Firms' Internal Networks and Local Economic Shocks*

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Abstract

This paper shows that firms' internal networks of establishments constitute an important channel through which local shocks propagate across U.S. regions. Using confidential data at the establishment level from the U.S. Census Bureau, we find that local establishment-level employment responds strongly to shocks in distant regions in which the firm is operating. Consistent with theory, the elasticity with respect to such shocks is increasing in firms' financial constraints. To account for general equilibrium adjustments, we examine aggregate employment at the county level. We find that county-level employment is highly sensitive to shocks in other counties linked through firms' internal networks.

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1 Introduction

An important feature of resource allocation within firms is that individual business units must compete for scarce resources. As Williamson (1975, p. 147) writes when describing the advantages of the multidivisional (M-form) organization, "cash flows in the M-form firm are not automatically returned to their sources but instead are exposed to an internal competition." Such competition naturally creates an interdependence among otherwise unrelated business units. When a business unit experiences a negative shock to its cash flows, such as one arising from a drop in local consumer demand, corporate headquarters does not simply cut resources in the affected business unit. Rather, it optimally spreads the cash-flow shock across multiple business units so as to equate their marginal revenue products (normalized by factor prices).[1] As a result, local consumer demand shocks not only lead to employment declines at local business units but also at business units in other regions. Our paper shows empirically how local consumer demand shocks spill over to distant regions through firms' internal networks, and how such spillovers matter economically by affecting aggregate employment in those regions.

To examine how local consumer demand shocks propagate through firms' internal networks, we build a complete spatial network of the firm's internal organization using confidential data at the establishment level from the U.S. Census Bureau's Longitudinal Business Database (LBD). We obtain regional variation in local consumer demand shocks by focusing on the massive collapse in house prices during the Great Recession. As prior research has shown, the collapse in house prices caused a sharp drop in local consumer spending by households (Mian, Rao, and Sufi 2013; Stroebel and Vavra 2014; Kaplan, Mitman, and Violante 2016). This drop in consumer spending, in turn, has led to large employment losses in the non-tradable sector: across different U.S. regions, those with larger declines in housing net worth experienced significantly larger declines in non-tradable employment (Mian and Sufi 2014; Giroud and Mueller 2017).

[1] This is illustrated in a simple model in Section 2. As is shown there, financial constraints are crucial for local cash-flow shocks to spill over to other business units. See also Inderst and Mueller (2003), where financially constrained firms smooth out cash-flow shocks to individual business units by withdrawing scarce resources from other business units, as well as Stein (1997), where financially constrained firms reallocate scarce resources towards business units whose investment opportunities have increased. Stein (2003) provides an overview of the literature on within-firm resource allocation.

A defining feature of non-tradable industries (e.g., restaurants, supermarkets, retail stores) is that they rely on local consumer demand. This makes non-tradable employment particularly well-suited to study the effects of local consumer demand shocks, such as those originating from falling house prices. The same feature also makes non-tradable employment particularly well-suited to study how local consumer demand shocks spill over to distant regions through firms' internal networks. While these shocks may directly affect non-tradable employment at the local level, they should *not directly* affect non-tradable employment in distant regions. Consequently, if a department store experiences a decline in employment in response to a local consumer demand shock in some other region in which the firm is operating, then it is unlikely that this employment decline is due to a *direct* demand effect from that other region.

We find that non-tradable establishment-level employment responds strongly to local consumer demand shocks in other regions in which the firm is operating. Controlling for changes in local house prices, a ten percent drop in house prices in other regions translates into a 0.28 percent decline in local establishment-level employment. Importantly, what matters is that establishments are linked to other regions in which their parent firm is operating, not other regions in general. If we link establishments to other regions using equal weights, population weights, income weights, or household debt weights, or if we link them to randomly selected regions, their elasticity of employment with respect to house prices in other regions is close to zero and highly insignificant.

A key empirical challenge arises from separating regional spillovers through firms' internal networks from common shocks to regions in which the firm is operating. We account for such common shocks by saturating our empirical model with highly granular ZIP code $\times$ industry fixed effects, where industries are measured at the 4-digit NAICS code level. We thus compare non-tradable establishments in the same ZIP code and 4-digit NAICS code industry that are exposed to the same regional shock but that belong to different firms and hence are exposed to different shocks in other regions.

Regional shocks may differentially affect establishments even within a given 4-digit NAICS code industry. A classic example is clientele effects. A low-end department store may be affected differently by a regional shock than a high-end department store, even though both are in the same industry (NAICS 4522). We account for clientele effects in various ways, for example, through Placebo tests based on counterfactual firm networks. The idea is that if firms in the same industry mutually overlap in almost all of their locations, then they are likely to cater to similar clienteles. To illustrate, suppose firms A and B are in the same 4-digit NAICS code industry and mutually overlap in 90 percent of their ZIP codes (2 to 10), but firm A is additionally present in ZIP code 1, while firm B is additionally present in ZIP code 11. If our estimates are confounded by clientele effects, then firm A's establishments—those in ZIP codes 1 to 10—should also be sensitive to changes in house prices in ZIP code 11, even though firm A itself has no presence in that ZIP code. Likewise, firm B's establishments should also be sensitive to changes in house prices in ZIP code 1. All our Placebo estimates are insignificant, suggesting that our results are unlikely to be confounded by differential shocks to firms' clienteles.

We additionally account for common regional shocks by focusing on establishments that switch firm affiliation. If firms' networks merely cluster around regions that are affected by common shocks, then establishments should remain sensitive to those regions even if their firm affiliation changes (since their location does not change). However, we find that establishments that switch firm affiliation are no longer sensitive to house prices in regions that were part of their original firm network.

Consumers may go to restaurants and grocery stores in neighboring regions. Thus, another empirical challenge arises from separating regional spillovers through firms' internal networks from confounding *direct* demand effects from nearby regions. We account for the possibility of direct demand spillovers in various ways. For instance, we control for changes in house prices in nearby regions, exclude all regions up to a 500 mile radius or within the same state, and exclude regional firms from our sample. We also aggregate establishments at either the firm-county or the firm-state level. By construction, this aggregation accounts for any direct demand spillovers across different ZIP codes within a county and different counties within a state, respectively.

Prior research shows that falling house prices in the Great Recession caused a drop in local consumer spending, thereby affecting non-tradable employment.[2] But changes in house prices may also affect local employment through another channel, namely, by

[2]Berger et al. (2017) construct a model that generates large consumption responses to changes in house prices in line with the estimates found in empirical studies.

affecting the collateral value of firms' real estate. Under this "collateral channel," firms' internal networks still matter, but not because they propagate local consumer demand shocks. Rather, they matter because they propagate shocks to firms' collateral value. We examine the collateral channel in two ways. First, we consider tradable industries. While the collateral channel should matter in these industries, the local demand channel should not matter, because demand for tradable goods is national or global. Second, we consider a setting in which firms are unlikely to own their real estate: restaurants and retail stores in shopping malls. While the local demand channel should matter in this setting, the collateral channel should not matter. Based on these tests, we conclude that our results are unlikely to be explained by the collateral channel.

We conclude our establishment-level analysis with additional tests. Theory predicts that local consumer demand shocks should only spill over to other regions if firms are financially constrained. Consistent with this prediction, we find that establishments of more financially constrained firms have larger elasticities of employment with respect to house prices in other regions in which the firm is operating. In fact, for the least financially constrained firms in our sample, we find no evidence that establishment-level employment responds to changes in house prices in other regions. Theory also predicts that establishments of multi-region firms should be less sensitive to (their own) local shocks than single-unit firms located in the same region. Consistent with this prediction, we find that establishments of multi-region firms exhibit relatively smaller elasticities of employment with respect to local house prices. Lastly, we find that establishments that are located closer to headquarters have smaller elasticities of employment with respect to both local house prices and house prices in other regions in which the firm is operating, suggesting that they are more insulated from economic shocks.

Regional spillovers through firms' internal networks may not matter in the aggregate if workers of multi-region firms that are laid off due to shocks in other regions are re-employed by (local) firms that are less exposed to those regions. To see whether the distribution of firm networks also matters in the aggregate, the final part of our paper considers *total* non-tradable employment at the county level. Similar to what we found at the establishment level, we find that non-tradable county-level employment responds strongly to local consumer demand shocks in other counties linked through firms' internal networks. Hence, regional spillovers through firms' internal networks matter economically by affecting aggregate employment in distant regions.

Our paper contributes to several strands of literature. A growing literature in urban, macro-, and financial economics studies how shocks propagate throughout the economy. This literature focuses on input-output networks (e.g., Acemoglu et al. 2012; Caliendo et al. 2014; Jacobson and von Schedvin 2015; Acemoglu, Akcigit, and Kerr 2016; Barrot and Sauvagnat 2016; Bigio and La'O 2016), financial networks (e.g., Acemoglu, Ozdaglar, and Tahbaz-Salehi 2012; Cabrales, Gale, and Gottardi 2015), and social networks (Bailey et al. 2017a). Relatedly, a literature in banking documents how shocks in distant regions affect local bank lending (e.g., Peek and Rosengren 1997, 2000; Schnabl 2012; Gilje, Loutskina, and Strahan 2016). By contrast, little is known about whether, and how, shocks propagate across U.S. regions through firms' internal networks of establishments. In this regard, an important benefit of using U.S. Census Bureau data is that it allows us to build a complete spatial network of the firm's internal organization: the LBD includes the ZIP codes and firm affiliations of *all* (payroll) establishments in the U.S.

Second, our paper contributes to a recent literature that studies the collapse in house prices in the Great Recession and its implications for consumer spending (Mian, Rao and Sufi 2013; Stroebel and Vavra 2014; Kaplan, Mitman, and Violante 2016) and employment (Mian and Sufi 2014; Giroud and Mueller 2017). Our paper shows that local consumer demand shocks not only affect local non-tradable employment but also non-tradable employment in other regions. Indeed, we find large elasticities of non-tradable employment with respect to demand shocks in other regions, echoing a point made in Beraja, Hurst, and Ospina (2016) that it is difficult to draw inferences about aggregate economic activity based on local elasticities alone. As we show, including elasticities with respect to demand shocks in other regions *strengthens* the role of consumer demand in explaining the sharp decline in U.S. employment during the Great Recession.

Third, a large literature in urban, macro-, and public economics focuses on the role of public policy in redistributing resources across regions through a federal system of tax and transfer policies, including "place-based" subsidy and investment programs (e.g., Glaeser and Gottlieb 2008; Kline and Moretti 2013, 2014a, 2014b; Moretti 2014; Nakamura and

Steinsson 2014; Beraja 2016; Farhi and Werning 2017).[3,4] By contrast, our empirical study focuses on the role of *firms* in redistributing resources across regions through their internal networks of establishments.

The rest of this paper is organized as follows. Section 2 presents a simple model of within-firm resource reallocation. Section 3 describes the data, variables, empirical specification, and summary statistics. Section 4 contains our main establishment-level results. Section 5 accounts for the possibility of common regional shocks. Section 6 examines the role of regional firms. Section 7 contrasts the consumer demand channel with the collateral channel. Section 8 explores cross-sectional heterogeneity. Section 9 considers aggregate employment at the county level. Section 10 concludes.

2 Resource Reallocation in Multi-Region Firms

This section provides a simple model illustrating how multi-region firms reallocate internal resources in response to local economic shocks. Consider a firm operating in n regions. Each regional firm unit produces output using labor input according to the production function $f_i(L_i)$ satisfying the regularity conditions ${f_i}'(L_i) > 0$, ${f_i}''(L_i) < 0$, $f_i(0) = 0$, $\lim_{x\to 0} {f_i}'(L_i) = \infty$, and $\lim_{x\to\infty} {f_i}'(L_i) = 0$, where $i = 1, ..., n$.[5] Regional firm units may differ in their labor productivity, as indicated by the subscript i in the production function, f_i. When transforming labor input into output, each regional firm unit takes output prices p_i and factor input prices w_i as given. Labor input in period t generates cash flows in period $t + 1$, which are discounted using the per-period discount factor δ. Factor input costs are funded out of the firm's current (period t) cash flows. (See below for a

[3] Regional transfers may be explicit or implicit. For instance, Hurst et al. (2016) show that the lack of regional variation in mortgage interest rates on loans secured by government-sponsored enterprises (GSEs) constitutes an implicit transfer to regions that are likely to be hit by adverse shocks.

