Multi-establishment Firms, Pricing and the Propagation of Local Shocks: Evidence from US Retail

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Abstract

Do centralized pricing decisions by retail chains with a presence in multiple markets contribute to the propagation of local economic shocks? Using store-level scanner data linked to county-level house prices during the Great Recession, I show that prices in a county respond to house price-induced demand shocks in distant counties served by the same chains. This pattern is consistent with a model of uniform pricing. Counterfactual analysis reveals that uniform pricing, combined with the geographic dispersion of retail chains, reduced cross-county dispersion of inflation by 50%, amplifying the effects of the Great Recession in areas more severely affected.

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1 Introduction

The propagation of local shocks through the economy has been a central topic in economics. Research has primarily focused on trade linkages between firms and sectors, as well as on flows of factors of production. However, more than 75% of US output is generated by multi-establishment firms that operate in many regions.[1] What is the role of the centralized decisions of multi-establishment firms with a presence in many regions in shaping the propagation of local shocks? Do these firms connect regions economically beyond the traditional networks?

If the various establishments of these firms operate independently, these firms will play no additional role in propagating shocks. However, some characteristics of these firms can create inter-dependencies between their establishments. My focus lies on centralized pricing decisions. If firms do not perfectly discriminate prices across their establishments, then shocks in one region could affect prices in other locations where the same firms operate. I study this phenomenon for an important sector of the US economy, the retail trade sector: i.e., grocery, supermarkets, drugstore, and mass merchandise stores. Given the importance of this sector in households expenditure, the decisions made by retail chains directly impact the prices paid by millions of consumers.[2] If different retail chains are spread across different regions and if they do not perfectly discriminate prices across regions, then their networks of stores may affect how prices in different regions are connected. Yet, existing research has paid relatively little attention to the spatial networks of retail chains and how they shape the propagation of local shocks to consumer prices in distant markets.

In this paper, I study whether and how local demand shocks propagate to food-at-home consumer prices in distant regions through retail chain networks. Can food-at-home consumer prices in Houston decline because there is a negative shock in Miami and Miami happens to be an important market for Houston's dominant retail chains? Exploiting regional variation in local consumer demand from the collapse in house

[1] Multi-state firms represent 70% of total employment in the US (Giroud and Mueller (2019)).

[2] An average family spends 12% of their household expenditure on food and beverages bought in grocery stores (Based on 2017 data from U.S. Bureau of Labor Statistics (BLS))

prices during the Great Recession (2007-2011), I find that the county-level food-at-home consumer price index depends not only on local demand conditions, but also on shocks in distant regions that are served by the same retail chains.

My main analysis is based on store-level scanner data from the NielsenIQ-Kilts retail panel. The data includes sales and prices in more than 35,000 participating grocery, drug, and mass merchandise stores that operate in more than 2,000 counties. I combine this with data on county-level changes in house prices during the Great Recession (2007-2011) from the Federal Housing Finance Agency (FHFA).

In order to identify the role of retail chains in propagating shocks across counties in the U.S., I use NielsenIQ data to construct a spatial network of the retail chains' stores. Since retail chains are unevenly distributed in space, their spatial network creates linkages between counties. I construct a new measure of connectedness that characterizes how retail chains connect counties economically. The bilateral exposure of county c to county k is a weighted average of the share of each retail chain's national sales that take place in county k, where the weights are given by the market share of each retail chain in county c. Intuitively, a county c will be more exposed to county k if county k is an important market for the dominant retail chains in county c. I use these bilateral weights to compute county c's exposure to house price changes as the network-weighted percentage change in house prices.

My main empirical finding is that county-level food-at-home prices are sensitive to house price-induced local demand shocks in distant counties that are linked by the retail chains' networks. To deal with endogeneity of house price changes, I follow the identification strategy in Mian and Sufi (2011) and use the local housing supply elasticity to instrument for local house price changes. More importantly, I use the network-weighted housing supply elasticity (in other counties) to instrument for network-weighted house price changes. Across various empirical specifications, I find that a ten percent drop in house prices in distant counties linked by the network of retail chains leads, on average, to a 1.4 percent decline in county-level food-at-home consumer prices.

My identification strategy faces some challenges. Since retail chains are not placed randomly across space, it is hard to distinguish the propagation of shocks through the network of retail chains from common regional shocks (correlated with housing supply elasticity) in the regions where the same retail chains operate. Notably, to minimize transportation costs, retail chains might locate their stores in nearby counties, where wages and prices co-move due to, for example, integrated labor markets or trade relationships. In a series of empirical exercises, I show evidence that common regional shocks are not driving my results.

First, I document that my results hold after conditioning on trade relationships due to geographic proximity. In fact, once the retail chains' channel is taken into account, geographic proximity play no role in propagating shocks. Second, I do not observe co-movement in other variables, such as wages, between counties linked by the retail chains' networks. Third, I show that shocks in similar counties do not explain my results. Finally, and more importantly, I turn to more granular data at the retailer-by-county level in a complementary empirical strategy. This allows me to include county-by-time fixed effects, which absorb any common variation within a county that is due to a regional shock, regardless of whether the shock is specific to that county or correlated with shocks in other counties. Using variation in price changes across stores within a county, I find an elasticity of store-level prices with respect to house price movements in other counties of 0.15-0.19.

County-level negative demand shocks can pressure retail chains' local prices downward through two channels: adjustments in the desired markup in that county or changes in the county's marginal costs. While the propagation of any of these components is interesting, evidence suggests that the marginal cost channel cannot be a significant factor, pointing to a markup related explanation.

In the final part of the paper, I propose a model of retail chains' pricing decisions to quantitatively interpret my findings and evaluate the role of retail chains in connecting economically counties in the U.S. Retailers compete under monopolistic competition and charge markups that can vary as a function of local demand conditions. In particular, I allow demand elasticity to vary with changes in local house prices. In the model, retail chains' headquarters can either set a uniform price or discriminate prices across their locations. If a retail chain sets uniform prices, its optimal price depends on a weighted average of the demand conditions in the different markets where it operates. Hence, when faced with a negative demand shock in a given region, the retail chain decreases its prices in all regions where it operates.

The model also highlights that the effect of local shocks on local price indices is heterogeneous: under uniform pricing, the pass-through of local shocks to local prices becomes a function of how important the local consumer market is in the national sales of the retailers that enter the local consumption basket.

I use the model to quantify the effects of the Great Recession under different pricing strategies. I consider flexible pricing strategies versus uniform pricing strategies. Compared to uniform pricing, under flexible pricing the counterfactual cross-county dispersion of inflation would have been 50% larger. This reveals novel consequences of the centralized decision-making of multi-establishment firms: they can exacerbate the negative impacts of a crisis in the local market. This is because such centralized decisions can dampen the downward adjustment of local prices, while reducing prices in unaffected regions.

This paper contributes to different strands of the literature. First, it contributes to the international and intra-national trade literature that studies how shocks propagate across regions. In the international context, a number of papers study how multinationals characteristics of parent companies and their affiliates generate co-movements between countries (e.g: Boehm et al. (2019), Cravino and Levchenko (2017), Hjort et al. (2020)). Unlike previous studies, my paper focuses on the role of firms' centralized pricing strategies and their effect on price co-movements across regions of the U.S. The advantage is that I can observe establishment level prices, usually unobserved in the international context.

Less has been done to understand the role of firms' networks within a country, with two exceptions: Hyun and Kim (2019) and Giroud and Mueller (2019). Hyun and Kim (2019) study U.S. manufacturers that are located in a given region who sell (*export*) multiple products to multiple regions (*multi-destination firms*). They find that a negative demand shock in a region can induce producers to substitute the production of high-quality products for low-quality products, creating co-movement in sales across markets. In contrast, I study firms in the non-tradable sector that have establishments in multiple regions and sell locally (*multi-establishment firms*). My findings are compatible with multi-market producers changing their product mix, but I focus on a different mechanism. Holding constant the set of products (and quality) sold by the retailer, local demand shocks affect prices of continuing products in distant markets that are connected by the retail chains' network of stores. My mechanism also has opposite implications for consumers: the local effects of a crisis make local consumers worse off, while benefiting consumers in unaffected regions.

More closely related, Giroud and Mueller (2019) find that financially constrained firms spread local demand shocks, affecting employment in distant regions where the parent firm operates. The channel I study is different: regardless of financial constraints, retail chains' pricing strategies create inter-dependencies between their establishments. While results in Giroud and Mueller (2019) have implications for firms' workers, my results have implications for firms' consumers. Note also that in Giroud and Mueller (2019) local employment is less sensitive to the local shock, attenuating the impacts of the local crisis. In contrast, my paper is the first one to propose a mechanism through which multi-establishment firms' centralized decisions can intensify the local effect of the crisis, benefiting regions that were less affected.

Second, this paper relates to the literature that studies the collapse in house prices during the Great Recession (Mian et al. (2013), Giroud and Mueller (2019), Kaplan et al. (2020), and Stroebel and Vavra (2019)). Stroebel and Vavra (2019) finds a high elasticity of local prices with respect to house price-induced local demand shocks during the Great Recession. I complement their results by showing that house price-induced local demand shocks affected not only local prices but also prices in distant regions linked by the retail chains' networks.

Third, this paper helps reconcile the puzzling findings in DellaVigna and Gentzkow (2019) and in Stroebel and Vavra (2019). While DellaVigna and Gentzkow (2019) show that retail chains charge similar prices in all their stores, Stroebel and Vavra (2019) find large effects of local demand shocks on retail prices. First, I show that once I control for shocks from regions linked by retail chains, the elasticity of local retail prices with respect to local house prices decreases by 35%. Second, the predictions from my model indicate that uniform pricing could actually be consistent with local price responses to demand shocks, as long as the regions experiencing the shocks are an important market for their own retail chains.

More generally, my paper contributes to papers that explore the cyclicality of markups. Studying predictable and recurring seasonal patterns Butters et al. (Forthcoming) and Chevalier et al. (2003) find counter-cyclical markups. In contrast, research examining markups across the business cycle, such as Stroebel and Vavra (2019) and Nekarda and Ramey (2020), finds procyclical markups. My paper shows that even in a context of uniform pricing local markups are procyclical across the business cycle. However, my results highlight that this procyclicality is lower when retail chains have centralized pricing decisions. The degree of the procyclicality in response to local shocks is higher when shocks occur in counties that are important for their dominant retail chains.

Fourth, my findings relate to literature that examines how retail prices respond to policy. In a recent paper, Handbury and Moshary (2021) study the effects of the National School Lunch Program (NSLP) on prices. Consistent with my results, they find that retail chains highly exposed to the NSLP reduced prices on all their outlets. While their study focuses on the policy implications of the NSLP, this paper studies the geography of retail chains to quantify a new mechanism through which local economic shocks propagate, connecting food-at-home inflation rates in different regions.

My paper is also related to Butters et al. (2022), which examines how retail chains respond to local cost policies, such as excise taxes on cigarettes, liquor, and soda. They find that local state-level excise taxes are passed on one to one to prices locally. My study complements Butters' findings in two ways. In contrast to their findings, I show that retail chains do propagate local demand shocks to distant markets. This indicates that the national responses of the retail chains to shocks depend on whether the local shock affects the marginal costs or demand of the retail chains. Second, my research analyzes a more extensive range of products representing households' retail consumption baskets and highlights the geographic links created by retail chains so I can draw conclusions at the aggregate regional level.

Finally, this paper contributes to the literature that uses micro-data to study pricing dynamics (e.g., Nakamura (2008), Coibion et al. (2015), among others). More specifically, recent literature that has documented the existence of imperfect price discrimination in different sectors. Nakamura (2008) shows that retail chains' effects explain a substantial share of price variation in the US. DellaVigna and Gentzkow (2019), Daruich and Kozlowski (2023), Adams and Williams (2019), Cavallo (2017) show evidence of firms charging near uniform pricing. I assess the role of retail chains decisions in shaping the propagation of local demand shocks across regions of a country.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 documents stylized facts regarding the geographic distribution of retail chains. Section 4 presents the empirical analysis. Section 5 presents the model. Section 6 presents the quantitative analysis and counterfactual analysis. Section 7 concludes.

2 Data

I combine data on county-level changes in house prices during the Great Recession (2007-2011) with store-level NielsenIQ Retail Scanner data.[3] Appendix Table A.I reports summary statistics.

2.1 Retailer Scanner Data:

I use the AC NielsenIQ Retail Scanner Database that has information on weekly price and quantity sold generated by point-of-sale systems for more than 100 participating retail chains across US markets between 2006 and 2016. The data includes more than 35,000 grocery, drug and mass merchandiser stores located in 2100 counties.

[3]Timing convention follows Stroebel and Vavra (2019) to facilitate comparisons. Results are robust to the alternative timing 2007-2009; following, for example, Mian et al. (2013).

Following DellaVigna and Gentzkow (2019), I define a retail chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. "Parent code" indicates the company that owns a chain and "retailer code" indicates the chain itself. I require retail chains to exist every year between 2007 to 2011. This reduces the number to 84 retail chains. I focus on frequently sold products available in at least 80% of the markets.

