts. *Tradable residential wages* are measured by private non-farm wages and salaries in manufacturing sector and are from the BEA regional accounts. *Non-tradable residential wages* are measured by private non-farm wages and salaries in retail trade sector and are from the BEA regional accounts. *Total employment* is total full-time and part-time employment from the BEA regional accounts. *Exports to GDP ratio* at the state-level is calculated using the Commodity Flow Survey (CFS) data on interstate shipments among the 48 contiguous US states.