[4] While factor mobility can, in principle, mitigate the adverse impacts of regional shocks, there is mounting evidence that the movement of capital and labor across regions in the aftermath of shocks is sluggish and, at best, incomplete (e.g., Blanchard and Katz 1992; Notowidigo 2011; Autor, Dorn, and Hanson 2013, 2016; Autor et al. 2014; Yagan 2017).

[5] We focus on labor input given that our empirical analysis considers employment changes within multi-region firms. That being said, the model can be extended to include both labor and capital input provided assumptions are made about the production function. See Section A.1 of the online Appendix for a model with labor and capital input based on the Cobb-Douglas production function.

discussion of the role of external funds.) Importantly, factor input choices and funding decisions are made centrally by the firm's headquarters, which has authority to move budgets across firm units to maximize overall firm value (e.g., Williamson 1975; Gertner, Scharfstein and Stein 1994; Stein 1997). Hence, the budget constraint is at the overall firm level, not at the individual firm unit level. Let C_i denote the (current) cash flow produced by regional firm unit i. The firm's budget constraint is $\sum_i w_i L_i \leq \sum_i C_i$.

The firm solves

$$\max_{L_i,\lambda} \delta \sum_i p_i f_i(L_i) - \sum_i w_i L_i + \lambda \left[\sum_i C_i - \sum_i w_i L_i \right], \tag{1}$$

where λ denotes the Lagrange multiplier associated with the budget constraint.

The Kuhn-Tucker conditions are

$$\delta p_i f_i{}'(L_i) = (1+\lambda)\, w_i \ \forall i, \tag{2}$$

$$\sum_i w_i L_i \leq \sum_i C_i, \tag{3}$$

and

$$\lambda \left[\sum_i C_i - \sum_i w_i L_i \right] = 0; \ \ \lambda \geq 0. \tag{4}$$

From equation (2), it follows that for any two regional firm units i and j it must hold that

$$\frac{\delta p_i}{w_i} f_i{}'(L_i) = 1 + \lambda = \frac{\delta p_j}{w_j} f_j{}'(L_j), \tag{5}$$

implying that a marginal dollar of funds has the same value at each regional firm unit.

As a benchmark, suppose that the firm is financially unconstrained, so that the budget constraint (3) is slack ($\lambda = 0$). In that case, equation (5) implies that headquarters allocates labor input to each regional firm unit until the (discounted) marginal revenue product of labor, $\delta p_i f_i{}'(L_i)$, equals the wage, w_i. Accordingly, labor input at each regional firm unit is at the first-best optimum.

Suppose next that the firm is financially constrained, so that the budget constraint (3) binds ($\lambda > 0$). By equation (5), a marginal dollar of funds has the same value at each regional firm unit. However, this (shadow) value strictly exceeds one—in contrast to the financially unconstrained firm, where it equals one—implying that the marginal revenue product of labor strictly exceeds the wage. Consequently, labor input at each regional firm unit is below the first-best optimum.

Importantly, what matters is only whether the firm's budget constraint binds or is slack at the optimum, not whether the firm has access to external funds. The firm could have no access to external funds, yet the budget constraint could be slack if the firm's internal funds are sufficient to attain the first-best optimal level of production. Conversely, the firm could have access to external funds, yet the budget constraint could bind at the optimum if the sum of the firm's internal and external funds are insufficient to attain the first-best optimal level of production. Hence, access to external funds is neither a necessary nor a sufficient condition for the firm's budget constraint to be slack.

Consider now a negative cash-flow shock in region j. The question we are interested in is whether and how this shock affects the firm's labor input choices in regions $i \neq j$. Intuitively, a negative cash-flow shock in region j raises the shadow value of a marginal dollar of funds, $1 + \lambda$. As a result, headquarters adjusts production in each region to ensure that the optimality condition (5) is satisfied. Since regional firm units exhibit decreasing returns to scale, $f_i''(L_i) < 0$, this implies that labor input must decline in *all* regions—including regions $i \neq j$ that are not directly affected by the shock. Formally, differentiating equations (2) and (3) with respect to C_j and solving yields

$$\frac{d\lambda}{dC_j} = \frac{1}{\sum_i \frac{w_i^2}{\delta p_i f_i''(L_i)}} < 0 \tag{6}$$

and

$$\frac{dL_i}{dC_j} = \frac{w_i}{\delta p_i f_i''(L_i)} \frac{d\lambda}{dC_j} = \frac{\frac{w_i}{\delta p_i f_i''(L_i)}}{\sum_i \frac{w_i^2}{\delta p_i f_i''(L_i)}} > 0 \;\forall i. \tag{7}$$

Hence, a negative cash-flow shock in one region leads to a decline in labor input in all regions, including those that are not directly affected by the shock. Moreover, this decline is larger the tighter is the firm's financial constraint, as expressed by the sensitivity of the shadow value of a marginal dollar to the cash-flow shock, $\frac{d\lambda}{dC_j}$.

Let us briefly comment on the regional shock dC_j. Prior research has shown that the collapse in house prices in the Great Recession is associated with large drops in regional consumer spending (Mian, Rao, and Sufi 2013; Stroebel and Vavra 2014; Kaplan, Mitman, and Violante 2016). Our model tries to capture a salient feature of consumer demand shocks: drops in consumer spending affect firms' cash flows. An alternative view is one in which falling house prices and drops in consumer spending are associated with regional productivity shocks.[6] A negative productivity shock lowers the first-best optimal level of production, implying that even financially unconstrained firms optimally cut employment. However, and in contrast to this prediction, Giroud and Mueller (2017) find that while financially constrained firms make large employment cuts in response to consumer demand shocks in the Great Recession, financially unconstrained firms make no significant employment cuts.[7] Moreover, given a negative productivity shock in one region, firms optimally allocate a smaller budget to, and hence cut employment in, that region. This frees up scarce funds, which financially constrained firms can use for other regions, since production in those regions is below the first-best optimum. Hence, for financially constrained firms, employment in other regions should *increase*, which runs counter to the evidence provided in this paper. Our model of regional cash-flow shocks, on the other hand, implies that i) only financially constrained firms make employment cuts, and ii) given a negative cash-flow shock in one region, firm-level employment in other regions *decreases*.

Our analysis illustrates a key implication of centralized resource allocation: to ensure that the optimality condition (5) remains satisfied, regional firm units must absorb some of the impacts of shocks in other regions. The flip side is that regional firm units become less sensitive to (their own) local shocks. Consider a single-unit firm operating in region j. Differentiating the firm's budget constraint with respect to C_j, we obtain

$$\frac{dL_j}{dC_j} = \frac{1}{w_j}. \tag{8}$$

By contrast, for a regional firm unit in region j that is part of a multi-region firm, the

[6]See Section A.2 of the online Appendix for a model in which firms reallocate scarce resources across regional firm units in response to a regional productivity shock.

[7]Giroud and Mueller (2017) argue that this is consistent with firms trying to smooth out cyclical demand shocks ("labor hoarding") provided they have sufficient financial resources.

sensitivity of labor input to a local cash-flow shock is given by

$$\frac{dL_j}{dC_j} = \frac{1}{w_j} \frac{\frac{w_j^2}{\delta p_j f_j''(L_j)}}{\sum_i \frac{w_i^2}{\delta p_i f_i''(L_i)}}, \tag{9}$$

which is strictly less than the corresponding sensitivity in equation (8).

Let us summarize the main predictions of our model. First, and most important, our model predicts that local cash-flow shocks spill over to other regions in which the firm is operating. As a result, firm-level employment not only declines in affected regions but also in other regions. Financial constraints are crucial for this result. If the firm's budget constraint is slack, local cash-flow shocks do not propagate to other regions. Second, the magnitude of the regional spillover depends on how tight the firm's financial constraint is. The tighter is this constraint, the more sensitive is regional firm-level employment to cash-flow shocks in other regions. Third, while regional firm units absorb some of the impacts of shocks in other regions, the flip side is that firm units in other regions absorb some of the impacts of local shocks. Consequently, regional firm units that are part of multi-region firms are less sensitive to (their own) local shocks than single-unit firms operating in the same region.

3 Data, Variables, and Summary Statistics

3.1 Data

We use confidential micro data at the establishment level from the U.S. Census Bureau's Longitudinal Business Database (LBD). An establishment is a "single physical location where business is conducted" (Jarmin and Miranda 2002; p. 5), e.g., a restaurant, grocery store, supermarket, or department store. The LBD covers all business establishments in the U.S. with at least one paid employee. Our data include information on employment, payroll, location, industry affiliation, and firm affiliation.

We focus on establishments in the non-tradable sector. A defining feature of non-tradable industries is that they rely on local consumer demand. As we discussed in the Introduction, this makes non-tradable employment well-suited to study how local consumer demand shocks spill over to distant regions through firms' internal networks: while these shocks may affect non-tradable employment at the local level, they should not directly affect non-tradable employment in distant regions. We classify industries as non-tradable based on the classification scheme in Mian and Sufi (2014). Accordingly, there are 26 non-tradable industries. Among those, the largest ones in terms of U.S. employment shares are full-service restaurants (3.76%), limited-service eating places (3.40%), grocery stores (2.13%), department stores (1.36%), other general merchandise stores (1.12%), clothing stores (1.06%), automobile dealers (1.05%), health and personal care stores (0.89%), and gasoline stations (0.73%).

We match establishments to ZIP code-level house prices using house price data from Zillow. Our sample period is from 2006 to 2009.[8] Changes in house prices from 2006 to 2009 based on Zillow data are highly correlated with the "housing net worth shock" in Mian, Rao and Sufi (2013) and Mian and Sufi (2014), "Δ Housing Net Worth, 2006–2009." The correlation at the MSA level is 86.3 percent. They are also highly correlated with changes in house prices from 2006 to 2009 using data from the Federal Housing Finance Agency (FHFA). The correlation at the MSA level is 96.4 percent.

In our establishment-level analysis, we focus on firms operating in multiple ZIP codes ("multi-region firms"). Our sample consists of 385,000 non-tradable establishments representing 64.7 percent of non-tradable U.S. employment in 2006.[9] The high employment share of multi-region firms is reflective of the prominent role of national restaurant and retail chains in the non-tradable sector. In our county-level analysis, we examine *total* non-tradable employment at the county level, that is, we also include employment by single-region firms. Our county-level sample consists of 1,000 counties representing 85.8 percent of non-tradable U.S. employment in 2006.

We use control variables from various data sources, including the 2000 Decennial Census (population), 2006 American Community Survey (age, education, race, gender), Internal Revenue Service (adjusted gross income per capita in 2006), Federal Reserve

[8] Zillow house price data have been used in, e.g., Mian, Sufi, and Trebbi (2015), Kaplan, Mitman, and Violante (2016), Bailey et al. (2017a), Di Maggio et al. (2017), and Giroud and Mueller (2017).

[9] All sample sizes are rounded to the nearest hundred following disclosure guidelines by the U.S. Census Bureau.

Bank of New York Consumer Credit Panel (household debt in 2006), and Facebook (Social Connectedness Index).[10] In addition, we compute measures of firms' financial constraints using data from Compustat (firm leverage, KZ-index, WW-index, all in 2006). To this end, we match establishments in the LBD to firms in Compustat using the Compustat-SSEL bridge maintained by the U.S. Census Bureau. As this bridge ends in 2005, we extend the match to 2009 using employer name and ID number following the procedure described in McCue (2003).

3.2 Variables and Empirical Specification

We examine how non-tradable establishment-level employment in the Great Recession responds to changes in local house prices in the establishment's ZIP code as well as to changes in house prices in other ZIP codes in which the establishment's parent firm is operating. We estimate the following equation:

$$\Delta \text{ Log}(\text{Emp}_{i,j,k})_{07-09} = \alpha + \eta_1 \ \Delta \text{ Log}(\text{HP}_k)_{06-09} + \eta_2 \ \textstyle\sum_{l \neq k} \omega_{j,k,l} \ \Delta \text{ Log}(\text{HP}_l)_{06-09} + \varepsilon_{i,j,k}, \tag{10}$$

where Δ Log$(\text{Emp}_{i,j,k})_{07-09}$ is the percentage change in employment from 2007 to 2009 at establishment i of firm j in ZIP code k, Δ Log$(\text{HP}_k)_{06-09}$ is the percentage change in house prices from 2006 to 2009 in ZIP code k, and $\sum_{l \neq k} \omega_{j,k,l}$ Δ Log$(\text{HP}_l)_{06-09}$ is the network-weighted percentage change in house prices from 2006 to 2009 in ZIP codes $l \neq k$ based on 2006 firm network weights. For brevity, we write Δ Log$(\text{HP})_{06-09}$ (other) in lieu of $\sum_{l \neq k} \omega_{j,l,k}$ Δ Log$(\text{HP}_l)_{06-09}$ in our tables and figures. The elasticities of interest are η_1 and, especially, η_2. Our model in Section 2 predicts that $\eta_2 > 0$.[11] All regressions are weighted by establishment size (number of employees) and include either industry, ZIP code, or ZIP code $\times$ industry fixed effects. When ZIP code or ZIP code $\times$ industry fixed effects are included, Δ Log$(\text{HP}_k)_{06-09}$ is absorbed by the fixed effects. Industries are measured at the 4-digit NAICS code level. Standard errors are double clustered at

[10] The Social Connectedness Index is described in Bailey et al. (2017b). We thank Mike Bailey from Facebook for providing us with the data.