I aggregate data to construct half-year prices, reducing high-frequency noise. The half-year price of an item is calculated by dividing total sales value by total units sold during the period. As the paper focuses on (a) prices of existing products and (b) variation in price indices over time, I include items with positive sales in both 2007 and 2011.

County-level Price Index: In the main analysis, I assume that consumer behavior features multi-stage budgeting in two stages. In the last stage, consumers choose within NielsenIQ product modules. I construct product-module price indices by aggregating continuing varieties, defined as store-barcode combination, as in Sato Vartia (1976). Next, I construct the county-level Laspeyres price indices by weighting these product-module price indices by initial-year revenue shares of the product module. Retail chain price indices by county are constructed similarly. Details in Appendix B.

The NielsenIQ county-level inflation rate that I constructed closely aligns with the food-at-home inflation reported by the BLS. Appendix Figure A.III illustrates that both series exhibit similar national CPI trends and demonstrate a strong correlation between BLS and NielsenIQ regional inflation rates.

In the body of the paper I concentrate on a single benchmark price index, but in Appendix D, I show that the main results hold for price indices constructed under alternative assumptions, including adjusting the price index for entry and exit of barcodes and stores (Appendix D.4).

2.2 Wholesale cost data

To explore whether the price changes are triggered by changes in demand or costs, I incorporate data from National Promotion Reports' PRICETRAK database (Promo-

Data). The data provides wholesale costs of products sold by retailers. It has information from major confidential wholesalers and contains data for 32,000 individual UPCs from 2006 to 2012, covering 30 markets in 2007 and 13 markets in 2011.

2.3 House price data and housing supply elasticity

I obtain House price data at the county-level from the Federal Housing Finance Agency (FHFA). The agency constructs a House Price Index (HPI), a broad measure of the movement of single-family house prices. The HPI is a weighted, repeat-sales index, meaning that it measures average price changes in repeat sales on the same properties. [4] For the main analysis, I focus on long differences between the first half of 2007 and the first half of 2011.[5] Throughout the period, house prices dropped 18% (see Figure A.I). It is well known that the changes in house prices were highly heterogeneous in space: some counties like Miami suffered large reductions on house prices (more than 50%), while others such as Houston were almost unaffected.

The other major data set related to house prices used in the paper is obtained from the 2005 Wharton Regulation Survey. Gyourko et al. (2008) use the survey to produce indexes that provides information on local land use control environments, including the general characteristics of the regulatory process, statutory limits on development, density restrictions, open space requirements, infrastructure cost sharing and approval delay. Lower values in the Wharton Land Regulation Index (WLRI, henceforth) indicate the adoption of less restrictive policies toward real estate development. In contrast, high values of the WLRI are associated with municipalities that have zoning regulations or project approval practices. I process the original municipal-based data to create average regulation indexes at the county level. The WLRI is only available for 924 counties, out of the 2100 counties in NielsenIQ Data. However, these 924 counties represent more than 70% of total sales in the NielsenIQ Data and cover more than 70% of the U.S. population.

[4] These data are highly correlated with data from Zillow (96%)

[5] This timing convention follows Stroebel and Vavra (2019) to facilitate comparisons with their results. Additionally, the house-price collapse started at the end of 2006/beginning of 2007 and from the second half of 2011, house prices stopped declining (See Figure A.I in the appendix). All results are robust to the alternative timing 2007-2009; following, for example, Mian et al. (2013)

3 Facts on the geographic distribution of retail chains

Retail chains are multi-establishment firms operating across many regions with uneven spatial distribution. More than 60% of retail chains operate in two states or more.

In addition, retail chains exhibit substantial variation in their geographic layout. To quantify this, I construct a Geographic Dispersion Index (GDI) for each retail chain, defined as $GDI_r = 1 - \sum_c S_{rc}^2$, where $S_{rc} \equiv \frac{Sales_{rc}}{\sum_c Sales_{rc}}$ denotes the share of chain r's total national sales that occur in county c. A higher value of GDI_r reflects a more geographically dispersed chain, while lower values indicate sales concentrated in fewer locations. The distribution of this index is plotted in Figure I to reflect this heterogeneity. Fewer than 20% of the retail chains in the sample have a GDI below 0.5.

Finally, retail chain's networks have different geographic layouts. Some retail chains are spread over several regions in the US and are active in many states. Others cover an extensive area but are spread across counties in those areas. Finally, other retail chains are concentrated in a specific geographic area.[6]

The documented heterogeneity in the spatial distribution of retail chains can also create varying connections between counties, depending on whether they share the same retail chains. The next section characterizes these linkages and study the role of retail chains in propagating local shocks.

4 Empirical analysis

I begin the analysis by constructing bilateral weights that characterize how connected each pair of counties is. Given these weights, I construct the exposure of each county to house price shocks in other counties and study the sensitivity of county-level prices to house price-induced shocks in other counties. I then discuss the identification assumptions and address potential threats to the validity of those assumptions.

[6]To safeguard the confidentiality of individual retail chains, NielsenIQ does not permit the disclosure of results for any specific retail parent company. To illustrate the different geographic layouts without referencing any chain included in the data, the reader is referred to publicly available examples at the following link: https://flowingdata.com/2013/06/26/grocery-store-geography/

4.1 Bilateral linkages and exposure variables

I use NielsenIQ Scanner data to characterize the bilateral linkages between each pair of counties and the exposure of stores and counties to shocks in other counties.

Define the retail chain's network weights S_{rc} as the share of retail chain r's national sales that takes place in county c in 2007: $S_{rc}^{2007} \equiv \frac{Sales_{rc}^{07}}{\sum_c Sales_{rc}^{07}}$. These weights measure the importance of the market c for the retail chain r.

Then, the exposure of retail chain r in county c to house price shocks in other counties k is a weighted average of house price changes across US counties:

$$\text{Store}\Delta \log HP(others)_{rc} \equiv \sum_{k \neq c} S_{rk}^{07} \Delta \log(HP_k)^{07-11}, \tag{4.1}$$

where $\Delta \log(HP_k)^{07-11}$ is the log change in house prices between 2007 and 2011 in k. The network of retail chains creates links between each pair of counties. These links will also depend on which retail chains are important in the county. Define $l_{rc}^{07} = \frac{Sales_{rc}^{07}}{\sum_r Sales_{rc}^{07}}$ as the share of county c's total retail sales from retail chain r in 2007.

I define a county's exposure to house price changes in other counties as the weighted average exposure of retail chains that operate in that county. Formally,

$$\text{County}\Delta \log HP(others)_{c} \equiv \sum_{k \neq c} \sum_{r} l_{rc}^{07} S_{rk}^{07} \Delta \log(HP_k)^{07-11}. \tag{4.2}$$

Weights $\omega_{ck}^{07} = \sum_r l_{rc}^{07} S_{rk}^{07}$ summarize the bilateral exposure of county c to county k. Equation 4.2 is the main variable in my analysis. The exposure of a county to shocks in other counties is the network-weighted average HP changes in other counties, where the weights are given by the bilateral exposure of county c to each county k.

The weights ω_{ck} are at the center of my analysis. Intuitively, a county c will be more exposed to shocks in county k if county k is an important market (S_{rk}) for the dominant chains that operate in c (l_{rc}). As an illustrative example, in Figure II I show how counties in the sample are exposed to shocks in Los Angeles County (LA, from now on). The map plots $\omega_{c,LA}$ for every county c in the sample. I segment the sample in deciles and assign colors ranging from light yellow to red, with red counties c being those that are more exposed to shocks in Los Angeles (high $\omega_{c,LA}$). We can observe three patterns. First, counties located near LA tend to be more connected to LA. Second, we also observe strong linkages with counties that are far away. For example, Santa Barbara is less exposed to shocks in LA than some counties located in Michigan.[7] Third, even counties next to each other have heterogeneous exposure to LA.

4.2 Main analysis: OLS and Instrumental Variables

I empirically estimate how house price-induced local demand shocks propagate through the network of retail chains. I start by examining the sensitivity of county-level food-at-home prices to changes in house prices in other counties. Formally, I estimate the following equation in long differences from 2007 to 2011:

$$\Delta \log(P_c)^{07-11} = \beta_0 + \beta_1 \Delta \log(HP_c)^{07-11} + \beta_2 \sum_{k \neq c} \omega_{ck}^{07} \Delta \log(HP_k)^{07-11} + X_c + \epsilon_c, \quad (4.3)$$

where $\Delta \log(P_c)^{07-11}$ denotes the log change in county-level retail price index for continuing varieties in county c. $\Delta \log(HP_c)^{07-11}$ denotes the local change in house prices in county c. This variable controls for the direct effect of house price changes on retail prices and its coefficient is also useful to compare with papers studying the local effects of house prices changes on prices (e.g. Stroebel and Vavra (2019)). My main variable of interest is the county-level exposure to shocks in other counties. X_c is a vector of time-varying controls at the county-level. It includes changes in local wages, changes in employment, changes in number of retail establishments. The vector also includes county's own weight (ω_{cc}) as a county-level control to account for the incomplete weights in the leave-out exposure variable.[8] S.E. are clustered at the state level.[9]

I start by reporting the OLS results In Columns (1) to (3) of table I. The first row reports the direct effect of the shock. The second row reports the elasticity of county-level prices with respect to house price changes in other counties that are linked by the network of retail chains. In Column (1), I report the direct effect of house price changes on county-level prices. Similar to previous papers, I find that there is a pos-

[7]In section 4.3, I discuss in detail the role of proximity in explaining my results.

[8]Results are robust to other combinations of controls at the county-level. See A.VII of Appendix D.3.

[9]In a sensitivity analysis, in Table A.XXIII of Appendix D.3, I compute standard errors allowing for arbitrary cross-regional correlation in the regression residuals as suggested by Adao et al. (2019).

itive relationship between house price changes and local retail prices. In Column (2), I add the main variable, the network-weighted house price changes in other counties. I find that a 10 percent drop in network-weighted house prices in other counties is associated with a 0.85 percent reduction in county-level prices. This result remains almost unchanged in Column (3), after including county-level controls such as changes in employment, wages and number of establishments.[10]

Although the OLS estimates constitute suggestive evidence of the spillovers, both the local change in house prices and, more importantly, the exposure to house price changes in other counties can suffer from endogeneity. For instance, contemporaneous negative productivity shocks could lead to an increase in retail prices and, at the same time, a decrease in house prices. This would lead to a downward bias in our estimate for the direct effect. Even when the shift-share variable is arguably less problematic, it could also present problems. The location of retail chains' stores is not random. For example, to reduce transportation costs, retail chains' might be clustered geographically. If this were the case, regional productivity shocks correlated with house prices could generate co-movement in prices between counties connected by retailers.

My first strategy to deal with these issues is to instrument the two main variables. Regarding local house prices changes, I follow an extensive literature that exploits across county variation in housing supply elasticity (e.g. Mian and Sufi (2011), Adelino et al. (2015), Stroebel and Vavra (2019), among others). In particular, in my baseline specification, I use the county-level Wharton Land Regulation Index (WLRI) from Gyourko et al. (2008) to instrument for local house price changes. The idea is that in response to a national level negative housing demand shock, areas with lower housing supply elasticity (e.g.: high WLRI) will experience a larger drop in house prices.[11]

[10] Appendix Figure A.VIII visually illustrates the variability behind the OLS relationship in Column (3).

[11] Note that the variability of the instrument implicitly comes from the interaction of housing initial supply elasticity (WLRI) with the national demand shock that took place between 2007 and 2011. This is what allows a time-invariant instrument to predict time-varying house prices. Specifically, the instrument is equivalent to: $\text{WLRI}_c^{2006} \times \Delta\text{HP}^{\text{USA07-11}}$. In a complementary analysis, I repeat the estimations using the Saiz (2010) Housing supply elasticity (Saiz HSE), based on the geography of the county. The coefficient across different IV strategies is remarkably similar and I cannot reject the hypothesis that they are equal (See Table A.IX of Appendix D.3).

More importantly, I combine the WLRI with the location of the retail chains to construct an instrument for retail chains' exposure to house price shocks. I instrument network-weighted changes in house prices with network-weighted changes in WLRI.

$$WLRI_c \rightarrow \Delta \log(HP)_c \quad ; \quad \sum_{k \neq c} \omega_{ck}^{2007} WLRI_k \rightarrow \sum_{k \neq c} \omega_{ck}^{2007} \Delta \log(HP)_k$$

Intuitively, a county will be more exposed to house prices drops in other counties if the county's dominant chains have higher sales in counties with tighter land regulations. While house price changes in counties linked by the retail chains might correlate with regional productivity changes that generate co-movement in prices, the WLRI isolates variability in house prices that is not correlated with those productivity changes.