[11] In our model, firms are financially constrained and optimally reallocate internal resources across regions in response to local shocks. Under the null hypothesis, $\eta_2 = 0$, firms are either not financially constrained or, if they are, do not reallocate internal resources in response to local shocks.

the firm and county level.

The firm network weights $\omega_{j,k,l}$ specify the relative weight of changes in house prices in ZIP code l for an establishment of firm j in ZIP code k. We impose the minimal assumption that these weights be proportional to the firm's non-tradable employment in a given ZIP code:

$$\omega_{j,k,l} = \frac{\text{Emp}_{j,l}}{\sum_{m \neq k} \text{Emp}_{j,m,}}. \tag{11}$$

Accordingly, a local economic shock in ZIP code l matters more for an establishment of firm j in ZIP code k if the firm is more exposed to ZIP code l, as measured by its employment in ZIP code l relative to other ZIP codes $m \neq k$. Simply put, an establishment is more exposed to a given ZIP code if its parent firm is more exposed to the ZIP code. Naturally, a given ZIP code has zero weight if the establishment's parent firm has no employees in that ZIP code.

Our main identifying assumption is that, in the absence of firm networks, changes in establishment-level employment are uncorrelated with changes in house prices in other regions in which the establishment's parent firm is operating. There are many empirical challenges to our identification strategy, notably common shocks to regions in which the establishment's parent firm is operating and direct demand spillovers from nearby regions. We address these challenges in Sections 5 and 6, respectively.

In the final part of our analysis, we consider aggregate non-tradable employment at the county level. Specifically, we examine how non-tradable county-level employment responds to changes in county-level house prices as well as to changes in house prices in other counties which are linked through firms' internal networks. Analogous to our establishment-level analysis, we estimate the following equation:

$$\Delta \text{ Log}(\text{Emp}_i)_{07-09} = \alpha + \eta_1 \ \Delta \text{ Log}(\text{HP}_i)_{06-09} + \eta_2 \ \textstyle\sum_{j \neq i} \lambda_{i,j} \ \Delta \text{ Log}(\text{HP}_j)_{06-09} + \varepsilon_i, \tag{12}$$

where Δ Log$(\text{Emp}_i)_{07-09}$ is the percentage change in non-tradable employment from 2007 to 2009 in county i, Δ Log$(\text{HP}_i)_{06-09}$ is the percentage change in house prices from 2006 to 2009 in county i, and $\sum_{j \neq i} \lambda_{i,j} \ \Delta$ Log$(\text{HP}_j)_{06-09}$ is the network-weighted percentage change in house prices from 2006 to 2009 in counties $j \neq i$ based on 2006 county network weights. Like above, we write Δ Log(HP)$_{06-09}$ (other) in lieu of $\sum_{j \neq i} \lambda_{i,j} \, \Delta \, \text{Log}(\text{HP}_j)_{06-09}$ for brevity. All regressions are weighted by county size (number of employees). Standard errors are clustered at the state level.

The county network weights $\lambda_{i,j}$ specify the relative weight of changes in house prices in county j for non-tradable employment in county i. They are computed as the employment-weighted average of individual firm network weights $\zeta_{h,i,j}$ within a given county:

$$\lambda_{i,j} = \sum_h \frac{\text{Emp}_{h,i}}{\sum_k \text{Emp}_{k,i}} \zeta_{h,i,j}. \tag{13}$$

The firm network weights $\zeta_{h,i,j}$ are constructed similarly to above, except that establishments are aggregated at the firm-county level and exposure is measured with respect to counties instead of ZIP codes. Hence, a local economic shock in county j matters more for county i if its establishments are more exposed to county j and these establishments have relatively high employment shares within county i.

3.3 Summary Statistics

Table 1 provides basic summary statistics. In the top part of Panel (A), the sample consists of firms operating in multiple ZIP codes ("multi-region firms"). As is shown, non-tradable establishments have on average 28.9 employees. Moreover, their parent firms have on average 15.4 establishments with 445 employees and operate in 1.9 states, 5.9 counties, and 12.7 ZIP codes. That being said, the firm-size distribution is skewed due to the presence of large restaurant and retail chains in our sample. In our empirical analysis, we show that our results hold if we exclude either the largest or smallest firms in our sample, or if we divide our sample into terciles based on firm size (see Table 3 as well as Tables B.1 and B.2 in the online Appendix). Lastly, during the Great Recession, non-tradable employment at the establishment level declined by 3.1 percent, while house prices at the ZIP code level fell by 14.5 percent.

In the bottom part of Panel (A), the sample consists of *all* non-tradable firms in a county, that is, including single-region firms. As is shown, the average county has 1,074 establishments and 18,490 employees in the non-tradable sector, representing 18.6 percent of total county-level employment. During the Great Recession, aggregate non-tradable employment at the county level declined by 3.6 percent, which is slightly higher than the 3.1 percent decline shown above for multi-region firms.

Panel (B) reports pairwise correlations of the firm (ω) and county (λ) network weights with corresponding weights based on proximity, population, income, education, age, and household debt. While most of these correlations are insignificant, those with proximity and population are significant. Both correlations are intuitive. First, some firms in our sample are regional firms. Second, national restaurant and retail chains are likely to have more establishments in regions with more potential customers. We address both correlations in our empirical analysis. As for population, we find that (counterfactual) networks based on population weights are unable to generate spillovers across regions (see Tables 2 and 12). As for proximity, we show that our estimates are robust to excluding nearby regions and controlling for proximity-weighted changes in house prices in other regions (see Tables 7 and B.21 of the online Appendix).

4 Propagation of Shocks across Regions

Figure 1 provides a visual impression by plotting the relationship between changes in establishment-level employment during the Great Recession and either changes in ZIP code-level house prices (top panel) or changes in house prices in other ZIP codes in which the establishment's parent firm is operating (bottom panel). To filter out any confounding effects of Δ Log(HP)$_{06-09}$ (other) when plotting the relationship between Δ Log(Emp)$_{07-09}$ and Δ Log(HP)$_{06-09}$, we estimate the residuals from a regression of Δ Log(Emp)$_{07-09}$ on a constant and Δ Log(HP)$_{06-09}$ (other). These residuals represent the variation in Δ Log(Emp)$_{07-09}$ that is unexplained by Δ Log(HP)$_{06-09}$ (other). For a given percentile of Δ Log(HP)$_{06-09}$, the plot shows the mean values of the residuals and Δ Log(HP)$_{06-09}$. We proceed analogously in the bottom panel when plotting the relationship between Δ Log(Emp)$_{07-09}$ and Δ Log(HP)$_{06-09}$ (other).

As is shown in the top panel, there is a positive association between changes in establishment-level employment and changes in local house prices at the ZIP code level. The elasticity of employment with respect to local house prices is 0.116, implying that a ten percent decline in local house prices is associated with a 1.16 percent drop in establishment-level employment. (The average decline in house prices at the ZIP code level between 2006 and 2009 is 14.5 percent.) The bottom panel shows the association between changes in establishment-level employment and changes in house prices in other ZIP codes in which the firm is operating. The elasticity of employment with respect to house prices in other ZIP codes is 0.029, implying that a ten percent decline in house prices is associated with a 0.29 percent drop in establishment-level employment. Thus, employment at the establishment level is highly sensitive not only to local house prices but also to house prices in other regions in which the firm is operating.

Table 2 confirms this visual impression. All regressions include industry fixed effects. Industries are measured at the 4-digit NAICS code level. In column (1), the elasticity of employment with respect to local house prices is 0.109, which is only slightly lower than in our graphical analysis. Column (2) includes the effects of house prices in other ZIP codes in which the firm is operating. While the coefficient associated with local house prices, Δ Log(HP)$_{06-09}$, drops slightly, the coefficient associated with house prices in other ZIP codes, Δ Log(HP)$_{06-09}$ (other), is highly significant. The elasticity of employment with respect to house prices in other ZIP codes is 0.028, which is almost identical to the elasticity in our graphical analysis. Hence, establishment-level employment declines in response to both a drop in local house prices and a drop in house prices in other regions in which the establishment's parent firm is operating.

Importantly, what matters is that establishments are linked to other regions in which the firm is operating, not other regions in general. In column (3), we assign equal weight to all other ZIP codes. In columns (4) to (6), we replace the firm network weights ω with corresponding weights based on either population, income, or household debt.[12] Lastly, in column (7), we randomly select other ZIP codes. Precisely, for each establishment, we replace all ZIP codes to which the establishment is currently linked ($\omega > 0$) with randomly selected ZIP codes. We then estimate equation (10) and store the coefficients and standard errors. We repeat this process 1,000 times. The results in column (7) display the average coefficients and standard errors based on the 1,000 regressions. As can be

[12] Mian and Sufi (2011, 2014), Mian, Rao, and Sufi (2013), Berger et al. (2017), Di Maggio et al. (2017), and Baker (2017) emphasize the importance of household debt in the Great Recession.

seen, in all of these Placebo tests, house prices in other regions have no significant effect on establishment-level employment.

5 Common Regional Shocks

5.1 Within ZIP-Code Estimation

A main empirical challenge arises from separating regional spillovers through firms' internal networks from common shocks to regions in which firms are operating. If some firms have relatively more operations in regions affected by common shocks, this could potentially explain why changes in establishment-level employment, Δ Log(Emp)$_{07-09}$, are positively correlated with changes in house prices in other regions in which the firm is operating, Δ Log(HP)$_{06-09}$ (other).

To filter out confounding effects due to common regional shocks, we include ZIP code fixed effects in our regression. These fixed effects absorb any common variation within a ZIP code due to a regional shock, regardless of whether the shock is region-specific or correlated with shocks in other regions. They also account for spillovers from one region to another, e.g., due to price or other general equilibrium adjustments. We thus compare non-tradable establishments in the same ZIP code that are exposed to the same regional shock but that belong to different firms and hence are exposed to different shocks in other regions.[13] As column (1) of Table 3 shows, the elasticity of employment with respect to house prices in other regions in which the firm is operating is similar to the elasticity previously estimated in Table 2. A potential concern is that regional shocks may differentially affect establishments in different industries. We address this concern in column (2) by including highly granular ZIP code $\times$ industry fixed effects. Compared to column (1), which includes both ZIP code fixed effects and industry fixed effects, the coefficient on Δ Log(HP)$_{06-09}$ (other) remains virtually unchanged. Thus, our results are not driven by within-ZIP code variation across industries or within-industry variation

[13] Suppose employment at establishment j in region A declines in response to a shock in region B, where the firm has other operations. If the employment decline is due to a common shock affecting regions A and B, then employment should also decline at other establishments $i \neq j$ in region A whose parent firms do not have operations in region B.

across ZIP codes, consistent with non-tradable industries being a relatively homogeneous group of industries which are widely dispersed across ZIP codes. In the remainder of this paper, we use the specification with ZIP code $\times$ industry fixed effects as our baseline establishment-level specification.

Columns (3) to (8) of Table 3 show that our main results are not driven by outliers. Column (3) excludes the largest ten percent of firms in our sample. Given that many of these firms are national restaurant and retail chains with many establishments, the number of observations drops by much more than ten percent. Column (4) excludes the smallest ten percent of firms in our sample. As these firms have only few establishments, the number of observations drops by much less than ten percent. Lastly, columns (5) to (8) exclude the top and bottom ten percent of ZIP codes in our sample based on either changes in house prices or employment. Our results are always similar.

The online Appendix contains further robustness checks. Table B.1 is similar to columns (3) to (8) of Table 3, except that the cutoff is at the five percent level. Table B.2 divides our sample into terciles based on firm size. As is shown, our results hold for small and large firms alike. Table B.3 considers 4-digit NAICS code industries that are "particularly" non-tradable, in the sense that it is difficult to move inventory around across locations: full-service restaurants, limited-service eating places, drinking places, special food services, grocery stores, and specialty food (e.g., meat, fish, fruit) stores. Table B.4 divides our sample into Census regions. Table B.5 adds individual establishment-level controls, including size (number of employees) and past employment volatility. Table B.6 weighs observations based on either ZIP code, county, state, or industry employment. Finally, Table B.7 uses distance-adjusted network weights, whereby less weight is placed on nearby ZIP codes within the firm's internal network.

Table B.8 of the online Appendix considers changes in house prices and changes in establishment-level employment in the years prior to the Great Recession. While the results are qualitatively similar, they are significantly weaker: the elasticity of establishment-level employment with respect to either local house prices or house prices in other ZIP codes in which the establishment's parent firm is operating is about half of the corresponding elasticities shown in Tables 2 and 3. Hence, non-tradable employment appears to be more sensitive to negative consumer demand shocks than to positive ones.

Lastly, we examine whether and how wages adjust to changes in house prices in the Great Recession. As is shown in Table B.9 of the online Appendix, the elasticity of establishment-level wages with respect to either local house prices or house prices in other ZIP codes in which the firm is operating, though positive, is insignificant. Thus, and consistent with Keynesian wage rigidity, wages at non-tradable establishments do not appear to fall in response to consumer demand shocks in the Great Recession, in contrast to employment.[14]

5.2 Clientele Effects

Common regional shocks may differentially affect establishments even within a given 4-digit NAICS code industry. A classic example is clientele effects. Low-end department stores may be more sensitive to a given regional shock than high-end department stores and consequently experience larger employment losses. If low-end department stores also have relatively more operations in regions affected by common shocks, then this could potentially explain why Δ Log(Emp)$_{07-09}$ and Δ Log(HP)$_{06-09}$ (other) are positively correlated even *within* a given ZIP code and industry.[15] To account for confounding effects due to differential shocks to firms' clienteles, we include as additional controls the average income, education, age, race, gender, and population density in other ZIP codes in which the firm is operating. Effectively, we thus compare establishments in the same ZIP code and 4-digit NAICS code industry that belong to parent firms catering to similar demographic segments of the population. As is shown in Table 4, including these additional controls has no effect our results.

[14] One possible reason is that workers' pay in many restaurant and retail jobs may be already at or near the minimum wage. See Table B.22 of the online Appendix for similar results at the county level.

[15] During the housing boom of 02-06 that preceded the Great Recession, firms with higher sensitivity to consumer demand may have expanded into regions in which house prices, and hence consumer demand, increased more strongly. In many instances, those were also regions in which house prices fell more strongly during the subsequent housing bust (see Figure OA.8 in the online Appendix of Charles, Hurst, and Notowidigdo 2016). Consequently, firms with higher sensitivity to regional shocks may have expanded into regions with stronger negative shocks in the Great Recession. To see whether our results are driven by firms' expansion during the housing boom, we estimate our baseline specification using firms' networks in 2001 instead of 2006. As Table B.10 of the online Appendix shows, our results remain similar, albeit the coefficient on Δ Log(HP)$_{06-09}$ (other) is slightly attenuated given that 2001 networks are a noisy proxy of firms' (true) networks during the Great Recession.

The effects of demographics may differ across locations. For example, young people in urban areas may be hit harder during the Great Recession than young people in rural areas. In Table B.11 of the online Appendix, we include "more flexible" controls by interacting income, education, age, race, and gender each with population density. In Table B.12, we re-estimate columns (6) and (7) of Table 4 and column (1) of Table B.11 using an "urban" dummy in lieu of population density. The urban dummy equals one if a given ZIP code is part of a Metropolitan Statistical Area (MSA). Lastly, in Tables B.13 and B.14, we interact all demographic controls in separate regressions with either population density or the urban dummy.

We further account for clientele effects by estimating Placebo regressions based on counterfactual firm networks. The underlying idea is that if firms in the same industry mutually overlap in almost all of their locations, then they are likely to cater to similar clienteles. To illustrate, suppose firms A and B are in the same industry and mutually overlap in 90 percent of their locations (2 to 10), but firm A is additionally present in location 1, while firm B is additionally present in location 11 (see Figure 2). Given that the two firms mutually overlap in 90 percent of their locations, the counterfactual assumption is that—based on the firms' common clienteles—firm A *could have been* in location 11, while firm B *could have been* in location 1. Hence, if our estimates are confounded by differential shocks to firms' clienteles, then firm A's establishments—those in locations 1 to 10—should also be sensitive to changes in house prices in location 11, even though firm A itself has no presence in that location. Likewise, firm B's establishments should also be sensitive to changes in house prices in location 1.

In our Placebo tests, we identify all non-tradable firms in the same industry that mutually overlap in at least 75 or 90 percent of their locations. Location is defined either at the ZIP code or county level. Industries are measured either at the 3- or 4-digit NAICS code level.[16] In the spirit of the above example, we estimate the elasticity of establishment-level employment with respect to house prices in (counterfactual) locations

[16] To obtain strong counterfactuals, we restrict our sample to "pure industry firms" that have *all* of their establishments in a single industry. As it turns out, this sample restriction does not impose a serious limitation. In the non-tradable sector, 94.6% (90.9%) of multi-region firms have all of their establishments in a single 3-digit (4-digit) NAICS code industry (based on 2006 figures).

in which the firm could have been.[17] As is shown in Table 5, this elasticity is always small and highly insignificant, suggesting that our results are unlikely to be confounded by differential shocks to firms' clienteles.

5.3 Changes in Firm Affiliation

If firms' internal networks merely cluster around regions which are affected by common shocks, then individual establishments should remain sensitive to shocks in those regions even if their firm affiliation changes (since their location does not change). To test this hypothesis, we identify all establishments in our sample that switched firm affiliation between 2002 and 2005. There are 15,600 establishment sales during this period.[18] As is shown in column (1) of Table 6, establishments that switched firm affiliation between 2002 and 2005 are no longer sensitive to house prices in regions that used to be part of their "old" 2001 firm network. However, as is shown in column (2), these establishments *are* sensitive to house prices in regions that are part of their "new" 2006 firm network. By comparison, columns (3) and (4) consider all remaining establishments that did not switch firm affiliation between 2002 and 2006. As can be seen, the results are similar regardless of whether we consider firms' 2001 or 2006 networks.

6 Regional Firms

Consumers may go to restaurants and grocery stores in neighboring regions. Therefore, another empirical challenge arises from separating regional spillovers through firms' internal networks from potentially confounding *direct* demand effects from nearby regions. Accounting for direct demand effects is important, because some firms in our sample are regional firms that have most, or all, of their establishments in a single region. Also, for regional firms, Δ Log(HP)$_{06-09}$ (other) may be correlated with Δ Log(HP)$_{06-09}$, thus possibly reflecting local demand shocks. Across all firms in our sample, the correlation

[17] Table B.15 of the online Appendix shows that firms' counterfactual locations are observationally similar to their actual locations based on employment or house price changes, income, education, age, race, gender, and population density.

[18] We focus on sales of individual establishments, and not mergers between firms. In the case of a merger, the "old" (pre-merger) and "new" (post-merger) firm networks overlap significantly.

between Δ Log(HP)$_{06-09}$ and Δ Log(HP)$_{06-09}$ (other) is 12.1 percent. However, as is shown below, this correlation is mostly driven by regional firms.

Table 7 addresses this issue in different ways. In Panel (A), we directly control for changes in house prices in nearby regions. In Panel (B), we exclude nearby regions when computing Δ Log(HP)$_{06-09}$ (other) or include only establishments when all of the firm's other establishments are located out of state. In Panel (C), we exclude regional firms from our sample. Since most of our observations are *not* from regional firms, the sample size remains always large. In all of those samples, the correlation between Δ Log(HP)$_{06-09}$ and Δ Log(HP)$_{06-09}$ (other) is very small.

In columns (1) to (3) of Panel (A), we control for changes in house prices within a 100, 200, or 300 mile radius around the establishment's ZIP code. As is shown, including this control mainly affects the coefficient on Δ Log(HP)$_{06-09}$—it becomes smaller the tighter is the control radius around the establishment's ZIP code—while the coefficient on Δ Log(HP)$_{06-09}$ (other) remains largely unaffected. Thus, Δ Log(HP)$_{06-09}$ (other) is not mainly picking up the effects of house prices from nearby regions. In column (4), we control for proximity-weighted changes in house prices in other regions. While this control is marginally significant, the coefficient on Δ Log(HP)$_{06-09}$ (other) drops only slightly and remains highly significant. Given that our proximity measures are based on ZIP codes' centroids, the controls in columns (1) to (4) exhibit no within ZIP-code variation. In column (5), we use a variant of the control in column (4) that exhibits within ZIP-code variation. As can be seen, the results are similar.

In columns (1) to (4) of Panel (B), we exclude all ZIP codes within a 100, 250, or 500 mile radius, or within the same state, when computing Δ Log(HP)$_{06-09}$ (other).[19] Hence, the regressions show how establishment-level employment responds to changes in house prices in *distant* regions in which the firm is operating. As can be seen, the coefficient on Δ Log(HP)$_{06-09}$ (other) is highly significant, albeit it becomes slightly weaker as we exclude increasingly larger parts of the firm's internal network. In column (5), we only include establishments if all of the firm's other establishments are located out of state.

[19] Precisely, we set their weights to zero and (re-)normalize the remaining weights to one. If all of the weights are zero—because all of the firm's establishments are located within an X mile radius or within the same state—the firm is dropped from the sample.

Thus, like in column (4), Δ Log(HP)$_{06-09}$ (other) is exclusively comprised of out-of-state house prices. As is shown, we obtain similar results.

In columns (1) to (4) of Panel (C), we require that firms operate in at least 10, 15, or 20 states, or in all four Census regions. In column (5), we rank firms based on their correlation between Δ Log(HP)$_{06-09}$ and Δ Log(HP)$_{06-09}$ (other) and include only the bottom five percent of firms with the lowest correlations. In all of those samples, the correlation between Δ Log(HP)$_{06-09}$ and Δ Log(HP)$_{06-09}$ (other) is very small, ranging from 1.2 percent to 2.9 percent. Our results always remain similar.

In Table 8, we aggregate establishments at either the firm-county or the firm-state level.[20] At the firm-county level, the coefficients on Δ Log(HP)$_{06-09}$ and Δ Log(HP)$_{06-09}$ (other) measure the elasticities of total firm-level employment in a county with respect to county-level house prices and house prices in other counties in which the firm is operating, respectively.[21] This aggregation accounts for any direct demand spillovers across different ZIP codes within a county. Similarly, at the firm-state level, the coefficients on Δ Log(HP)$_{06-09}$ and Δ Log(HP)$_{06-09}$ (other) measure the elasticities of total firm-level employment in a state with respect to state-level house prices and house prices in other states in which the firm is operating, respectively. This aggregation accounts for any direct demand spillovers not only across different ZIP codes but also across different counties within a state. Moreover, Δ Log(HP)$_{06-09}$ (other) is exclusively comprised of out-of-state house prices, alleviating concerns that it might capture local demand shocks. As can be seen, our results are similar to our baseline results.

7 Consumer Demand versus Collateral Channel

Prior research has shown that changes in house prices in the Great Recession affect local consumer demand (Mian, Rao, and Sufi 2013; Stroebel and Vavra 2014; Kaplan, Mitman,

[20]To include region × industry fixed effects, we restrict the sample to "pure industry firms" that have all of their establishments in a single 4-digit NAICS code industry.

[21]Based on the firm-county level aggregation, Table B.16 of the online Appendix examines if firms' internal networks are correlated with banking or social networks. Banking networks are constructed analogously to (non-tradable) firm networks by aggregating establishments of commercial banks (NAICS code 522110) at the firm-county level. The social network is the county-level network of Bailey et al. (2017b) based on Facebook data ("Social Connectedness Index"). Our results remain unchanged.

and Violante 2016) and thereby employment in the non-tradable sector (Mian and Sufi 2014; Giroud and Mueller 2017). But changes in house prices may also affect employment through another channel, namely, by affecting the collateral value of firms' real estate (Chaney, Sraer, and Thesmar 2012; Adelino, Schoar, and Severino 2015; Ersahin and Irani 2018). Under this "collateral channel," firms' internal networks may still matter, but not because they propagate local shocks to consumer demand. Rather, they matter because they propagate local shocks to firms' collateral value.