My main identifying assumption is that in the absence of linkages between counties through the retail chains' network, changes in county-level retail prices would be uncorrelated with WLRI in regions that are linked by the network of retail chains. Note that this assumption is milder than the assumption in studies that use housing supply elasticity to instrument house price changes (e.g: Stroebel and Vavra (2019)). Those studies rely on the assumption that local housing supply elasticity only affects the local outcomes through its impact on house prices. That is a sufficient condition (though not necessary) for exogeneity of the network-weighted housing supply elasticity. The intuition is straight-forward. If housing supply elasticity (combined with the national demand shock) does not directly affects local consumer prices, then it is even less likely that it will affect local consumer prices in distant markets.

Note also that in my shift-share design, identification relies on exogeneous variability in the shocks (e.g.: the combination between the county's WLRI and the national demand shock). As shown by Borusyak et al. (2018), if the shocks are as good as random, then we can identify the effect of interest even when, as in most applications, the exposure shares are not random.[12]

[12] In a recent paper, Goldsmith-Pinkham et al. (2020) provides conditions under which the shift-share instrument is exogeneous when the shares are exogeneous. However, in most of the interesting economic settings (including mine), the shares are not necessarily random. Borusyak et al. (2018) shows that as long as the shocks are as good as random, then identification is granted, even when the exposure shares are endogeneous. In section 4.3 I perform a series of robustness exercises and discuss

There are important remaining challenges to the identification assumptions. For example, if the WLRI is not as good as random and, at the same time, retail chains locate their stores in nearby locations, then unobserved regional shocks that correlate with housing supply elasticity could generate co-movement in prices, even in the absence of retail chains' networks. In this section, I present the main empirical results of the paper and I address this and other concerns in Section 4.3.

I begin by providing a visual impression of the first stage and the reduced-form coefficient of the indirect effect. In Panel (a) of Figure III, I plot the relationship between the network-weighted WLRI and the network-weighted change in house prices (first-stage). As expected, the network-weighted WLRI negatively correlates with the network-weighted house price change. Counties linked to counties with tighter land regulations are counties linked to counties that experienced higher drops in house prices. In Panel (b) of Figure III, I plot the relationship between network-weighted WLRI and local retail prices (reduced-form). The pattern is clear: counties more exposed to a higher network-weighted WLRI in other counties experienced a higher drop in local consumer food-at-home price index.

After inspecting the data visually, I report the main findings of the paper in Table I. Columns (4) to (6) present the IV estimates. In Column (4), I report the local elasticity of county-level retail prices with respect to house prices. The elasticity is 0.115.[13] In Column (5), I add the network-weighted change in house prices in other counties. First, note that once I control for the spillovers from other counties, the direct effect declines 40%. This indicates that past studies might have overestimated local elasticity by not considering these spillovers. More importantly, the second row of Column (5) reveals the elasticity of local retail prices in response to shocks from other counties. Conditional on the local changes in house prices, a 10 percent drop in house prices in other counties linked by the network of retail chains leads, on average, to a decrease of 1.30 percent in county-level consumer prices. Reassuringly, the coefficient remains

extensively the plausibility of my identification assumptions. In section, D.3.3 I exploit high-frequency data and variability from an alternative instrument, obtaining similar results.

[13]This is slightly below the estimates found by Stroebel and Vavra (2019), who, using a different database and a different level of geographic aggregation, report a range of 0.124 to 0.157.

stable after including county-level controls in Column (6).

At first glance, the larger spillover coefficient compared to the direct effect may seem surprising. However, the theoretical model in Section 5 will provide an explanation for this: in a context of uniform pricing, these coefficients are not directly comparable. To make them comparable, the local house price change must be adjusted by the county's importance to the dominant retail chains operating in that county, ω_{cc}. After this adjustment, the two coefficients become similar (see Table A.XXXI).

In Appendix D.3, I explore the sensitivity of my results to alternative specifications. First, I show that the main coefficient remains remarkably stable after adding different combinations of county-level controls (Table A.VII). Second, I repeat the analysis, but now instrumenting the endogeneous variables with the Saiz (2010) geography-based housing supply elasticity (Table A.IX). Third, I show that results are not sensitive to: a) constructing price indices under different assumptions (Table A.XI), b) replicating the analysis for the period 2007-2009 (Table A.XII), c) including different combinations of regional fixed effects (Table A.XIII), d) considering three digits zip code as the relevant market, e) excluding counties for which NielsenIQ sales are less representative (A.XVII), and f) excluding California (Table A.XVIII). Fourth, results remain significant in Table A.XXIII where follow Adao et al. (2019) to adjust standard errors. Finally, in section Appendix D.3.3 I extend the data to yearly frequency and employ a different empirical strategy based on an IV strategy proposed by Graham and Makridis (2023).

In the next section, I address the main challenges to my identification assumptions.

4.3 Validity of identification assumptions

The key identification assumption is that, in the absence of the retail chains' network of stores, changes in county-level prices are uncorrelated with housing supply elasticity in the regions that are linked by the retail chains networks. In regard to this assumption, the biggest challenge is to separate the propagation of shocks through retail chains' networks from common shocks in the regions in which the retail chains operate. For example, to minimize transportation costs, retail chains might locate their stores in neighboring counties where wages and prices co-move because of other reasons, such as integrated labor markets or trade links. In this section, I address these concerns.

First, I document that my results hold after controlling for trade relationships due to proximity in space. Second, I show that the network of retail chains does not affect other economic outcomes in distant locations, which suggests the absence of other factors creating co-movements. Third, I show that shocks in similar counties are not behind my results. Fourth, I filter out any remaining concerns about common regional shocks by turning to more granular data at the retail chain-by-county level, which allows me to include county $\times$ time fixed effects.

4.3.1. Retail chains' network of stores or proximity channel?: Thus far, I have abstracted from the role of geographic proximity. However, it is important to disentangle whether my results are explained by the network of retail chains or by trade relationships due to proximity in space that correlates with the network of retail chains.

I begin by showing that even shocks in out-of-state counties are propagated through the network of retail chains. I construct the network-weighted change in house prices, excluding changes in house prices in counties that are in the same state. I then estimate the leave-state-out version of my main specification (Equation 4.3), while also instrumenting with leave-state-out WLRI. Results are reported in Table II. I find that local prices are sensitive to shocks in distant counties (out-of-state).

Next, I directly compare the retail chain network channel with the trade network channel. This has two purposes. First, assess whether my findings could be driven by other networks correlated with retail chain networks. Second, explore the role of proximity in shaping shock propagation, offering a comparison between my new channel of propagation of shocks and the more traditional propagation of shocks through trade relationships due to proximity.

Specifically, I construct proximity-weighted house price changes in other counties, where the weights are given by $\delta_{ck}^{prox} = \frac{d_{ck}^{-\theta} Population_{k,2007}}{\sum_k d_{ck}^{-\theta} Population_{k,2007}}$. d_{ck} is the distance in miles between county c and k and I assume $\theta = 1$. [14] Then, I add this variable as a control.

[14] Distances are obtained from National Bureau of Economic Research (compiled by Jean Roth (2014)). In Appendix D.3.13, I construct the weights based on trade flows between states.

Table III reports results. Columns (1) to (3) present OLS estimates. Columns (4) to (6) report IV estimates. Focus on Column (1), where only proximity-weighted shocks are included to study the role of trade channel propagation. This is how we have traditionally approached the analysis of shock propagation. A 10 percent drop in house prices in nearby regions results in a 1.19 percent decrease in retail prices. In Column (2), controlling for local house price changes still shows that proximity matters. However, in Column (3), adding shocks in counties connected by retail chains makes the geographic proximity effect insignificant, while the effect through retail chains' networks becomes positive. In the preferred IV specification in Column (6), controlling for proximity-weighted and local house price changes, the elasticity of local retail prices with respect to distant house prices is 0.16 (see A.IV for the first stage). These results are striking. They indicate that county-level retail prices depend more on demand shocks to the retail chains that happen to be serving the county than on trade relationships due to proximity in space.

4.3.2. Other networks: similarity between counties: Even when not located nearby, counties similar in characteristics are more likely to be exposed to common shocks. For example, New York and San Francisco are not nearby, but their prices might co-move because counties with similar income levels are affected by the same shocks. Similarly, recent papers have documented that links between counties by their social networks might also be relevant (Bailey et al. (2018a)).

To explore these alternative explanations, I first construct a variable that captures a county's exposure to house price changes in similar counties and add it as a control. I define similarity-weighted exposure to shocks in other counties as $\sum_{k \neq c} \delta^{sim}_{ck,0} \Delta LogHP_k$. The weights are defined as $\delta^{sim}_{ck,0} = \frac{1/|X_{c,0} - X_{k,0}|}{\sum_k 1/|X_{c,0} - X_{k,0}|}$ if $X_{c,0} \neq X_{k,0}$, and $\delta^{sim}_{ck,0} = 1/C$ if $X_{c,0} = X_{k,0}$, where C is 1% of the 1st percentile of the variable's distance. Intuitively, weights place a higher weight to shocks in those counties that are similar in a set of characteristics X at 2007. Column (1), I report my preferred specification as a benchmark. Column (2) to (6) control for exposure to shocks in counties with similar income levels, similar employment rates, population, education, and household debt, respectively. Throughout specifications, the estimate for the retail chain networks is significant and remarkably stable, ranging from 0.130-0.171.

Second, I compare spillovers through the retail chains' networks with spillovers through social links. The social connectedness index developed by Bailey et al. (2018b) place a higher weight on counties that share more Facebook relationships. Results are reported in column (7). Reassuringly, the main coefficient remains stable.[15]

4.3.3. The effect of retail chains' network of stores on other economic outcomes: If results were explained by common shocks to regions in which the retail chains operate, then we would expect co-movement not only in retail prices but also in other economic outcomes. For example, if results were explained by trade relationships between counties where retail chains operate, we would expect house price movements also to affect wages in distant counties. In contrast, it is less clear why the retail chains' network would affect wages in distant counties. Retailers represent a large share of household expenditure, affecting food-at-home prices directly, but they only represent a small share of aggregate employment. I estimate Equation 4.3 for other dependent variables such as: county-level employment, number of retail establishments, and average annual wages. Results reported in Table V indicate that local shocks have no significant effect these outcomes in distant counties.

Note that this result has another interesting implication. In response to local shocks, retail chains' centralized pricing decisions affect prices in distant regions, but not average wages. Hence, their decisions have consequences for consumers' real income.

As an illustrative example, Appendix Figure A.IX examines similar counties in Pennsylvania where house prices remained relatively stable. While prices in more connected counties showed greater responsiveness, retail chain networks did not exhibit a correlation with wage changes.

4.3.4. Retail by county level analysis: In order to address remaining concerns about separating the effect of the network of retail chains from common regional shocks, I turn to more granular data at the county-by-chain level. This allows me to include

[15] Appendix Table A.XXII also considers similarity in voting patterns and age as proxy of preferences.

county-level fixed effects to absorb any common variation within a county due to a regional shock, regardless of whether the shock is region-specific or correlated with shocks in other regions. Formally, I estimate the following equation:

$$\Delta \log(P_{rc})^{07-11} = \beta_2 \sum_{k \neq c} S_{rk}^{2007} \Delta \log(HP_k)^{07-11} + \gamma_c + X_r^{2007} + S_{rc} + \epsilon_{rc}, \tag{4.4}$$

where the weights S_{rk} are the share of the retail chain r's national sales that take place in county k. I aggregate stores of a retail chain in a given county to the retail chain by county level. Therefore, $\Delta \log(P_{rc})^{07-11}$ denotes the percentage change in price index for retail chain r in county c from 2007 to 2011. Analogously to the county-level analysis, I instrument the local changes in house prices and the store-level network-weighted changes in house prices with WLRI and store-level network-weighted WLRI. To account for incomplete weights, retail chain controls include the retail chain weight in the county, S_{rc}. Standard errors are clustered at both the retail chain and the state level.

Table VI reports results for the OLS (Columns 1 to 3) and the IV estimations (Columns 4 to 6). Panel B reports the Kleibergen-Paap F-statistic for the first stage, while first-stage coefficients are reported in Table A.V of the Appendix. Focus first on the OLS estimates. In Column (2), I include county fixed effects. Hence, I compare price changes of stores operating in the same county that are exposed to the same regional shocks, but that are exposed differently to shocks in other locations because they belong to different retail chains. The elasticity of retail chains' prices with respect to house prices in other regions is similar to the corresponding elasticity without county fixed effects. In Column (3), I add controls at the national retail chain level to account for differential trends for different retailers. Reassuringly, the elasticity of store-level prices with respect to house prices in other locations remains stable. When analyzing the IV estimates, we observe a similar pattern. In Column (6), my preferred specification, I include county fixed effects and retail chain controls. The elasticity of prices with respect to house price changes in other counties is 0.198. In Appendix D.3.9 I present a binscatter to illustrate the variability underlying this coefficient, along with additional robustness checks conducted at the county-level for the retail chain.

In Appendix D.3, I present additional tests. Two are noteworthy. First, I focus on counties where house prices changed by less than 5% during the period, minimizing the likelihood of common shocks similar to those affecting harder-hit counties (Table D.3.8). Second, I explore whether shocks affecting retail chains catering to different income groups could explain the results. The main conclusions hold (Table D.3.9).

4.4 Effects on consumption patterns

I have shown that retail chains can influence the transmission of local shocks to prices in distant markets. This, in turn, might affect household consumption patterns and retail chain quantities sold. In Table VII, I analyze the sensitivity of retail and county-level sales with respect to shocks in distant counties. Columns (1) to (3) report results from my main specification at the retail-by-county level, while including county fixed effects. Columns (4) to (6) present the results at the county level. I also include a decomposition of sales into changes in quantities and prices in each case. Results in Column (1) suggest that retail chains more exposed to house price declines in distant counties experienced a moderate sales increase, though significant only at the 15% level. In Column (2) we analyze the effect on quantities sold. We observe an elasticity of quantities sold with respect to shocks in distant counties of -0.54, which is consistent with the fact that retail chains more exposed to crisis elsewhere reduce prices relatively more, thereby increasing quantities sold. We observe a similar pattern at the county-level.

The observed substitution between retailers could affect the estimation of the impact of shocks on price indices, depending on the assumptions of the index regarding substitution. To assess this, I examine three indices that differ in their treatment of product substitution: (1) CES price indices for continuing varieties (benchmark), which partially account for substitution using initial and final period weights; (2) the Paasche index, fully accounting for substitution with only final period weights; and (3) the Laspeyres index, which does not account for substitution, relying solely on initial weights. The results are reported in the Appendix Table A.XI. The elasticity of county-level price index with respect to shocks in other counties across the different price indices is similar, ranging from 0.12 (Paasche) to 0.16 (Laspeyres).

4.5 Costs or markups

I have shown that house price-induced local demand shocks affect consumer prices in distant markets via retail chains. Price responses of retail chains to local demand shocks could be reflecting changes in markups or marginal costs (e.g: lower demand in a county leads to lower local wages). While either of the channels would be interesting, I discuss which is more consistent with the data. I find suggestive evidence that the empirical patterns are more consistent with a mechanism in which house price-induced local demand shocks pressured local markups downward.

First, it is important to understand the cost structure of retail chains. Retail chains' costs can be divided into two categories: wholesale costs of goods sold and operational expenses (e.g: labor costs, rent). Most of the costs are wholesale. To see this, I collected information from Form 10K official reports for the major US supermarkets and pharmacies.[16] Appendix Table A.XXVI reports the cost structure of the thirteen major companies in the sector. For a typical retail chain, 76% of costs are wholesale. The remaining 24% are operational expenses. Within operational expenses, labor costs are the most important category.

Next, I consider the role of local wholesale or labor costs.

Wholesale costs of goods: Since wholesale costs represent the majority of retail chains' marginal costs, a cost channel hypothesis requires that house price-induced demand shocks in a location affect retailers' wholesale costs in that location. However, retailers' products are tradable goods usually not produced locally. Hence, their price is less likely to be sensitive to local demand shocks. [17] Furthermore, The Robinson-Patman Anti–Price Discrimination Act explicitly limits how much wholesalers can charge different prices for the same product. To directly test the extent to which wholesale costs vary geographically, I use PromoData for 2007, which provides av-

[16] Data from https://last10k.com/sec-filings/swy, accessed on January, 2023.

[17] According to commodity flows survey data in 2007, only 14 percent of food and beverage shipments by gross value added are shipped from less than 50 miles.

erage monthly wholesale prices for approximately 32,000 UPCs across 30 metro areas. I find that geographic variation in wholesale costs is remarkably small. In a typical month, 83% of the products were sold at a price within 2% of the modal price. Aggregating wholesale prices at the metro area level produces a similar pattern (see Figure A.XI in the Appendix). To further test this, I examine the degree of geographic variability in the changes in the wholesale costs of goods across 12 metropolitan areas for which we observe data from PromoData for the years 2007 and 2011. Again, there is minimal geographic variation in wholesale cost changes, and this variation is not correlated with local house price movements (see Appendix Figure A.XII).

The fact that wholesale costs do not vary across markets is not new. It has been previously documented in the literature by Nakamura (2008), Stroebel and Vavra (2019), among others. Given the little geographic variation in wholesale costs, it is less likely that house price movements would affect the local wholesale costs of goods sold by a retail chain.

Labor costs: Wholesale costs are the primary component of our retail marginal costs and cannot drive empirical patterns. Next, I consider if the labor costs component could be the trigger of retail chains' price responses. Since labor costs are a small fraction of the overall marginal cost of retail chains in the data, explaining retail price movements in the period through this channel would require huge responses of local labor costs to local demand. To test the role of wages, in Appendix Table A.XXVII I augment my main specification with controls for local change in wages and weighted average changes in wages. I find that the cost channel is not a key driver, as the additional variables do not affect my main estimate.

Based on the analysis above, retail chains' price responses to house price-induced local demand shocks cannot be solely attributed to local wholesale or labor costs. Results in this section suggests a mechanism in which local demand shocks have increased county-level demand elasticity, leading to reduced markups for retail chains. Combined with centralized pricing decisions, this results in downward price pressure in distant counties.

I have shown empirically that retail chains play a key role in shaping the propagation of local shocks. I now turn to a model of retail chains' pricing decisions.

5 A model of retail chains' pricing decisions

I develop a model of retailers' pricing decisions to quantitatively interpret the findings and assess the role of retail chains in propagating shocks across regions.

5.1 Demand

Consider a country that has a finite number of markets, $c = 1, .., C$. The market definition I use is county, so retail chains only compete for consumers within a county.

Define Ω_c as the set of active retail chains in county c, Ω_r as the set of counties in which retail chain r is active, p_{rc} as the price of retail r in county c, and P_c as the price index in county c. Assuming direct separability, the demand for retail chain r in county c when prices are $\mathbf{p} \equiv \{p_{rc}\}_{r \in \Omega_c}$ is given by $q_{rc} = D(p_{rc}/P_c)$. I assume $D(x) \in C^2(x)$ is twice differentiable with $D'(x) < 0$ and partial price elasticity given by $\sigma_c = \frac{\partial q_{rc}}{\partial p_{rc}} \frac{p_{rc}}{q_{rc}}$. I allow variable markups by letting σ_c vary with demand conditions in county c.

I now turn to the price setting of retail chains. I consider two extreme pricing strategies: uniform pricing and flexible pricing. First, I briefly discuss the standard case of flexible pricing. Then, I solve the model for uniform pricing: a case in which firms are constrained to set the same price in all their markets.

5.2 Retail chains pricing decisions

I assume that retail chains engage in monopolistic competition. Since the empirical section suggests that extensive margin is not a first order margin of adjustment, I assume there is no store entry and exit (for a discussion on the extensive margin, see Appendix D.4). Guided by the empirical patterns, I emphasize the markup channel. Therefore, I assume that marginal costs are national and that local marginal costs are not affected by local shocks $c_{rc} = c_r$.[18]

Flexible pricing: If firms perfectly discriminate prices across markets, each store

[18]Results presents in section 4.5 suggests that wholesale costs have minimal geographic variation. In addition, variations in labor costs do not play a significant role. See section . In Appendix E.3, I formally discuss the relevance and implications of this assumption and also discuss a model with local costs.

maximize as an independent business unit. Price of retailer r in county c is $p_{rc}^{flex} = \frac{\sigma_c}{\sigma_{c-1}} c_r \;\; \forall \;\; c \in \Omega_r$. Note that optimal price is independent of demand shocks in markets $k \neq c$. I aggregate prices at the county-level with a Geometric weighted average price index, where the weights are given by l_{rc}: $P_c^{Flex} = \prod_r \left(\frac{\sigma_c}{\sigma_c - 1} c_r \right)^{l_{rc}}$.

Uniform Pricing: If firms set uniform prices, a retail chain solves:

$$\max_{\bar{p}_r} \quad \sum_{c \in \Omega_r} \pi_{rc} = \sum_{c \in \Omega_r} (\bar{p}_r - c_r) q_{rc}$$

Solving the maximization problem, the optimal price of retail chain r is,

$$p_{rc}^{u} = \bar{p}_r = c_r \frac{\sum\limits_k \sigma_k S_{rk}}{\sum\limits_k S_{rk}(\sigma_k - 1)} \quad \forall c \in \Omega_r. \tag{5.1}$$

As in the empirical section, S_{rc} is map to the share of retail chain's sales that take place in c. Equation 5.1 anticipates the mechanism through which uniform pricing operates. The price of a retail chain in a county is a weighted average of demand conditions in each of its active markets, where the weights are proportional to its sales.

5.2.1. Implications of Uniform and Flexible Pricing:

(I) Propagation of shocks: Under uniform pricing, within a given county, retail chains with higher exposure to demand shocks in other counties will exhibit a stronger price response. The intensity of this response is proportional to the retailer's sales in the affected markets. In contrast, with flexible pricing, local prices remain unaffected by shocks originating in other regions.

(II) Direct effect of local shocks within a retail chain: Under uniform prices, comparing within a retail chain, a local shock is not expected to affect its local prices relative to its prices in other locations, as the adjustment happens in all locations. In contrast, under flexible pricing, a local shock will affect the retail chain local prices compared to its prices in other locations.

(III) Direct effect of local shocks across retail chain: In both pricing scenarios, local retailer's prices react to local shocks when comparing across different retailers.

Evidence at the retail-by-county level supports each implication. My main empirical analysis at the retail-by-county level tests Implication (I). Column (6) of Table VI shows a positive elasticity of retail chain local prices to shocks in other counties, even after including county fixed effects. This rejects flexible pricing models. I test Implication (II) in Appendix Figure A.XIII. The Figure shows that once retail chain fixed effects are added to Equation 4.4 to compare price changes of the same retail chain across its locations, the direct effect coefficient becomes zero. This rejects flexible pricing model where this elasticity would be expected to be positive. Finally, my main empirical analysis at retail-by-county level also supports Implication (III), as evidenced by the positive elasticity of local prices to local house price changes shown in Columns (4) and (5) of Table VI where I do not include retailer fixed effects.[19]

5.2.2. Aggregation: To explore the theoretical implications at the county-level, I aggregate optimal prices in a given period by taking a geometric weighted average:[20] $P_c^U = \prod_r (P_{rc})^{l_{rc}}$, where, as in the empirical section, the weights l_{rc} represent the share of retail chain r in county c annual revenues. Replacing optimal uniform prices:

$$P_c^U = \prod_r \left(\frac{\sum_k \sigma_k S_{rk}}{\sum_k S_{rk}(\sigma_k - 1)} c_r \right)^{l_{rc}}$$

Consider the partial equilibrium elasticity of county-level prices with respect to changes in the demand elasticities, while holding the shares constant. Differentiating around the initial equilibrium and holding s_{rk} and l_{rc} constant at the initial equilibrium, I obtain an equation that characterizes the first-order effects of shocks under uniform pricing strategies (See proof in appendix E.2).

$$d \log P_c^U = - \left[\sum_r l_{rc}^{07} \theta_{rc}^{07} \right] d \log \sigma_c - \sum_{k \neq c} \sum_r l_{rc}^{07} \theta_{rk}^{07} d \log \sigma_k + \sum_r l_{rc}^{07} d \log c_r, \qquad (5.2)$$

[19] Implication (III) is not informative about the pricing strategy, as it holds true in both cases.

[20] This is a Laspeyers geometric price aggregator, which is consistent with a Cobb-Douglas utility function with shifters l_{rc} and is the aggregator that the BLS use.

$$\text{where } \theta_{rk}^{07} = \frac{S_{rk}^{07}\sigma_k^{07}}{\left[\sum_k S_{rk}^{07}\sigma_k^{07}\right]\left[\sum_k S_{rk}^{07}(\sigma_k^{07}-1)\right]}.$$

θ_{rk}^{07} is increasing in S_{rk}^{07} and determines the importance of county k for retail chain r. Define the theoretical exposure of county c to county k as $\kappa_{ck}^{07} = \sum_r l_{rc}^{07}\theta_{rk}^{07}$ which resembles empirical weights $\omega_{ck}^{07} = \sum_r l_{rc}^{07} S_{rk}^{07}$.

Equation 5.2 summarizes the three sources of variation for the county-level price index under uniform prices. First, local demand shocks will affect the local consumer price index, as long as the county is important for its dominant chains (high κ_{cc}). Second, demand shocks in other locations will also affect the local price index. The extent to which demand shocks in a county k affect county c price index depend on how important is market k (θ_{rk}^{07}) for dominant chains (l_{rc}^{07}) in county c (l_{rc}^{07}). Finally, changes in the national costs of retail chains that operate in the county (c_r) also affect the county-level price.

6 Quantitative analysis

In this section, I use Equation 5.2 to take the model to the data to test for uniform pricing, interpret the results and conduct counterfactual analysis.

6.1 Taking the model to the data

First, I introduce assumptions about the relationship between house price changes and the parameters in the model in order to rationalize the main findings.