In Table 9, we examine the collateral channel hypothesis in two different ways. In Panel (A), we consider tradable industries.[22] While the collateral channel should matter in these industries, the local demand channel should not matter, because demand for tradable goods is national or global. We construct tradable firms' internal networks in the same way as we construct non-tradable firms' internal networks. As columns (1) and (2) show, tradable establishment-level employment is not sensitive to changes in local house prices, echoing similar findings by Mian and Sufi (2014) at the county level. Furthermore, as columns (2) and (3) show, tradable establishment-level employment is also not sensitive to changes in house prices in other regions in which the firm is operating. Altogether, these results are inconsistent with the collateral channel.

One possible reason why the collateral channel may be less important is that non-tradable firms—especially large restaurant and retail chains—often tend to rent or lease their real estate rather than owning it. In Panel (B), we consider a setting where it is unlikely that firms own their real estate: establishments that are located in shopping malls. We identify a given location as a shopping mall if i) at least five non-tradable establishments are located at the same address (i.e., same street name and number), or ii) the establishment's address field contains "MALL," "SHOPPING CENTER," or "SHOPPING CTR." To ensure that shopping malls constitute a major part of firms' networks, we restrict our sample to firms that have at least 75 or 90 percent of their establishments in shopping malls. Moreover, we only include firms' *actual* shopping mall locations in Δ Log(HP)$_{06-09}$ (other). Thus, the coefficient on Δ Log(HP)$_{06-09}$ (other) measures the elasticity of establishment-level employment with respect to house prices

[22] Industries are classified as tradable if imports plus exports exceed \$10,000 per worker or \$500M in total (Mian and Sufi 2014). Tradable industries are essentially manufacturing industries.

in locations where it is unlikely that firms own their real estate. Under the collateral channel, this coefficient should not be significant. As is shown, however, the coefficient is significant and of similar magnitude as the coefficient in Table 3. Hence, our results are unlikely to be explained by the collateral channel.

8 Cross-Sectional Heterogeneity

8.1 Financial Constraints

Our model in Section 2 predicts that local consumer demand shocks only spill over to other regions if firms are financially constrained. The magnitude of the regional spillover depends on how tight the firm's financial constraint is. The tighter is this constraint, the more sensitive is regional firm-level employment to demand shocks in other regions. In Table 10, we take these predictions to the data using different measures of firms' financial constraints. In column (1), we use firm leverage. This measure is based on Giroud and Mueller (2017), who argue that firms with higher leverage in 2006, at the onset of the Great Recession, are more financially constrained during the Great Recession.[23] In columns (2) and (3), we use the Kaplan-Zingales index (Kaplan and Zingales 1997) and Whited-Wu index (Whited and Wu 2006), respectively. Both indices are widely used in the finance literature. All three measures are only available for public firms. Accordingly, we restrict our sample to firms in the LBD that have a match in Compustat.

As can be seen, regardless of how we measure firms' financial constraints (FC), the interaction term Δ Log(HP)$_{06-09}$ (other) $\times$ FC is always positive and highly significant. Thus, establishments of more financially constrained firms exhibit larger elasticities of employment with respect to house prices in other regions in which the firm is operating. In fact, for the least financially constrained firms in our sample, we find no evidence that establishment-level employment responds to changes in house prices in other regions.

[23] Survey evidence by Campello, Graham, and Harvey (2010) supports the idea that firms' financial constraints matter during the Great Recession. The authors asked 574 U.S. CFOs in 2008 whether their firms are financially constrained and what they are planning to do in 2009. Firms classified as constrained based on tangible measures—credit rationing, high costs of borrowing, and difficulties in initiating or renewing a credit line—said they would cut employment by 10.9 percent in the following year. By contrast, firms classified as unconstrained said they would cut employment only by 2.7 percent.

Finally, we find that establishments of more financially constrained firms also exhibit larger elasticities of employment with respect to *local* house prices. Overall, these results suggest that financial constraints matter, both for how demand shocks spill over to other regions and how firm-level employment responds locally to these shocks.

8.2 Scope of Firms' Regional Networks

There are two sides to being part of a multi-region firm. One is that local firm units absorb some of the impacts of shocks in other regions. The flip side is that firm units in other regions absorb some of the impacts of local shocks. Accordingly, our model in Section 2 predicts that establishments of multi-region firms should be less sensitive to (their own) local shocks than establishments of single-region firms.[24]

In Table 11, we provide suggestive evidence that establishments of firms with more expansive regional networks are less sensitive to their own local consumer demand shocks. We use three different measures of the scope of firms' regional networks. In column (1), we use a dummy indicating whether the firm operates in multiple ZIP codes ("multi-region firm"). In column (2), we use the number of ZIP codes in which the firm operates. In column (3), we use a firm-level Herfindahl-Hirschman Index (HHI) measuring the firm's regional concentration based on its employment at the ZIP code level. (We use one minus the HHI to allow all three measures to have the same interpretation.) In column (1), our sample includes both multi- and single-region firms. In columns (2) and (3), we use our original sample of multi-region firms since differences between single- and multi-region firms have already been captured in column (1). In all three columns, we additionally control for firm size and Δ Log(HP)$_{06-09}$ $\times$ firm size to account for the fact that firms with more expansive regional networks also tend to be larger in general. As can be seen,

[24] Whether establishments of multi-region firms exhibit smoother employment overall depends on the net effect. On the one hand, their employment is less sensitive to local shocks. On the other hand, it is sensitive to shocks in distant regions. Tables B.17 and B.18 of the online Appendix document that establishments of multi-region firms exhibit lower 10- and 20- year employment volatility than establishments of single-region firms, even after controlling for firm size and including ZIP code $\times$ industry fixed effects. Of course, this evidence is merely suggestive. Ultimately, quantifying the tradeoff between weaker exposure to local shocks on the one hand and exposure to shocks in distant regions on the other requires performing counterfactual analyses within a quantitative model. See Guiso, Pistaferri, and Schivardi (2005) and Ellul, Pagano, and Schivardi (2014) for empirical studies documenting how firms provide risk-sharing to their workers by smoothing output shocks intertemporally.

regardless of how we measure the scope of firms' regional networks (RN), the interaction term Δ Log(HP)$_{06-09}$ $\times$ RN is always negative and significant. Naturally, the evidence in this section is only suggestive, as firms may differ for many reasons besides the scope of their regional networks.

8.3 Proximity to Headquarters

In Table B.19 of the online Appendix, we explore if firm units that are located closer to headquarters are more insulated from shocks. For instance, it may be easier for such units to lobby headquarters, or headquarters may interact more with, and hence care more about, firm units that are located nearby. Alternatively, proximity may facilitate information flows and monitoring, leading to higher returns, in which case it may be efficient to favor nearby firm units.[25] We measure proximity using either geographical distance or a dummy indicating whether the establishment is located in the same ZIP code and county, respectively, as headquarters. We find that establishments which are located closer to headquarters exhibit smaller elasticities of employment with respect to both local house prices and house prices in other regions in which the firm is operating, suggesting they are more insulated from shocks.[26]

9 Aggregate Employment at the County Level

Regional spillovers through firms' internal networks may not matter in the aggregate if workers of multi-region firms that are laid off due to shocks in other regions are re-employed by (local) firms that are less exposed to those regions. To see whether the distribution of firm networks matters in the aggregate, we consider *total* non-tradable employment by all firms in a county, including single-region firms. Hence, our setting accounts for the possibility that workers laid off due to shocks in other regions are re-employed either by other multi-region firms or by (local) single-region firms. County-level

[25] Giroud (2013) shows that proximity to headquarters positively affects plant-level productivity.

[26] Table B.20 of the online Appendix considers financial constraints (firm leverage, Kaplan-Zingales index, Whited-Wu index), scope of firms' regional networks (number of ZIP codes), and proximity to headquarters (same ZIP code) in the same regression. All our results are similar.

linkages are based on firms' internal networks, as described in Section 3.2.

9.1 Main County-Level Results

Figure 3 provides a visual impression by plotting the relationship between changes in non-tradable county-level employment during the Great Recession and either changes in county-level house prices (top panel) or changes in house prices in other counties linked through firms' internal networks (bottom panel). The plots are constructed analogously to those in Figure 1. As can be seen, non-tradable county-level employment responds strongly both to changes in local house prices and to changes in house prices in other counties linked through firms' internal networks.

Table 12 provides suggestive empirical evidence. All regressions include demographic controls (income, age, education) as well as the county-specific employment shares of all 2-digit NAICS industries to account for the possibility that counties with exposure to certain industries are harder hit during the Great Recession (see Mian and Sufi 2014). In column (1), the elasticity of employment with respect to local house prices is 0.122. This is larger than in our establishment-level analysis, reflecting the fact that our sample now includes small single-region firms, which respond more strongly to local shocks.[27] In column (2), the elasticity of employment with respect to house prices in other counties linked through firms' internal networks is 0.024, which is only slightly lower than in our establishment-level analysis. Accordingly, regional spillovers through firms' internal networks matter economically by affecting aggregate employment in other regions. Lastly, in columns (3) to (7), we perform the same Placebo tests as in our establishment-level analysis. In all of these Placebo tests, house prices in other counties have no significant effect on county-level employment. Hence, what matters is that counties are linked to other counties through firms' internal networks, not other counties in general.[28]

[27] That single-region firms respond more strongly to local shocks is confirmed in Table B.23 of the online Appendix. A possible reason is that single-region firms—which include local "mom-and-pop shops"—are more financially constrained. See Section III.F in Giroud and Mueller (2017) for a similar discussion.

[28] Table B.21 of the online Appendix shows that our county-level results hold if we control for proximity-weighted changes in house prices in other counties, exclude all counties within a 500 mile radius or within the same state when computing Δ Log(HP)$_{06-09}$ (other), or form county-level networks based exclusively on large, national firms operating in at least 20 states or in all four Census regions. In the latter case, the correlation between Δ Log(HP)$_{06-09}$ and Δ Log(HP)$_{06-09}$ (other) at the county level is only 5.1 percent.

9.2 Discussion

Back-of-the-Envelope Calculation

Beraja, Hurst, and Ospina (2016) argue that it is difficult to draw inferences about aggregate economic activity based on local elasticities alone. In our case, local consumer demand shocks not only affect local non-tradable employment but also non-tradable employment in other regions. Indeed, including elasticities with respect to demand shocks in other regions *strengthens* the role of consumer demand in explaining the sharp decline in U.S. employment during the Great Recession (Mian and Sufi 2014). As is shown in Table 1, non-tradable county-level employment dropped by 3.6 percent during the Great Recession, while county-level house prices fell by 14.5 percent. Given the elasticities in column (2) of Table 12, consumer demand shocks can thus explain about 56 percent $(= (0.115 + 0.024) \times 14.5\% \ / \ 3.6\%)$ of the decline in non-tradable employment during the Great Recession. Importantly, about 10 percent $(= 0.024 \times 14.5\% \ / \ 3.6\%)$ of this decline is due to demand shocks in other regions linked through firms' internal networks.

Frictions

Labor market frictions may prevent workers of multi-region firms that are laid off due to shocks in other regions from being re-employed by local firms. Empirical evidence suggests that labor market frictions were particularly severe during the Great Recession. Davis (2011) and Davis, Faberman, and Haltiwanger (2013) find a sharp drop in both search and recruiting intensity, and Şahin et al. (2014) find a significant increase in mismatch between job seekers and vacant jobs. Overall, Foster, Grim, and Haltiwanger (2016) note that the intensity of labor reallocation fell rather than rose in the Great Recession, contrary to previous recessions. The authors conclude that "job reallocation (creation plus destruction) is at its lowest point in 30 years during the Great Recession and its immediate aftermath" (p. S305).

Besides search and matching frictions, wage rigidity constitutes an important friction that may help us understand why our establishment-level results also show up in county-level aggregates. For local firms to absorb additional labor, wages would have to decline. However, as is shown in Table B.22 of the online Appendix, the elasticity of non-tradable county-level wages with respect to both local house prices and house prices in other counties is small and insignificant. This is true regardless of whether we consider wages at single-county firms (e.g., local "mom-and-pop shops"), multi-county firms, or all firms in a county. In all of these cases, wages do not appear to fall in response to either local consumer demand shocks or consumer demand shocks in other regions linked through firms' internal networks.[29]

Local Spillover Effects

In Table B.23 of the online Appendix, we estimate our county-level regression in column (2) of Table 12 separately for single- and multi-county firms. Two results stand out. First, single-county firms are highly sensitive to local consumer demand shocks. Their elasticity of employment with respect to local house prices is 0.161, which is almost twice as large as the corresponding elasticity for multi-county firms. Second, layoffs at multi-county firms due to consumer demand shocks in other regions appear to negatively affect (local) single-county firms. One possible channel is that workers of multi-county firms that are laid off cut back on their spending at local restaurants and retail stores (see Moretti 2010). Indeed, we can almost fully explain the elasticity of total county-level employment with respect to house prices in other regions as the sum of this local spillover effect and the original effect on multi-county firms. As is shown in Table B.23 of the online Appendix, the coefficient on Δ Log(HP)$_{06-09}$ (other) is 0.031 for multi-county firms and 0.011 for single-county firms (local spillover effect).[30] Given that multi-county firms account for 61.2 percent of total non-tradable county-level employment, this implies a weighted average elasticity of employment with respect to house prices in other regions of 0.023 ($= 0.031 \times 61.2\% + 0.011 \times 38.8\%$), which is almost identical to the elasticity of total county-level employment with respect to house prices in other regions of 0.024 shown in column (2) of Table 12.