To emphasize the demand channel, I let the demand elasticity to vary with house prices. Let $\beta^H = -\frac{\partial \log \sigma_c}{\partial \log HP_c}$. As my focus is in the average effect, β^H does not vary by county. Allowing β^H to vary by county would allow to explore heterogeneous effects depending on county's characteristics. I discuss this in Appendix E.5.2. [21]

Combining β^H and Equation 5.2 and scaling terms by the average elasticity, $\tilde{\sigma}-1$:

$$d\ln P_c = \frac{\beta^H}{\tilde{\sigma}^{07}-1}\kappa_{cc}^{07}(\tilde{\sigma}^{07}-1)d\ln HP_c + \frac{\beta^H}{\tilde{\sigma}^{07}-1}\sum_{k\neq c\in\Omega_r}\kappa_{ck}^{07}(\tilde{\sigma}^{07}-1)d\ln HP_k + \sum_r l_{rc}^{07} d\ln c_r, \quad (6.1)$$

[21]For example, one might be interested to include interaction variables to capture whether counties with specific characteristics are more sensitive to house price shocks.

Equation 6.1 resembles my main empirical Equation 4.3 with two important differences that I account for. The main difference is related to the direct effect of a house price change (first term RHS in blue). The model highlights that the effect of local shocks on local retail is a function of how important the local consumer market is for retailers operating in that county (κ_{cc}). Intuitively, if a shock occurs in a county with national retailers, local prices remain largely unaffected. Conversely, shocks in counties dominated by local retailers lead to greater price reactions.[22]

This has three important implications. First, it implies that uniform pricing strategies can be consistent with large local price elasticity; as long as the shocks occur in regions that are important for their own retail chains (high κ_{cc}). Given that counties with higher κ_{cc} were more affected by the house price slump, this helps reconcile the evidence of uniform pricing in DellaVigna and Gentzkow (2019) with evidence of large local elasticity of county-level prices with respect to local shocks in Stroebel and Vavra (2019). Second, it implies that researchers interested in recovering the elasticity of prices with respect to local economic shocks should weigh the local shocks by the importance of the own county for its dominant retail chains. Third, it helps to rationalize why the direct effect coefficient was lower than the spillover coefficient in the empirical analysis. To compare these two coefficients it is necessary to weight the county-level house price variable by the importance of the local market for local retailers. After this adjustment, Table A.XXXI shows that the two coefficients are similar.

The second difference is related to the weights (second term RHS). The theoretical weights θ_{rk}^{07} are increasing in the empirical weights S_{rk}^{07}, but they would only be equal if there is no initial differences in cross-county demand elasticity. I use estimates of σ_c by quartile of population from Hottman (2014) to construct θ_{rk}^{07}.

6.2 Recovering β^H

I estimate Equation 6.1 to recover β^H, reporting results for various specifications in Appendix Table A.XXXI. Preferred specification in Column (6) shows $\hat{\beta}_2 = 0.16$, which, scaled by $\bar{\sigma} - 1 = 3.1$, implies an average demand elasticity response of $\hat{\beta}_H =$

[22] κ_{cc} varies greatly across US counties. The mean is 0.03 and ranges from 0.0001 in the 5th percentile to 0.12 in the 95th percentile, with a standard deviation of 0.06.

0.48. In addition, I cannot reject that direct and indirect effect coefficients are equal, which is indicative that the uniform pricing model can explain county-level price co-movements. Although this conclusion needs to be interpreted with caution as it depends on assuming constant β^H (see appendix E.5.2).

6.3 Counterfactuals

We now have the theoretical structure, the estimates of key parameters, and the data to carry out a quantitative assessment of the influence of retail chains on the spread of demand shocks to prices during the Great Recession. In particular, I hold constant changes in retail chains' costs ($d \log c_r = 0$), initial shares, and use Equation 6.1 to evaluate how demand shocks during the Great Recession would have affected cross-county inflation in different scenarios of retail chains pricing strategies, while maintaining constant the geographic distribution of retail chains.

I map the shares S_{rk}^{07} and l_{rc}^{07} to retail chains in the data and analyze two polar opposite pricing strategies: uniform pricing (benchmark) and flexible pricing. I use these counterfactuals to quantitatively answer two questions: What would have been the cross-county dispersion of inflation rates during the Great Recession if retailers' pricing strategies were different? Which consumers would have benefited?

Table VIII reports the average change in retail prices during the Great Recession by quintiles of house price changes. The first quintile represents counties more directly exposed to the house price slump. Column (1) reports the change in prices for the uniform pricing case, while Column (2) reports it for the flexible pricing case.

The average inflation rate under the two alternative pricing strategies is similar. However, there are important differences in the dispersion induced by the demand shocks during the Great Recession. Comparing the coefficient of variation (CV), we observe that the dispersion in cross-county inflation under uniform pricing is 40% lower. Compared to flexible prices, the reduction in consumer prices under uniform pricing is 1.25 percent points lower for the quintile most affected by the house price slump, while it was 2.23 percent points higher for the quintile least affected. This indicates that uniform pricing reduced risk-sharing between regions. First, it attenuated the downward response of local prices to the local shock. Intensifying the effect of the crisis in the local market. Second, regardless of the local shock, counties connected to affected counties experienced a decline in their consumer prices.

As a general result, Retail chains' centralized pricing decisions intensify the adverse consequence of a local crisis and benefit counties less affected. If Miami is hit hard by the recession, retail chains do not reduce prices as much there and, instead, they reduce prices in counties that were less affected by the crisis. This also implies that even in a context of uniform pricing, local markups are procyclical, but less procyclical than if retail chains perfectly discriminate prices.

This result highlights a key difference between the implications of my mechanism and those in prior studies. For instance, Hyun and Kim (2019) suggests that producers reduce varieties in all their market destinations in response to local crises, which adversely affects unaffected regions by limiting variety access. In contrast, my mechanism implies that unaffected regions benefit through lower prices and increased consumption. That is, my mechanism implies lower risk-sharing between regions. I discuss in detail this and other qualitative and quantitative differences with other propagation mechanisms in in Appendix D.6.

In terms of distributive consequences, in the specific context of the shocks that occurred during the Great Recession, uniform pricing and the mechanism described above benefited low-income counties. These counties were less directly exposed to the house price slump, yet they experienced a lower inflation rate due to their connection with counties that were affected by the shocks. However, this conclusion is specific to the locations in which this particular shock took place. In Appendix F.2 I analyze this in detail and quantify the distributive consequences of uniform pricing during the Great Recession.

7 Conclusion

Large firms with a presence in many regions are a key feature of the economy. I study if the centralized pricing decisions of multi-establishments firms can lead to the propagation of shocks, beyond the traditional channels. I study this in the context of the retail sector because it directly affects consumer prices and because there is unusually rich micro-data to observe detailed information about retail chains' prices in their different stores across the geography of the U.S.

My main empirical finding is that county-level consumer prices are sensitive to shocks in distant counties linked by the retail chain networks. In addition, I show that the economic linkages created by the retail chains go beyond the traditional linkages that arise from, for example, trade and proximity in space. The key mechanism behind the effects is the centralized pricing decisions of retail chains.

The way in which retail chains connect counties in the US economically has important consequences for the spread of local demand shocks. First, uniform pricing dampens the pro-cyclical behavior of local prices. Second, it increases the synchronization of consumer prices across counties. During a negative demand shock, uniform pricing worsens the outcomes for consumers in the most affected counties while benefiting those less exposed.

My findings have important policy implications. Centralized retail pricing limits regional risk-sharing, intensifying local crisis. This suggests that targeted policies may be needed to address local recessions. Uneven distribution of retail chains also influences how local demand shocks affect prices across regions. Therefore, when weighing the costs and benefits of a policy, policymakers should consider not only the impact on local prices but also the indirect impact on prices in distant regions. This paper provides the necessary bilateral weights to inform these policies.

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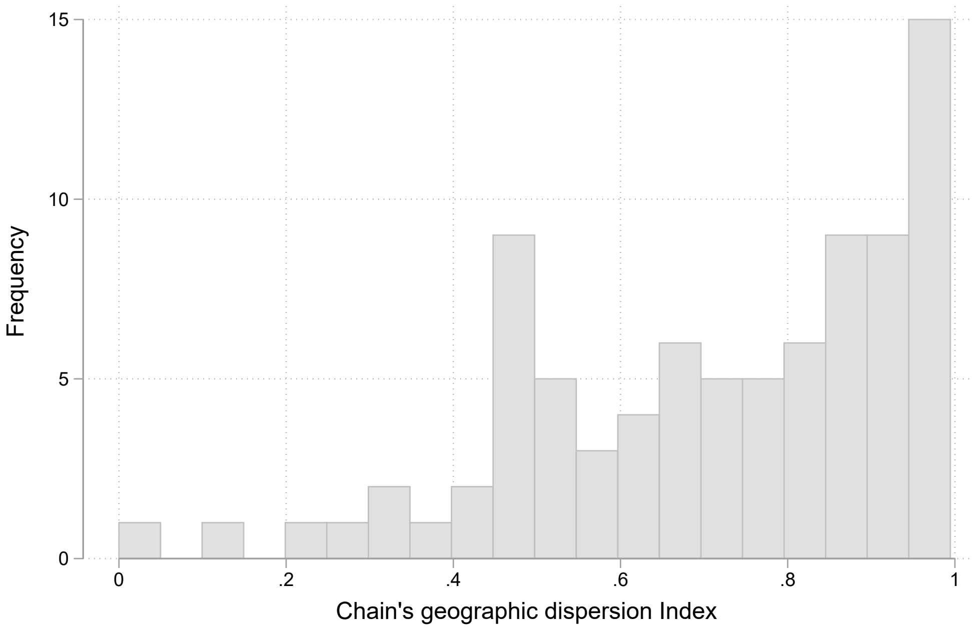
Tables and Figures

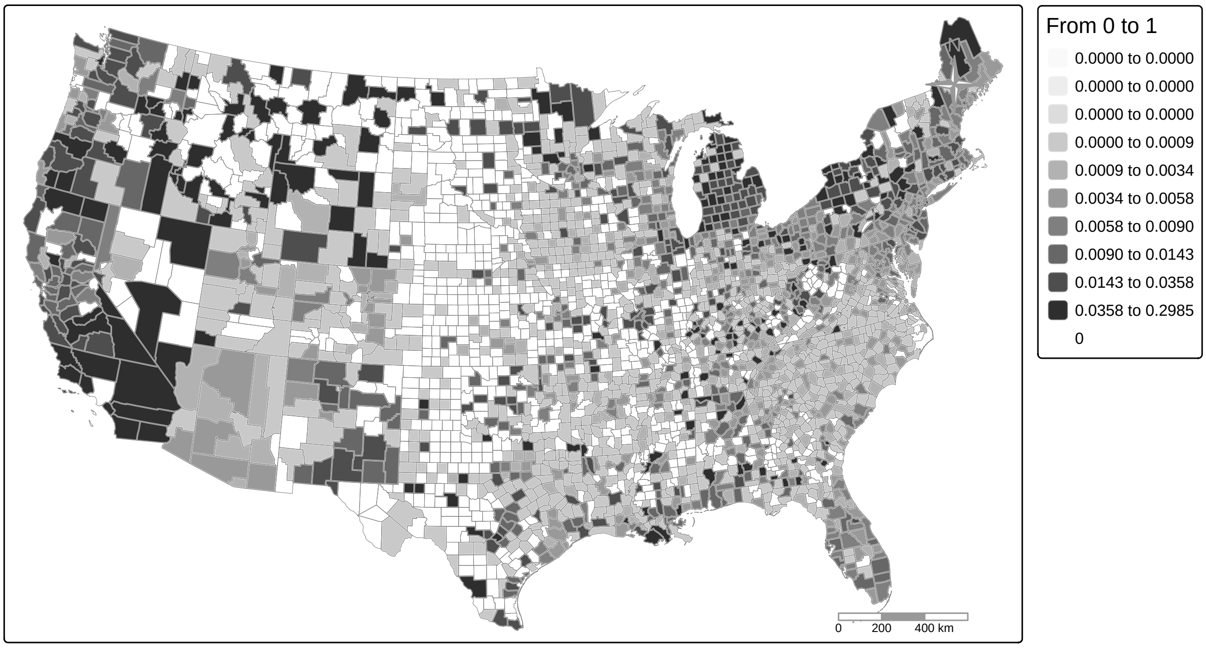
7.1 Figures

Figure I: Geographic Dispersion Index



Note: Histogram with 20 bins showing the distribution of retail chains by their Geographic Dispersion Index (GDI), defined as $GDI_r = 1 - \sum_c S_{rc}^2$. The x-axis reports the value of GDI_r, while the bars represent the number of retail chains falling within each bin. Source: NielsenIQ Retailer Scanner Data.

Figure II: $\omega_{c,LA}$: Exposure of counties c to shocks in Los Angeles

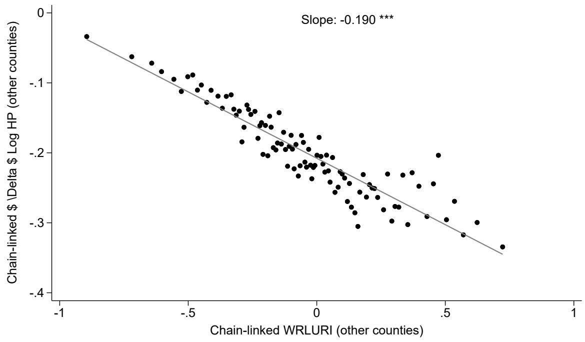


Note: The sample is segmented in deciles. The gray color scale represents the degree to which counties are exposed to shocks in L.A., based on $\omega_{c,LA}$ (See Equation 4.2). Darker colors indicate higher $\omega_{c,LA}$. Includes all counties covered by the NielsenIQ scanner data. Source: NielsenIQ Retailer Scanner Data.

Figure III: Propagation of local shocks: first stage and reduced-form

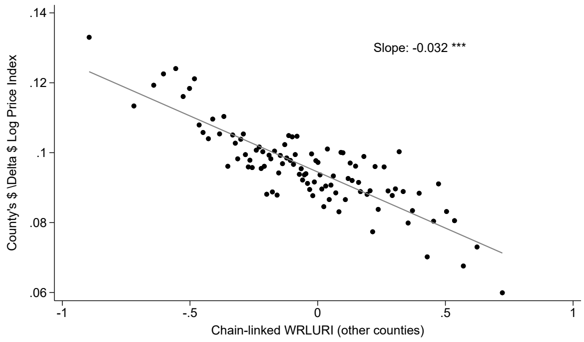
Panel a: First Stage

$\sum_{k \neq c} \omega_{ck} WLRI_k \longrightarrow \sum_{k \neq c} \omega_{ck} \Delta \log(HP)_k$



Panel b: Reduced Form

$\sum_{k \neq c} \omega_{ck} WLRI_k \longrightarrow \Delta \log(P_c)$



Note: The binscatter plots the first stage and reduced-form relationship. Panel A plots the first stage: the relationship between the network-weighted WLRI (x-axis) and the network weighted house price changes (y-axis). Panel B reports the reduced-form coefficient: the relationship between network-weighted WLRI (x-axis) and county-level change in consumer prices (y-axis). Counties are sorted into percentile bins based on their value on network-weighted change in house prices (Panel A) and county-level changes in consumer prices (Panel B), respectively. The sample includes 924 counties, so each percentile bin therefore represents 9 counties. To filter out any confounding effects, I control in both cases for the local change in house prices (so the dot indicates the average value of the (residual) outcome variable.

7.2 Tables

Table I: Propagation of local shocks through retail chains' network

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County Δ Log HP	0.053***	0.030**	0.025*	0.115***	0.070**	0.064*
	(0.014)	(0.012)	(0.014)	(0.025)	(0.029)	(0.034)
Chain-linked Δ Log HP (other counties)		0.085***	0.091***		0.130***	0.139***
		(0.026)	(0.026)		(0.031)	(0.033)
Panel B: First Stage						
F-stat				21.952	21.838	13.665
County controls	no	no	yes	no	no	yes
Observations	924	924	924	924	924	924
R-squared	0.147	0.251	0.265	0.060	0.082	0.110

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta \log(P_c)$). County's $\Delta \log HP$ is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) denotes the network-weighted percentage change in house prices in other counties ($\sum_{k \neq c} \omega_{ck} \Delta \log(HP_k)$), as defined in Equation 4.2. Columns (1) to (3) report results for OLS estimations. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument network-weighted percentage change in house prices ($\sum_{k \neq c} \omega_{ck} \Delta \log(HP_k)$) with network-weighted WLRI ($\sum_{k \neq c} \omega_{ck} WLRI_k$). County-level controls in columns (3) and (6) include changes in log wages, changes in log number of retail establishments, changes in log employment, and the county's own weight ω_{cc}. Panel A reports the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parentheses. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels. Source: Prices, quantities, and sales are obtained from NielsenIQ Retail Scanner Data. Housing price data is obtained from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008). County-level macroeconomic variables are obtained from the Bureau of Labor Statistics.

Table II: Propagation of house price-induced local shocks to out-of-state counties

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.053***	0.054***	0.052***	0.115***	0.123***	0.125***
	(0.014)	(0.013)	(0.015)	(0.025)	(0.023)	(0.026)
Chain-linked Δ Log HP (other counties)		0.078***	0.084***		0.125***	0.131***
(exc state)		(0.024)	(0.024)		(0.031)	(0.030)
Panel B: First Stage						
F-statistic				21.952	15.403	11.116
County controls	no	no	yes	no	no	yes
Observations	924	924	924	924	924	924
R-squared	0.147	0.245	0.260	0.060	0.031	0.029

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta \log(P_c)$). County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (out-of-state counties) is the network-weighted percentage change in house prices in other counties, excluding the state in which the county is located. County-level controls in columns (3) and (6) include changes in log wages, changes in log number of retail establishments, changes in log employment, and county's own weight ω_{cc}. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument network-weighted percentage change in house prices with network-weighted WLRI in out-of-state counties ($\sum_{k \neq State} \omega_{ck} WLRI_k$). Panel A reports the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels. Source: NielsenIQ Retail Scanner Data, Federal Housing Finance Agency (FHFA) and Wharton Land Regulation Index from Gyourko et al. (2008).

Table III: Channels of propagation of shocks: retail chains versus geographic proximity

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instruments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
Prox-weighted Δ Log HP (other counties)	0.119***	0.087***	0.017	0.198***	-0.068	-0.125
	(0.009)	(0.015)	(0.016)	(0.046)	(0.095)	(0.082)
County's Δ Log HP		0.020***	0.020***		0.143***	0.155***
		(0.007)	(0.007)		(0.052)	(0.048)
Chain-linked Δ Log HP (other counties)			0.087***			0.165***
			(0.009)			(0.028)
Panel B: First Stage						
F-statistic				12.506	23.725	15.996
Observations	924	924	924	924	924	924
R-squared	0.175	0.179	0.264	0.103	0.104	0.102

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta \log(P_c)$). County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the network-weighted percentage change in house prices in other counties ($\sum_{k \neq c} \omega_{ck} \Delta \log(HP_k)$) as defined in Equation 4.2. Trade-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, where the weights are given by proximity between counties: $\sum_{k \neq c} \delta_{c,k}^{prox} \Delta \log(HP_k)^{07-11}$. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parentheses. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: NielsenIQ Retail Scanner Data, FHFA, Wharton Land Regulation index from Gyourko et al. (2008).

Table IV: Controlling for similarity-weighted shocks

	Dep Variable: County's Δ Log Price Index							
	IV: WLRI instrument							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Second Stage								
County Δ Log HP	0.064*	0.062*	0.061*	0.064*	0.064*	0.099**	0.030*	0.020
	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)	(0.049)	(0.017)	(0.018)
Chain-linked Δ Log HP (others)	0.139***	0.140***	0.138***	0.138***	0.138***	0.130***	0.171***	0.174***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.036)	(0.032)	(0.031)
Income-weighted Δ Log HP (others)		0.029***						0.022**
		(0.011)						(0.031)
Employment-weighted Δ Log HP (others)			0.019					0.024
			(0.014)					(0.015)
Population-weighted Δ Log HP (others)				0.004				0.003
				(0.016)				(0.015)
Education-weighted Δ Log HP (others)					0.012			0.012
					(0.009)			(0.009)
HH debt-weighted Δ Log HP (others)						-0.062*		0.002
						(0.033)		(0.013)
SocialConnectedness-weighted Δ Log HP							0.066***	0.063***
							(0.023)	(0.023)
Panel B: First Stage								
First Stage F-stat	13.665	13.809	13.787	13.659	13.530	11.002	19.212	11.153
County controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	924	924	924	924	924	924	924	924
R-squared	0.110	0.122	0.126	0.114	0.116	0.129	0.132	0.211

A unit of observation is a county. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in counties linked by retail chains. Columns (2) to (6) control for similarity-weighted changes in house prices. Column (7) controls for social connectedness-weighted changes in house prices. Column (8) includes all controls together. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: NielsenIQ Scanner Data, FHFA.

Table V: Propagation of house price-induced local shocks to other economic outcomes

county-level	Δ Log Price Index	Δ Log L	Δ Log # of establish	Δ Log Wages
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
County's Δ Log HP	0.070**	0.159*	0.123*	0.303*
	(0.029)	(0.082)	(0.073)	(0.161)
Chain-linked Δ Log HP (others)	0.130***	-0.051	0.048	-0.156
	(0.031)	(0.111)	(0.041)	(0.143)
Panel B: First Stage				
F-statistics	21.838	21.838	21.838	21.838
Observations	924	924	924	924
R-squared	0.082	0.078	0.117	0.090

A unit of observation is a county. Each column has a different dependent variable: Column (1) shows $\Delta \log(P_c)$. Column (2) shows the percentage change in employment rate ($\Delta \log(L_c)$), Column (3) shows the percentage change in the county's # of establishments. Column (4) shows the percentage change in wages. County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the network-weighted percentage change in house prices in other counties. All columns report IV estimates. Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Retail Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008). County-level macroeconomic variables are obtained from the BLS.

Table VI: Propagation of local shocks: within county analysis

	Dep Variable: Chain's Δ Log Price in county c					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.031***			0.070***		
	(0.004)			(0.021)		
Store Δ log HP (others)$_{rc}$	0.079**	0.087**	0.075**	0.151***	0.193***	0.198***
	(0.037)	(0.036)	(0.030)	(0.050)	(0.041)	(0.036)
Panel B: First Stage						
F-statistic				18.430	31.864	37.446
County controls	yes	-	-	yes	-	-
Retail chain controls	no	no	yes	no	no	yes
County FE	no	yes	yes	no	yes	yes
Observations	3,666	3,666	3,666	3,666	3,666	3,666
R-squared	0.162	0.571	0.582	0.108	0.100	0.085
# retailers	84	84	84	84	84	84
# counties	924	924	924	924	924	924

A unit of observation is a retail chain by county. The dependent variable is the percentage change in the retail chain by county price index between 2007 and 2011. County's Δ Log HP is the county-level percentage change in house prices between 2007 and 2011. Store $\Delta \log HP(others)_{rc}$ is the store-level network-weighted percentage change in house prices in other counties. County-level controls include log wage changes , employment and # of establishment. Retail chain-level controls include log national sales at 2007. Columns (4) to (6), use WLRI instruments. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at both the retail-chain level and state-level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Retail Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008). County-level macroeconomic variables are obtained from the BLS.

Table VII: Effects on retail chain sales

	Dep Variable: Δ Log					
	Store Level			County-level		
	Δ Log Sales	Δ Log Quantities	Δ Log Price index	Δ Log Sales	Δ Log Quantities	Δ Log Price index
Panel A: Second Stage						
Δ Log HP				0.480**	0.402*	0.078**
				(0.211)	(0.210)	(0.034)
Chain-linked Δ Log HP (others)	-0.346	-0.544***	0.198***	-0.638***	-0.777***	0.139***
	(0.244)	(0.236)	(0.036)	(0.246)	(0.252)	(0.033)
Observations	3,666	3,666	3,666	924	924	924
County controls	-	-	-	yes	yes	yes
County FE	yes	yes	yes	no	no	no
First Stage F-stat	37.446	37.446	37.446	14.944	14.944	14.944

Column (1) to (3) observations are at retail-by-county. Column (4) to (6) at county-level. The dependent variables are $\Delta LogSales$, $\Delta LogQuantities$ and $\Delta LogPrice$. County's $\Delta LogHP$ is the percentage change in house prices between 2007 and 2011. $Chain - linked \Delta LogHP$ is the exposure variable at the retail chain by county level in column (1) to (3) and at store level in columns (4) to (6). Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006)rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: NielsenIQ Retail Scanner Data, Federal Housing Finance agency (FHFA), Gyourko et al. (2008).

Table VIII: Inflation Rates

Quintile of Δ House Price	Uniform ΔP^u_c	Flexible ΔP^{flex}_c	Δ^{Losses} ΔP^u_c-ΔP^{flex}_c
Most affected	-4.19%	-5.44%	1.25%
2	-2.67%	-2.07%	-0.60%
3	-2.61%	-1.55%	-1.06%
4	-2.56%	-1.13%	-1.43%
Least Affected	-2.59%	-0.36%	-2.23%
Mean	-3.42%	-3.22%	-0.20%
SD	1.52%	2.75%	
CV	44.44%	85.47%	

The quintiles are defined in terms of the house price changes. The largest drop in house prices corresponds to the first quintile. Observations are weighted by population in 2007.