[29] See also the discussion in Section 5.1. As we noted there, one possible reason for the downward wage rigidity in our data is that workers' pay in many restaurant and retail jobs may be already at or near the minimum wage.

[30] While this magnitude may seem large, one must bear in mind that single-county firms (e.g., local "mom-and-pop shops") are highly sensitive to any shocks, as is illustrated by their large elasticity with respect to local consumer demand shocks. Our results are consistent with Moretti (2010), Huber (2017), and Bernstein et al. (2017), who all find large spillover effects on local non-tradable employment.

9.3 Extensions

In Table B.24 of the online Appendix, we focus on counties in which house prices did *not* fall during the Great Recession but which are linked (through firms' networks) to other counties in which house prices fell sharply. The implicit assumption is that counties in which house prices did not fall and those in which house prices fell sharply are not hit by a common shock (see Section 5), or else they would display more similar patterns with respect to house prices. Regardless of whether we consider counties in which house prices increased or changed only little (± 2.5 percent), we find that the elasticity of employment with respect to house prices in other counties is similar to the corresponding elasticity in our main county-level regression in column (2) of Table 12.[31]

Local consumer demand shocks may *indirectly* affect non-tradable employment in other counties, namely, through the trade channel. Precisely, they may lead to employment losses in other counties' *tradable* sectors, which may spill over to the non-tradable sector if workers of tradable firms that are laid off cut back on their spending at local restaurants and retail stores. In Table B.26 of the online Appendix, we approach the trade channel hypothesis in two ways. First, we consider tradable county-level employment. Second, we consider non-tradable county-level employment but form county-level linkages based on tradable firms' internal networks. In both of these Placebo tests, the elasticity of county-level employment with respect to house prices in other counties is small and insignificant. Thus, our results are unlikely to be explained by the trade channel hypothesis.

10 Conclusion

Using establishment-level data from the U.S. Census Bureau's Longitudinal Business Database, this paper shows that local economic shocks spill over to distant regions through firms' internal networks of establishments. Consistent with a simple model of optimal

[31] Wage frictions can potentially explain why workers of multi-county firms that are laid off due to demand shocks in other regions are not re-employed by local firms, despite the fact that we focus on counties that experienced no demand shocks of their own. As Table B.25 of the online Appendix shows, wages in these counties do not appear to fall in response to demand shocks in other regions. This is true regardless of whether we consider wages at single-county firms, multi-county firms, or all firms within a county.

within-firm resource allocation, we find that i) establishment-level employment responds strongly to shocks in other regions in which the firm is operating, ii) the elasticity of establishment-level employment with respect to such shocks increases with firms' financial constraints, and iii) establishments of multi-region firms exhibit relatively smaller elasticities with respect to (their own) local shocks.

Importantly, what matters is that establishments are linked to other regions in which their parent firm is operating, not other regions in general. If we link establishments to other regions using equal weights, population weights, or income weights, or to randomly selected regions, their elasticity of employment with respect to shocks in other regions is small and insignificant. We account for the possibility of common shocks to regions in which the firm is operating by saturating our empirical model with highly granular ZIP code × industry fixed effects, besides performing counterfactual analyses based on Placebo firm networks and focusing on establishments that switch firm affiliation. To account for direct demand spillovers from nearby regions, we exclude all regions within a certain radius or the same state, exclude regional firms from our sample, and aggregate establishments at either the firm-county or the firm-state level.

To account for general equilibrium adjustments, we consider aggregate employment by all firms in a county. Similar to what we found at the establishment level, we find large elasticities of county-level employment with respect to shocks in other counties linked through firms' internal networks. Hence, regional spillovers through firms' internal networks matter economically by affecting aggregate employment in distant regions.

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Figure 1
Non-Tradable Establishment-Level Employment

This figure shows bin scatterplots depicting the relationship between changes in non-tradable establishment-level employment, Δ Log(Emp)$_{07\text{-}09}$, and either changes in house prices in the establishment's ZIP code, Δ Log(HP)$_{06\text{-}09}$ (top panel) or changes in house prices in other ZIP codes in which the establishment's parent firm is operating, Δ Log(HP)$_{06\text{-}09}$ (other) (bottom panel). To filter out any confounding effects of Δ Log(HP)$_{06\text{-}09}$ (other) when plotting the relationship between Δ Log(Emp)$_{07\text{-}09}$ and Δ Log(HP)$_{06\text{-}09}$, we compute the residuals from a regression of Δ Log(Emp)$_{07\text{-}09}$ on a constant and Δ Log(HP)$_{06\text{-}09}$ (other). We proceed analogously in the bottom panel when plotting the relationship between Δ Log(Emp)$_{07\text{-}09}$ and Δ Log(HP)$_{06\text{-}09}$ (other). ZIP codes are sorted into percentile bins based on their values of Δ Log(HP)$_{06-09}$ (top panel) and Δ Log(HP)$_{06-09}$ (other) (bottom panel), respectively. There are about 16,600 ZIP codes in our sample. Each bin thus represents about 166 ZIP codes. For each bin, the corresponding dot indicates the average value of (residual) Δ Log(Emp)$_{07-09}$ and either Δ Log(HP)$_{06-09}$ (top panel) or Δ Log(HP)$_{06-09}$ (other) (bottom panel) based on all ZIP codes included in the bin.

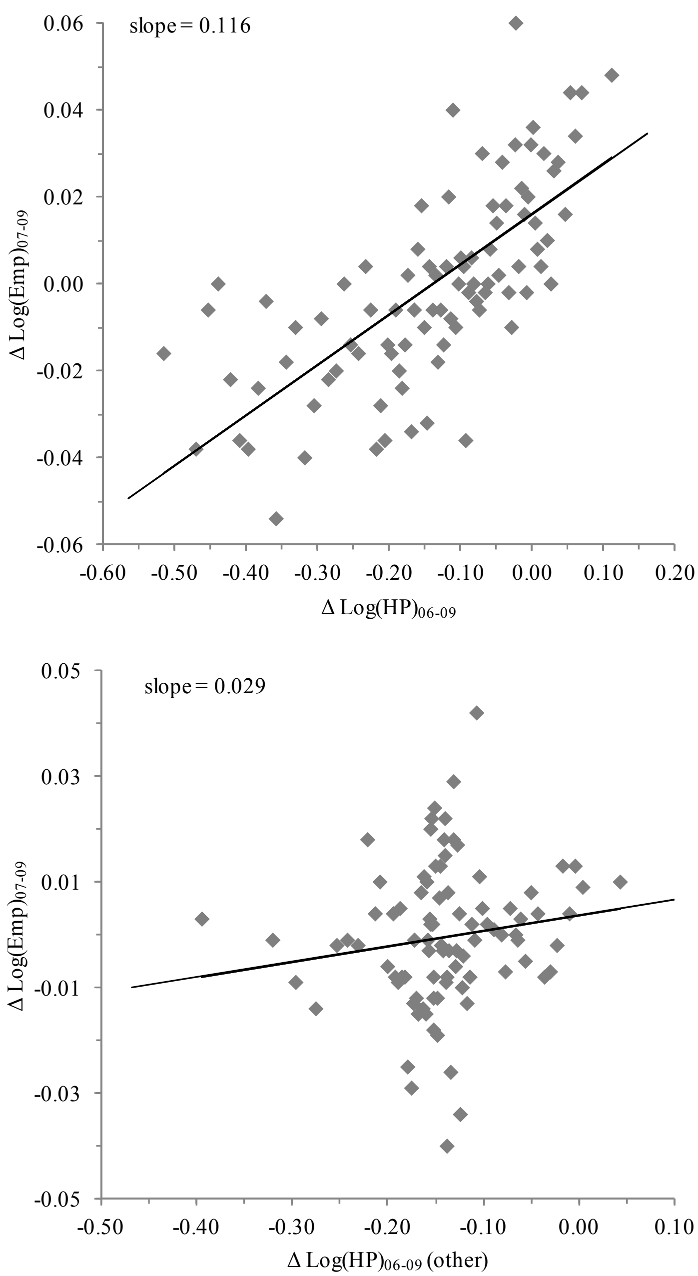


Figure 2
Counterfactual Firm Networks

This figure illustrates how the counterfactual firm networks used in the Placebo tests described in Section 5.2 are constructed. Firms A and B are in the same industry and mutually overlap in 90 percent of their locations (2 to 10), but firm A is additionally present in location 1, while firm B is additionally present in location 11. The counterfactual assumption is that, based on the firms' common industry and mutual overlap of their locations, firm A *could have been* in location 11, while firm B *could have been* in location 1.

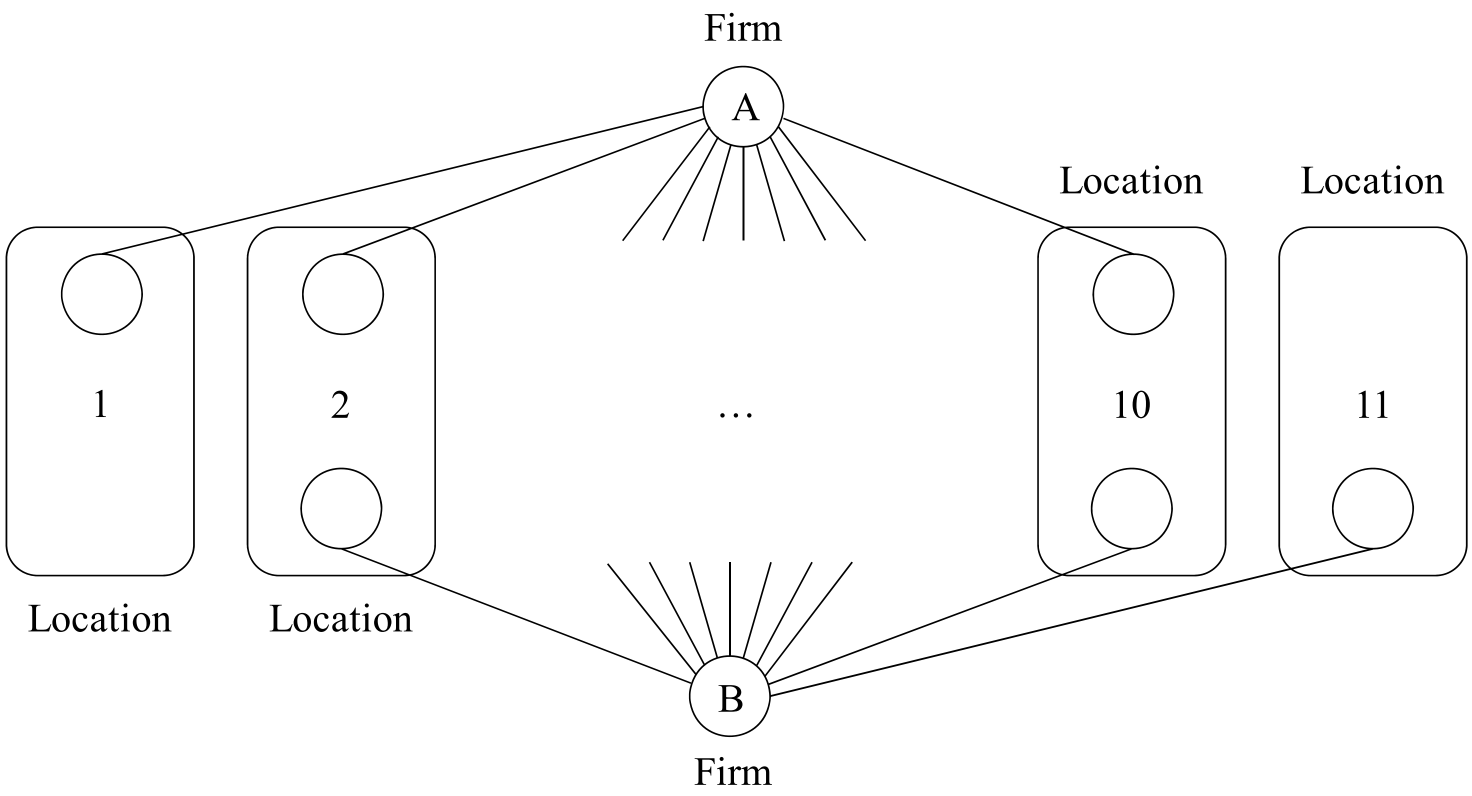
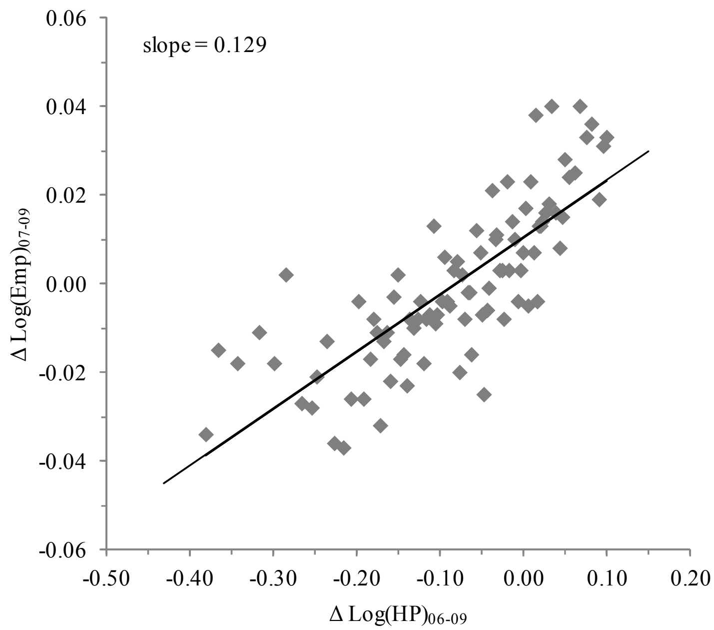