ONLINE APPENDIX

Multi-establishment Firms, Pricing and the Propagation of Local Shocks: Evidence from US Retail

by Ezequiel Garcia-Lembergman

A Data

A.1 Summary Statistics

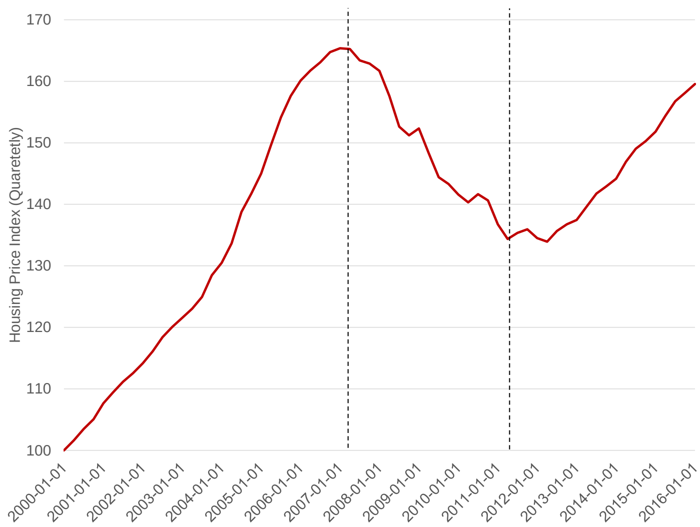
Table A.I: Summary Statistics

	(1) Average	(2) Median	(3) Std. Dev	(4) N	(5) Data Source
County-level Variables					
Retail chain's linked Δ Log HP changes	-0.20	-0.18	0.10	924	NielsenIQ+FFHA
Sales ('000 US$)	35,506	8,330	98,878	924	NielsenIQ
# of Retail Chains	5.17	5.00	2.67	924	NielsenIQ
Δ Log Price Index (2011-2007)	0.10	0.10	0.03	924	NielsenIQ
Δ Log House Prices (2011-2007)	-0.13	-0.09	0.16	924	FFHA
Population (thousand)	209	74	494	924	BLS
WLRI	-0.36	-0.43	0.76	924	Gyuroko
Retail by county level					
Sales ('000 US$)	8,296	1,724	25,534	3818	NielsenIQ
Retail-chain average Δ Log HP changes (others)	-0.23	-0.24	0.09	3818	NielsenIQ
Δ Log Price Index (2011-2007)	0.09	0.09	0.03	3818	NielsenIQ
National retail level					
Sales (000 US$)	379,331	126,879	644,495	84	NielsenIQ
# of counties	44	8	115	84	NielsenIQ

A.2 House prices Data

Figure A.I depicts the evolution of the national house price index. We can observe the collapse in house prices started in the beginning of 2007. House prices continued declining until the second semester of 2011. Throughout that period, house prices dropped 18%.

Figure A.I: Evolution of House Price Index



Source: FFHA

A.3 Differences between counties in sample and out of sample

For my main analysis, I only consider counties for which I have information on change in house prices (2208), NielsenIQ Scanner Data (2300), and Wharton Land Regulation Index (910). Hence, in my baseline specification, I consider only 910 counties for which I have information about the WLRI. In Table A.II, I show that these 910 counties represent 70% of the population and 70% of the sales in the NielsenIQ Data. These counties where hit slightly more by the crisis and had a smaller initial unemployment rate.

Table A.II: Counties with and without data on Wharton Land Regulation Index

Data on WLRI avaiable	Counties #	Population Total (millions)	Sales Total (millions)	$\Delta Log(HP)^{2007-2011}$ % (mean)	Unemployment rate (mean)
No	1298	86.64	13798.59	-10.50	5.07
Yes	910	200.21	33638.94	-13.41	4.83
Total	2208	286.86	47437.53	-11.71	-4.97

B Price Indices: Main analysis.

As the paper's main focus is on a) prices of existing products that are similar within chain across stores, and b) variation of price indices across time, we include an item only if it has positive sales in 2007 and 2011. We track the price of identical items (UPC-store combinations) across time, so that changes in quality or issues with comparing nonidentical products are less relevant for our results.

We construct two price indices, at two different levels of aggregation: A) A price index for each County (P_{ct}), and a retail chain by county price Index (P_{rct}). I describe them in detail in next sections.

B.1 County level Price index

We construct county-level price index in two steps. We first construct a product-module level price index. Ignoring the introduction of new varieties, the exact price index of the CES utility function for product module m in county c is as in Sato (1976) and Vartia (1976):[23]

$$P_{mct} = \Pi_{u \in I_{mc}} \left(\frac{P_{umct}}{P_{umct-1}} \right)^{w_{umct}},$$

[23] This price index is consistent with the following utility function:

$$U_c(y_c) = \prod_{m \in R_c} \left[\sum_{u \in R_{mc}} q_{umc}^{\frac{\sigma_m(y_c)-1}{\sigma_m(y_c)}} \right]^{\alpha_{mc} \frac{\sigma_m(y_c)}{\sigma_m(y_c)-1}}$$

Consumer behavior features multi-stage budgeting in two stages. In the first stage, consumers in a county decide which of 1000 product modules to buy from based on the product module price index. In the second stage, conditional on the product module, consumers decide which variety to purchase; where variety is defined as a store-barcode combination.

where

$$w_{ucmt} = \frac{(s_{umct} - s_{umct-1})/(ln(s_{umct}) - ln(s_{umct-1}))}{\sum_{v \in I_{mc}}(s_{vmct} - s_{vmct-1})/(ln(s_{vmct}) - ln(s_{vmct-1}))} \; ; \; s_{umct} = \frac{P_{umct}Q_{umct}}{\sum_{v \in I_{mc}} P_{vmct}Q_{vmct}},$$

and I_{mc} is the set of varieties in product module m in county c that are consumed in both years (continuers). The weights w are ideal log-change weights and they are county specific to allow for spatial variation the relative weight of an item. [24]

I then construct an overall county-specific price index by weighting these category price indices by the revenue share of a particular product module in the initial year,

$$P_{ct} = \Pi_m \left(\frac{P_{mct}}{P_{mct-1}} \right)^{w_{mct-1}},$$

where

$$w_{mct-1} = \frac{\sum_{u \in m} Sales_{umct-1}}{\sum_u Sales_{uct-1}}$$

In figure A.II, I report the histogram of county-level inflation rate between 2007 and 2011. There is substantial heterogeneity in inflation rates by county in the US. The population-weighted average inflation rate of the counties in our sample is 8.34%, which contrast well with the variation in the food at home official CPI from BLS.

[24] Note that they are always bounded between the shares of spending in period t and period t-1.

Figure A.II: Histogram: County's percentage change in retail prices between 2007 and 2011

Retail chain by county Price Index

Similarly, we construct a price index at the retail chain by county level.

First, we first construct a product-module level price index within retail chain in a county.

$$P_{mrct} = \Pi_{u \in I_{mrc}} \left(\frac{P_{umrct}}{P_{umrct-1}} \right)^{w_{umrct}},$$

where

$$w_{umrct} = \frac{(s_{umrct} - s_{umrct-1})/(ln(s_{umrct}) - ln(s_{umrct-1}))}{\sum_{v \in I_{mrc}}(s_{vmrct} - s_{vmrct-1})/(ln(s_{vmrct}) - ln(s_{vmrct-1}))} \; ; \; s_{umrct} = \frac{P_{umrct}Q_{umrct}}{\sum_{v \in I_{mrc}} P_{vmrct}Q_{vmrct}},$$

and I_{mrc} is the set of varieties in product module m, sold by retailer chain r that are consumed in both years (continuers). The weights w are ideal log-change weights and they are retailer chain specific to allow for variation in the importance of items in different retailer chains.

We then construct a retail chain by county price index by weighting these category price indices by the revenue share in $t-1$ of a particular product module in the retail chain in the county.

$$P_{rct} = \Pi_m \left(\frac{P_{mrct}}{P_{mrct-1}} \right)^{w_{mrct-1}},$$

where

$$w_{mrct-1} = \frac{\sum_{u \in m} Sales_{umrct-1}}{\sum_u Sales_{urct-1}}$$

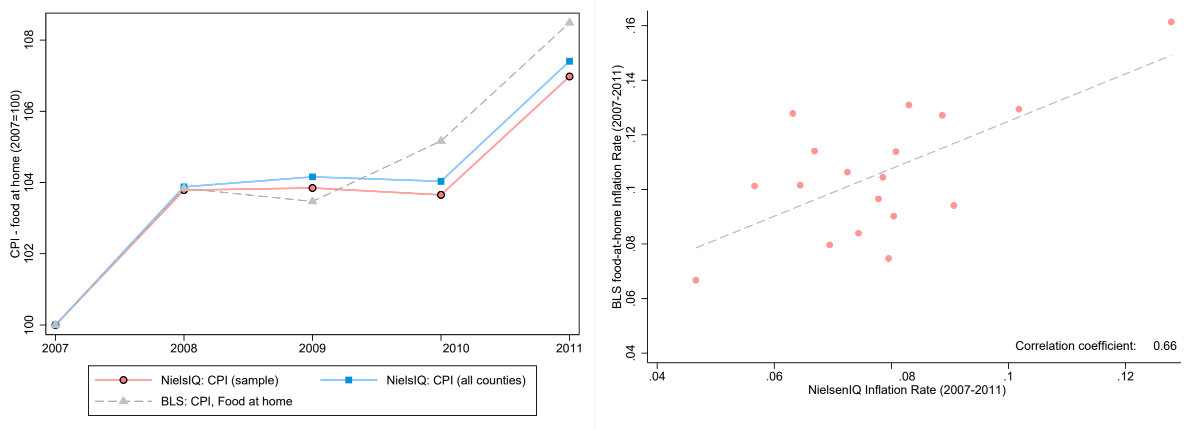
B.2 Nielsen IQ Representative of BLS food-at-home inflation rate

The NielsenIQ county-level inflation is representative of the food-at-home official inflation reported by the BLS, exhibiting similar national CPI trends and a high correlation between BLS and NielsenIQ regional inflation rates (see Appendix Figure A.III). Panel A shows that the national inflation follows a similar trend and Panel B shows that when aggregating at the same regional level, regional NielsenIQ inflation rates correlate with BLS inflation rates. It is not surprising that the relationship is not perfect since the counties and products I use in the data to construct the metro area price index do not match one-to-one with those sampled by the BLS in each metro area.

Figure A.III: NielsenIQ Price Index vs BLS food-at-home

Panel a: NielsenIQ versus BLS food-at-home CPI (national level)

Panel b: Metro-level comparison of NielsenIQ versus food-at-home Inflation rate



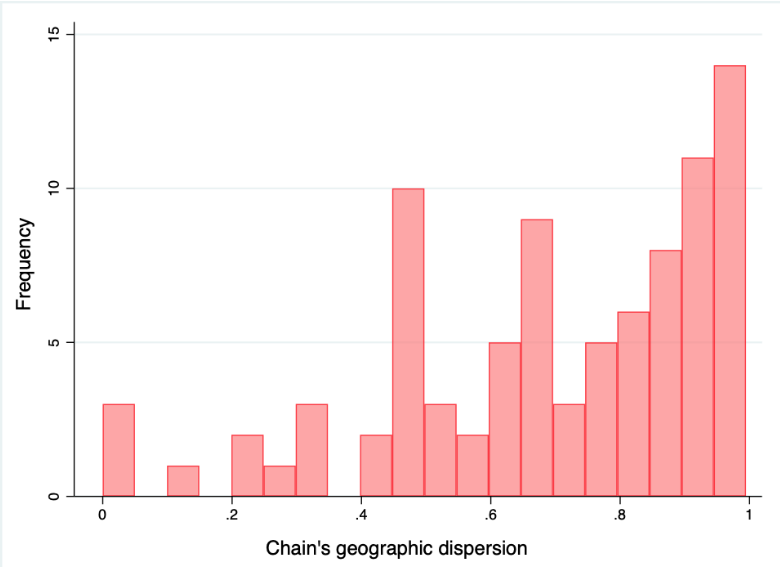
Note: : Panel a plots NielsenIQ and BLS food-at-home national CPI. Panel b compares the aggregate NielsenIQ change in prices between 2007 and 2011 and metro area BLS food-at-home price indices for the set of regions with overlapping data.

C Geographic Distribution of Retail Chains

C.1 Geographic Dispersion of retail chains

GDI index distribution:

Figure A.IV: Geographic Dispersion of retail chains

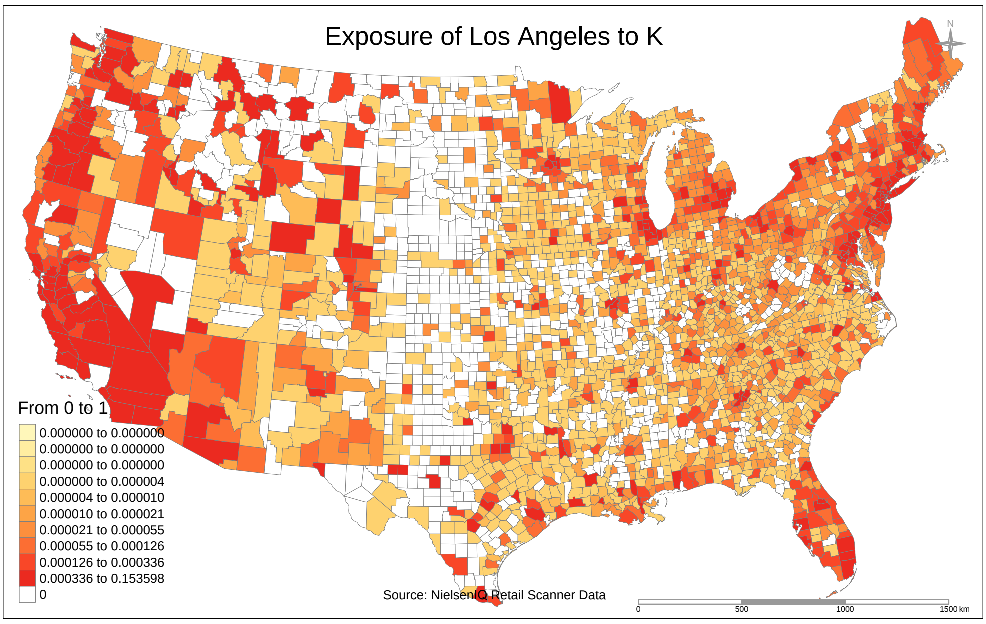


C.2 Maps of Bilateral linkages

In this section, I show other illustrative maps of the bilateral linkages between counties in the retail chains dimension.