Figure 3
Non-Tradable County-Level Employment

This figure is similar to Figure 1, except that it shows bin scatterplots depicting the relationship between changes in non-tradable county-level employment, Δ Log(Emp)$_{07\text{-}09}$, and either changes in county-level house prices, Δ Log(HP)$_{06\text{-}09}$ (top panel), or changes in house prices in other counties linked through firms' internal networks, Δ Log(HP)$_{06\text{-}09}$ (other) (bottom panel).



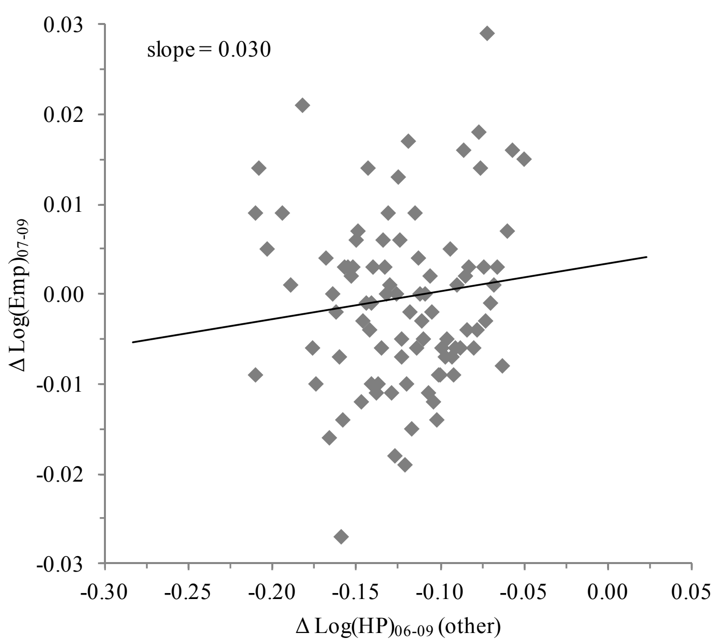


Table 1
Summary Statistics

Panel (A) provides summary statistics at the establishment, firm, and county level. All percentage changes are employment-weighted. The establishment-level summary statistics pertain to non-tradable establishments belonging to firms operating in multiple ZIP codes ("multi-region firms"). Employees is the number of employees in 2006. Δ Log(Emp)$_{07\text{-}09}$ is the percentage change in employment from 2007 to 2009. Δ Log(HP)$_{06\text{-}09}$ is the percentage change in house prices in the establishment's ZIP code from 2006 to 2009. The firm-level summary statistics pertain to the establishments' parent firms. Establishments and Employees are the number of establishments and employees, respectively, in 2006. States, Counties, and ZIP codes are the number of states, counties, and ZIP codes, respectively, in which the firm has operations in 2006. The county-level summary statistics pertain to all non-tradable establishments within a county, including those belonging to single-region firms. Establishments and Employees are the number of establishments and employees, respectively, in 2006. Employment share is the ratio of non-tradable county-level employment to total county-level employment in 2006. Δ Log(Emp)$_{07\text{-}09}$ is the percentage change in non-tradable county-level employment from 2007 to 2009. Δ Log(HP)$_{06\text{-}09}$ is the percentage change in county-level house prices from 2006 to 2009. Panel (B) shows correlations of the firm and county network weights ω and λ, respectively, with corresponding linkage weights based on proximity, population, income, education, age, and household debt. Proximity is the inverse of the geographical distance between regions' centroids. Population is based on 2000 figures. Income is adjusted gross income per capita in 2006. Education is the percentage of adults with a bachelor's degree or higher in 2000. Age is the median age in 2000. Household debt (mortgage, auto, and credit card debt) is measured per capita in 2006. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Summary statistics

	N	Mean	Std. Dev.
Establishment level (multi-region firms)			
Employees	385,000	28.9	47.0
Δ Log(Emp)$_{07\text{-}09}$	385,000	-0.031	1.614
Δ Log(HP)$_{06\text{-}09}$	385,000	-0.145	0.193
Firm level (multi-region firms)			
Establishments	25,000	15.4	132.0
Employees	25,000	445	7,182
States	25,000	1.9	4.2
Counties	25,000	5.9	32.1
ZIP codes	25,000	12.7	95.3
County level (all firms)			
Establishments	1,000	1,074	2,174
Employees	1,000	18,490	38,227
Employment share	1,000	0.186	0.531
Δ Log(Emp)$_{07\text{-}09}$	1,000	-0.036	0.883
Δ Log(HP)$_{06\text{-}09}$	1,000	-0.145	0.189

Table 1
(continued)

Panel (B): Correlation with network weights

	Correlation with firm network weights ω	Correlation with county network weights λ
Proximity	0.106***	0.103***
	(0.000)	(0.009)
Population	0.061***	0.073*
	(0.001)	(0.068)
Income	0.018	0.028
	(0.283)	(0.210)
Education	-0.027	-0.030
	(0.139)	(0.201)
Age	-0.019	-0.027
	(0.195)	(0.220)
Household debt	-0.006	-0.024
	(0.419)	(0.467)

Table 2
Propagation of Shocks across Regions

The dependent variable is the percentage change in non-tradable establishment-level employment from 2007 to 2009, Δ $Log(Emp)_{07\text{-}09}$. Δ $Log(HP)_{06\text{-}09}$ is the percentage change in house prices in the establishment's ZIP code from 2006 to 2009. Δ $Log(HP)_{06\text{-}09}$ (other) is the network-weighted percentage change in house prices from 2006 to 2009 in other ZIP codes in which the firm is operating based on 2006 firm network weights. The firm network weights are described in Section 3.2. In column (3), the firm network weights are replaced with equal weights. In columns (4) to (6), the firm network weights are replaced with Placebo weights based on population, income, and household debt, respectively. All three variables are described in Table 1. In column (7), ZIP codes to which the establishment is currently linked are replaced with randomly assigned ZIP codes. The sample consists of non-tradable establishments of firms operating in multiple ZIP codes ("multi-region firms"). All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ $Log(Emp)_{07\text{-}09}$						
			Placebo tests				
			Equal weights	Population weights	Income weights	HH debt weights	Random ZIP codes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ $Log(HP)_{06\text{-}09}$	0.109***	0.091***	0.109***	0.109***	0.110***	0.109***	0.107***
	(0.020)	(0.023)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Δ $Log(HP)_{06\text{-}09}$ (other)		0.028***					
		(0.006)					
Δ $Log(HP)_{06\text{-}09}$ (other, placebo)			0.001	-0.001	-0.003	0.001	0.003
			(0.017)	(0.014)	(0.014)	(0.015)	(0.010)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Observations	385,000	385,000	385,000	385,000	385,000	385,000	385,000

Table 3
Within ZIP-Code Estimation

This table presents variants of the specification in column (2) of Table 2 in which the industry fixed effects are replaced with either industry and ZIP code fixed effects (column (1)) or ZIP code × industry fixed effects (columns (2) to (8)). Δ Log(HP)$_{06\text{-}09}$ is absorbed by the fixed effects. Columns (3) and (4) exclude the largest and smallest ten percent of firms in our sample based on their employment in 2006. Columns (5) to (8) exclude the top and bottom ten percent of ZIP codes in our sample based on either Δ Log(Emp)$_{07\text{-}09}$ or Δ Log(HP)$_{06\text{-}09}$. All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ Log(Emp)$_{07\text{-}09}$							
			Excluding outliers (top or bottom ten percent)					
			Firms		ZIP codes			
			Largest	Smallest	Largest house price decline	Smallest house price decline	Largest employment decline	Smallest employment decline
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Log(HP)$_{06\text{-}09}$ (other)	0.026***	0.025***	0.022**	0.025***	0.024***	0.027***	0.023***	0.022***
	(0.006)	(0.006)	(0.010)	(0.006)	(0.009)	(0.008)	(0.005)	(0.006)
Industry fixed effects	Yes	–	–	–	–	–	–	–
ZIP code fixed effects	Yes	–	–	–	–	–	–	–
ZIP code × industry fixed effects	–	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.09	0.29	0.52	0.29	0.28	0.29	0.27	0.26
Observations	385,000	385,000	82,700	380,000	351,500	343,700	378,900	379,600

Table 4
Clientele Effects

This table presents variants of the specification in column (2) of Table 3 with additional demographic controls. Income is the weighted average income in other ZIP codes in which the establishment's parent firm is operating. Weights are based on the fraction of the firm's employment in the given ZIP code relative to its total employment. The other controls, Education, Age, Non-white, Male, and Population density, are constructed analogously. Income, Education, and Age are described in Table 1. Non-white and Male are based on 2006 figures. Population density is based on 2000 figures. All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ Log(Emp)$_{07\text{-}09}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Log(HP)$_{06\text{-}09}$ (other)	0.024***	0.024***	0.025***	0.025***	0.025***	0.025***	0.024***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Income	0.004*						0.004*
	(0.002)						(0.002)
Education		0.006*					0.004
		(0.004)					(0.005)
Age			0.001				-0.001
			(0.004)				(0.004)
Non-white				-0.002			-0.001
				(0.005)			(0.006)
Male					0.001		-0.000
					(0.002)		(0.002)
Population density						0.002	0.001
						(0.003)	(0.003)
ZIP code × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.29	0.29	0.29	0.29	0.29	0.29	0.29
Observations	385,000	385,000	385,000	385,000	385,000	385,000	385,000

Table 5
Counterfactual Firm Networks

This table presents variants of the specification in column (2) of Table 3 in which Δ Log(HP)$_{06\text{-}09}$ (other) is replaced with Δ Log(HP)$_{06\text{-}09}$ (other, placebo). Δ Log(HP)$_{06\text{-}09}$ (other, placebo) is the average value of Δ Log(HP)$_{06\text{-}09}$ (other) in counterfactual locations. Counterfactual locations are those in which peer firms have establishments but the given firm has no establishments. Peer firms are in the same 3- or 4-digit NAICS code industry and mutually overlap with the given firm in at least 75% or 90% of their locations. Location is defined either at the county or ZIP code level. See Section 5.2 for a full description of the Placebo tests. All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ Log(Emp)$_{07\text{-}09}$							
	County				ZIP code			
	≥ 75% overlap 3-digit NAICS	≥ 75% overlap 4-digit NAICS	≥ 90% overlap 3-digit NAICS	≥ 90% overlap 4-digit NAICS	≥ 75% overlap 3-digit NAICS	≥ 75% overlap 4-digit NAICS	≥ 90% overlap 3-digit NAICS	≥ 90% overlap 4-digit NAICS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Log(HP)$_{06\text{-}09}$ (other, placebo)	0.002	-0.002	0.002	0.001	-0.002	0.001	0.001	0.002
	(0.009)	(0.011)	(0.011)	(0.016)	(0.015)	(0.017)	(0.018)	(0.020)
ZIP code × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.40	0.65	0.57	0.62	0.77	0.79	0.65	0.65
Observations	39,900	28,600	16,200	9,900	4,500	2,900	2,500	1,200

Table 6
Changes in Firm Affiliation

This table presents variants of the specification in column (2) of Table 3 in which the sample is restricted to establishments that either switched (columns (1) and (2)) or did not switch (columns (3) and (4)) firm affiliation between 2002 and 2005. In column (1), Δ Log(HP)$_{06\text{-}09}$ (other, placebo) is based on the 2001 firm network of the establishment's former parent firm. In column (3), Δ Log(HP)$_{06\text{-}09}$ (other) is based on the 2001 firm network of the establishment's current parent firm. All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ Log(Emp)$_{07\text{-}09}$			
	Switched firm affiliation		Did not switch firm affiliation	
	2001 network	2006 network	2001 network	2006 network
	(1)	(2)	(3)	(4)
Δ Log(HP)$_{06\text{-}09}$ (other)		0.022**	0.021***	0.025***
		(0.010)	(0.007)	(0.006)
Δ Log(HP)$_{06\text{-}09}$ (other, placebo)	0.004			
	(0.007)			
ZIP code × industry fixed effects	Yes	Yes	Yes	Yes
R-squared	0.79	0.79	0.29	0.29
Observations	15,600	15,600	369,400	369,400

Table 7
Regional Firms

This table presents variants of the specifications in column (2) of Table 2 and column (2) of Table 3. In Panel (A), columns (1) to (3) control for changes in house prices within a 100, 200, or 300 mile radius around the establishment's ZIP code. Columns (4) and (5) control for proximity-weighted changes in house prices in other ZIP codes (more weight is given to nearby ZIP codes). In Panel (B), ZIP codes within a 100, 250, or 500 mile radius around the establishment's ZIP code (columns (1) to (3)) or within the same state (column (4)) are excluded from Δ Log(HP)$_{06\text{-}09}$ (other). In column (5), the sample is restricted to establishments whose parent firms have no other establishments within the same state. In Panel (C), the sample is restricted to firms operating in at least 10, 15, or 20 states (columns (1) to (3)) or in all four Census regions (column (4)). In column (5), the sample is restricted to firms whose correlation between Δ Log(HP)$_{06\text{-}09}$ and Δ Log(HP)$_{06\text{-}09}$ (other) lies in the bottom five percent across all firms in our sample. All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Controlling for house prices in nearby regions

	Δ Log(Emp)$_{07\text{-}09}$				
	(1)	(2)	(3)	(4)	(5)
Δ Log(HP)$_{06\text{-}09}$	0.076***	0.077***	0.089***	0.073***	
	(0.029)	(0.028)	(0.024)	(0.029)	
Δ Log(HP)$_{06\text{-}09}$ (other)	0.024***	0.026***	0.027***	0.021***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Δ Log(HP)$_{06\text{-}09}$ (other, 100 miles)	0.018*				
	(0.010)				
Δ Log(HP)$_{06\text{-}09}$ (other, 200 miles)		0.014			
		(0.010)			
Δ Log(HP)$_{06\text{-}09}$ (other, 300 miles)			0.005		
			(0.009)		
Δ Log(HP)$_{06\text{-}09}$ (other, proximity)				0.013*	0.011*
				(0.008)	(0.007)
Industry fixed effects	Yes	Yes	Yes	Yes	–
ZIP code × industry fixed effects	–	–	–	–	Yes
R-squared	0.02	0.02	0.02	0.02	0.29
Observations	385,000	385,000	385,000	385,000	385,000

Table 7
(continued)

Panel (B): Excluding nearby regions

	Δ Log(Emp)$_{07\text{-}09}$				
	≥ 100 miles	≥ 250 miles	≥ 500 miles	Out-of-state	No other in-state est.
	(1)	(2)	(3)	(4)	(5)
Δ Log(HP)$_{06\text{-}09}$ (other)	0.022***	0.021***	0.019***	0.020***	0.021**
	(0.005)	(0.005)	(0.007)	(0.007)	(0.010)
ZIP code × industry fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.29	0.30	0.31	0.31	0.74
Observations	365,100	340,800	310,700	295,000	8,900

Panel (C): Excluding regional firms

	Δ Log(Emp)$_{07\text{-}09}$				
	≥ 10 states	≥ 15 states	≥ 20 states	All Census regions	Lowest 5% correlation
	(1)	(2)	(3)	(4)	(5)
Δ Log(HP)$_{06\text{-}09}$ (other)	0.022**	0.025**	0.026**	0.028**	0.026***
	(0.010)	(0.011)	(0.011)	(0.012)	(0.009)
ZIP code × industry fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.34	0.34	0.36	0.39	0.33
Observations	226,600	210,700	197,700	170,900	247,500

Table 8
Firm-County and Firm-State Aggregation

This table presents variants of the specifications in column (2) of Table 2 and column (2) of Table 3 in which establishments are aggregated at either the firm-county (columns (1) and (2)) or the firm-state level (columns (3) and (4)). The firm network weights in Δ $Log(HP)_{06\text{-}09}$ (other) are replaced with corresponding firm-county and firm-state network weights, respectively. All regressions are weighted by firm-county (firm-state) employment. Standard errors (in parentheses) are double clustered at the firm and county (firm and state) level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ $Log(Emp)_{07\text{-}09}$			
	Firm-county level		Firm-state level	
	(1)	(2)	(3)	(4)
Δ $Log(HP)_{06\text{-}09}$	0.091***		0.085***	
	(0.016)		(0.022)	
Δ $Log(HP)_{06\text{-}09}$ (other)	0.026***	0.024***	0.023**	0.021**
	(0.009)	(0.008)	(0.011)	(0.010)
Industry fixed effects	Yes	–	Yes	–
County × industry fixed effects	–	Yes	–	–
State × industry fixed effects	–	–	–	Yes
R-squared	0.01	0.22	0.05	0.14
Observations	110,300	110,300	38,500	38,500

Table 9
Consumer Demand versus Collateral Channel

Panel (A) presents variants of the specifications in columns (1) and (2) of Table 2 and column (2) of Table 3 in which the sample is restricted to establishments in tradable industries. Panel (B) presents variants of the specification in column (2) of Table 3 in which the sample is restricted to firms that have at least 75% or 90% of their establishments in shopping malls, and where only firms' actual shopping mall locations are included in Δ Log(HP)$_{06\text{-}09}$ (other). Tradable industries and shopping mall locations are defined in Section 7. All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Tradable industries

	Δ Log(Emp)$_{07\text{-}09}$		
	(1)	(2)	(3)
Δ Log(HP)$_{06\text{-}09}$	0.010	0.009	
	(0.019)	(0.022)	
Δ Log(HP)$_{06\text{-}09}$ (other)		0.002	0.001
		(0.016)	(0.017)
Industry fixed effects	Yes	Yes	–
ZIP code × industry fixed effects	–	–	Yes
R-squared	0.05	0.05	0.35
Observations	29,700	29,700	29,700

Panel (B): Shopping malls

	Δ Log(Emp)$_{07\text{-}09}$	
	≥ 75% in malls	≥ 90% in malls
	(1)	(2)
Δ Log(HP)$_{06\text{-}09}$ (other)	0.024**	0.025**
	(0.011)	(0.012)
ZIP code × industry fixed effects	Yes	Yes
R-squared	0.38	0.41
Observations	83,800	56,900

Table 10
Financial Constraints

This table presents variants of the specification in column (2) of Table 3 in which Δ $Log(HP)_{06\text{-}09}$ and Δ $Log(HP)_{06\text{-}09}$ (other) are both interacted with measures of firms' financial constraints (FC) in 2006. In column (1), FC is firm leverage (ratio of the sum of debt in current liabilities and long-term debt to total assets). In column (2), FC is the financial constraints index of Kaplan and Zingales (1997). In column (3), FC is the financial constraints index of Whited and Wu (2006). Both indices are net of their minimum values. The sample is restricted to firms that have a match in Compustat. All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ $Log(Emp)_{07\text{-}09}$		
	Leverage	KZ-index	WW-index
	(1)	(2)	(3)
Δ $Log(HP)_{06\text{-}09}$ × FC	0.130***	0.003**	0.051***
	(0.045)	(0.001)	(0.014)
Δ $Log(HP)_{06\text{-}09}$ (other)	0.009	0.008	0.010
	(0.012)	(0.010)	(0.016)
Δ $Log(HP)_{06\text{-}09}$ (other) × FC	0.038**	0.001**	0.013**
	(0.015)	(0.000)	(0.006)
FC	-0.038***	-0.003**	-0.008**
	(0.006)	(0.001)	(0.004)
ZIP code × industry fixed effects	Yes	Yes	Yes
R-squared	0.42	0.42	0.42
Observations	124,100	124,100	124,100

Table 11
Scope of Firms' Regional Networks

This table presents variants of the specification in column (1) of Table 2 in which Δ $Log(HP)_{06\text{-}09}$ is interacted with firm size as well as measures of the scope of firms' regional networks (RN), both in 2006, and in which the industry fixed effects are replaced with ZIP code × industry fixed effects. In column (1), RN is a dummy variable indicating whether the firm operates in multiple ZIP codes ("multi-region firm"). The sample consists of all non-tradable establishments, including those belonging to single-region firms. In column (2), RN is the number of ZIP codes in which the firm operates. In column (3), RN is one minus the Herfindahl-Hirschman index (HHI) measuring the extent of the firm's geographical concentration based on its non-tradable employment at the ZIP code level. Firm size is the number of the firm's employees in 2006 (in logs). All regressions are weighted by establishment-level employment. Standard errors (in parentheses) are double clustered at the firm and county level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ $Log(Emp)_{07\text{-}09}$		
	Multi-region	# ZIP codes	RN-HHI
	(1)	(2)	(3)
Δ $Log(HP)_{06\text{-}09}$ × RN	-0.023**	-0.010***	-0.501***
	(0.011)	(0.003)	(0.095)
RN	0.006***	0.004**	0.049*
	(0.002)	(0.002)	(0.029)
Δ $Log(HP)_{06\text{-}09}$ × firm size	-0.002**	-0.002**	-0.003***
	(0.001)	(0.001)	(0.001)
Firm size	0.003***	0.004***	0.006***
	(0.001)	(0.001)	(0.001)
ZIP code × industry fixed effects	Yes	Yes	Yes
R-squared	0.20	0.29	0.29
Observations	910,300	385,000	385,000

Table 12
Aggregate Employment at the County Level

The dependent variable is the percentage change in non-tradable county-level employment from 2007 to 2009, Δ Log(Emp)$_{07\text{-}09}$. County-level employment is based on all firms in a county, including single-region firms. Δ Log(HP)$_{06\text{-}09}$ is the percentage change in county-level house prices from 2006 to 2009. Δ Log(HP)$_{06\text{-}09}$ (other) is the network-weighted percentage change in house prices from 2006 to 2009 in other counties linked through firms' internal networks based on 2006 county network weights. The county network weights are described in Section 3.2. The placebo tests in columns (3) to (7) are analogous to those in Table 2. Demographic controls are income, education, and age. All three variables are described in Table 1. Industry controls are the county-specific employment shares of all 23 two-digit NAICS code industries in 2006. All regressions are weighted by county-level employment. Standard errors (in parentheses) are clustered at the state level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Δ Log(Emp)$_{07\text{-}09}$						
			Placebo tests				
			Equal weights	Population weights	Income weights	HH debt weights	Random counties
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ Log(HP)$_{06\text{-}09}$	0.122***	0.115***	0.123***	0.118***	0.122***	0.122***	0.122***
	(0.006)	(0.012)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Δ Log(HP)$_{06\text{-}09}$ (other)		0.024***					
		(0.007)					
Δ Log(HP)$_{06\text{-}09}$ (other, placebo)			0.007	0.009	0.002	0.001	0.002
			(0.041)	(0.010)	(0.015)	(0.013)	(0.028)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.17	0.17	0.17	0.17	0.17	0.17	0.17
Observations	1,000	1,000	1,000	1,000	1,000	1,000	1,000