Bilateral Linkages for LA County: exposure of LA to other counties k, ω_{ck} The map in Figure A.V plots $\omega_{LA,k}$ for every county k in the sample. I segment the sample in deciles and assign colors ranging from light yellow to red, with red counties k being those that affect more Los Angeles (high $\omega_{LA,k}$).

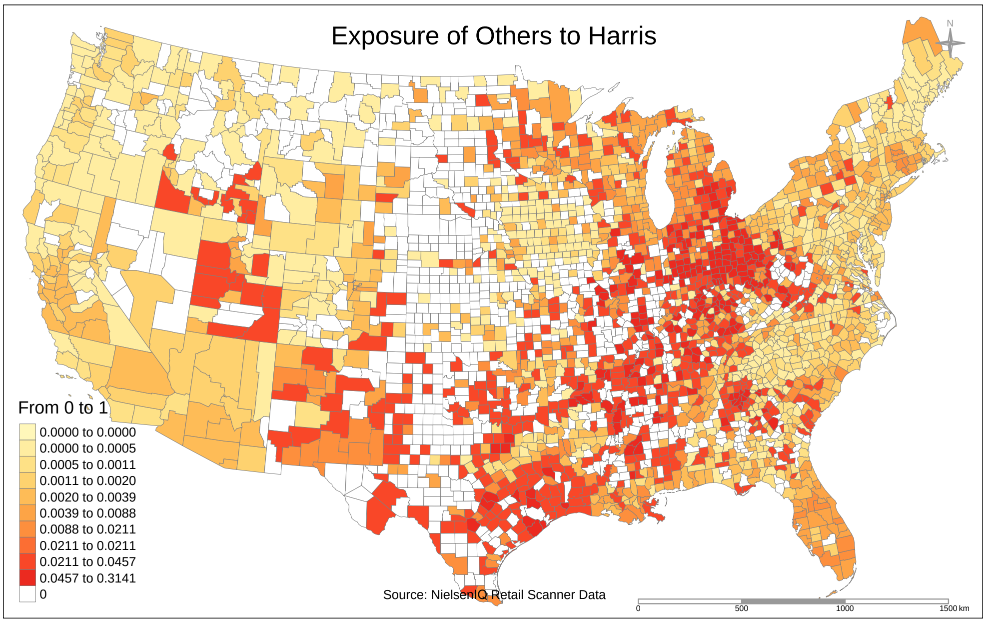
Figure A.V: $\omega_{LA,k}$: Exposure of Los Angeles to county k



Note: Based on deciles. The yellow-to-red color scale represents the degree to which LA is exposed to county k , based on $\omega_{LA,k}$ (See Equation **??**). Red indicates higher $\omega_{LA,k}$. Source: NielsenIQ Retail Scanner Data.

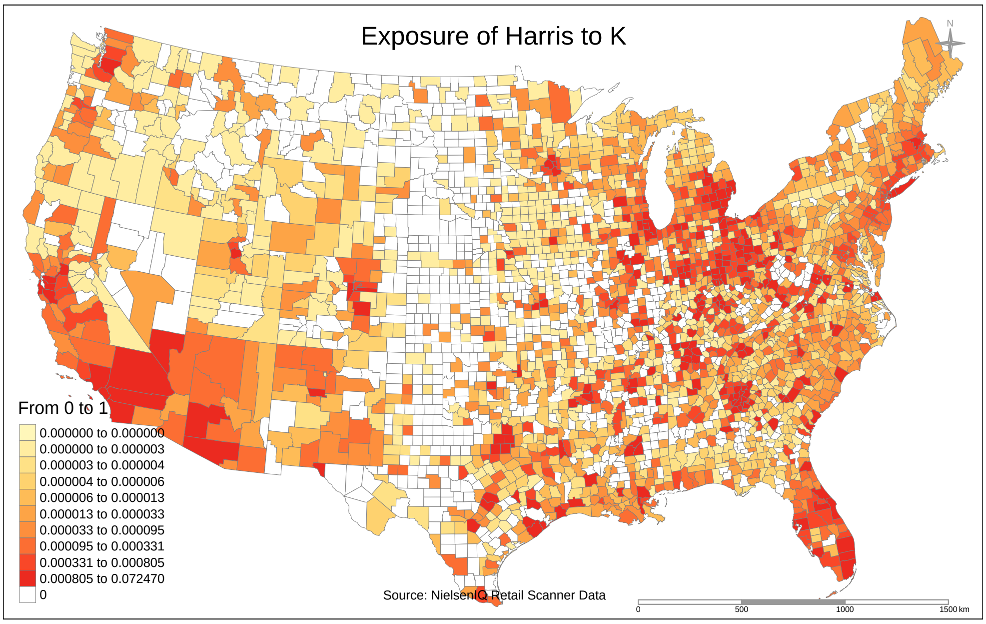
Bilateral linkages for Harris County

Figure A.VI: $\omega_{c,Harris}$: Exposure of county c to county Harris



Note: Based on deciles. The yellow-to-red color scale represents the degree to which a county is exposed to Harris county, based on $\omega_{c,Harris}$ (See Equation **??**). Red indicates higher $\omega_{c,Harris}$. Source: NielsenIQ Retail Scanner Data.

Figure A.VII: $\omega_{Harris,k}$: Exposure of Harris to county k



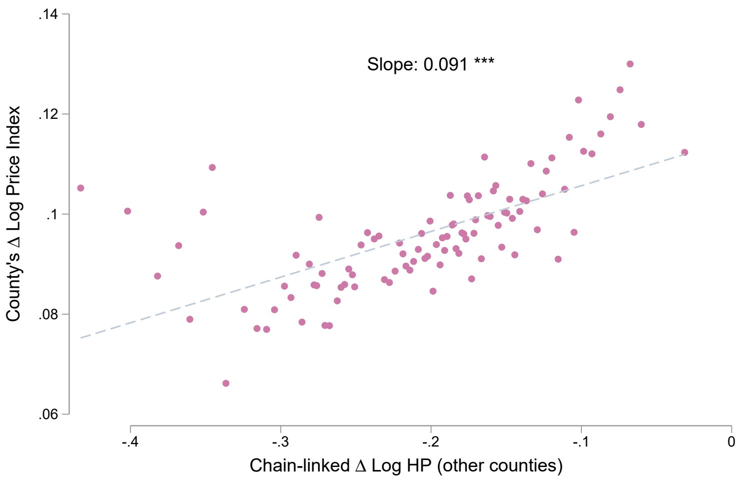
Note: Based on deciles. The yellow-to-red color scale represents the degree to which Harris is exposed to county k , based on $\omega_{Harris,k}$ (See Equation **??**). Red indicates higher $\omega_{Harris,k}$. Source: NielsenIQ Retail Scanner Data.

D Empirical Analysis

D.1 Binscatter: OLS relationship

Figure A.VIII provides a visual impression of the OLS relationship between changes in the county-level retail price index and changes in house prices in other counties as reported in Column (3) of the main table. Controlling for the local change in house prices, the elasticity of county-level prices with respect to changes in house prices in other counties is around 0.09.

Figure A.VIII: Network-weighted changes in house prices and county-level price changes



The binscatter plots the OLS relationship between the network weighted house price changes in other counties and county-level retail prices. Counties are sorted into percentile bins based on their value on $\Delta \log(P_c)$. Each percentile bin represents 9 counties. I control for the local change in house prices. Hence, the dot indicates the average value of (residual) $\Delta \log(P_c)$.

D.2 First Stage coefficients

In Table A.III I report the coefficients of the first stage for the estimations in columns (4), (5) and (6) of Table I. Two things worth noting. First, in line with the theory, more strict land regulation (lower HSE) is associated with a higher drop in house price after a national shock. Similarly, higher network-weighted WLRI is associated with a higher drop in network-weighted house price changes. Second, as expected, WLRI is more relevant to explain local house price changes, while netowork-weighted WLRI is more important to explain network-weighted house price changes.

Table A.III: First stage coefficients for Table I

Dep Variable:	Col (4) Δ Log HP	Col (5) Δ Log HP	 Chain-linked Δ Log HP	Col (6) Δ Log HP	 Chain-linked Δ Log HP
WLRI	-0.087***	-0.066***	0.009	-0.057***	0.003
	(0.019)	(0.016)	(0.009)	(0.015)	(0.009)
Chain-linked WLRI (other counties)		-0.097**	-0.187***	-0.081*	-0.185***
		(0.041)	(0.023)	(0.046)	(0.022)
County controls	no	no	no	yes	yes
Observations	924	924	924	924	924
R-squared	0.171	0.207	0.448	0.312	0.479

A unit of observation is a county. This table reports first stage coefficients for the estimation in Table I. The numbers of the columns correspond to those in Table I. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008).

In Table A.IV I report the coefficients of the first stage for the IV estimation in columns (6) of Table VI.[25] Once again, the sign of the coefficients of the first stage are all as expected and each instrument has more predictive power for its own endogeneous variable.

Table A.IV: First stage coefficients for Table III

county-level	(6) prox-weighted Δ Log HP	(6) Δ Log HP	(6) Chain-linked Δ Log HP
Prox-weighted WLRI	-0.185***	-0.263***	0.022
	(0.048)	(0.079)	(0.035)
WLRI	-0.000	-0.031**	0.001
	(0.006)	(0.012)	(0.007)
Chain-linked WLRI	0.020	0.017	-0.197***
	(0.018)	(0.039)	(0.024)
Observations	924	924	924
R-squared	0.351	0.291	0.478

A unit of observation is a county. This table reports first stage coefficients for the estimation in column (6) of Table III. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008).

In Table A.V I report the coefficients of the first stage for the IV estimations in columns (4), (5) and (6) of Table VI. The numbers of the columns corresponds to those in Table VI. Once again, throughout specifications, the coefficients sign is as expected.

[25] The conclusions are similar for columns (4) and (5).

Table A.V: First stage coefficients for Table VI

	(4) Δ Log HP	(4) chain-linked Δ Log HP	(5) chain-linked Δ Log HP	(6) chain-linked Δ Log HP
WLRI	-0.069***	0.008		
	(0.017)	(0.009)		
Store's chain-linked WLRI	-0.057*	-0.178***	-0.173***	-0.161***
	(0.030)	(0.027)	(0.024)	(0.023)
County controls	yes	yes	-	-
Retail chain controls	no	no	yes	yes
County FE	no	no	yes	yes
Observations	3,664	3,664	3,664	3,664
R-squared	0.303	0.393	0.804	0.821

A unit of observation is a retailer × county. This table reports first stage coefficients for the estimation in Table VI. The numbers of the columns correspond to those in the columns in VI. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008).

In Table A.VI I report the coefficients of the first stage for the IV estimations in columns (2) and (4) of Table A.X. The numbers of the columns corresponds to those in Table A.X. Once again, throughout specifications, the coefficients sign is as expected.

Table A.VI: First stage coefficients for Table A.X

	IV: WLRI-based instrument		Bartik-based instrument	
	(2)	(2)	(4)	(4)
Dep vble:	$\Delta LogHP_{ct}$	Chain-linked $\Delta LogHP_{ct}$ (others)	$\Delta LogHP_{ct}$	Chain-linked $\Delta LogHP_{ct}$ (others)
$WLRI_c \times \Delta LogHP_t$	0.245***	-0.034		
	(0.055)	(0.033)		
Chain-linked $WLRI_c \times \Delta LogHP_t$ (others)	0.269	0.578***		
	(0.169)	(0.120)		
$Bartik_{ct}$			0.031***	-0.012**
			(0.011)	(0.006)
Chain-linked Bartik (others)			-0.018*	0.051***
			(0.010)	(0.006)
County FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	9,379	9,379	7,776	7,776
R-squared	0.499	0.859	0.566	0.884

A unit of observation is a county × year. The table reports first stage coefficients for the estimation with year and county fixed effects in Table A.X. The numbers of the columns correspond to those in the columns in A.X. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively.

D.3 Robustness Checks

D.3.1. Alternative county-level controls: I begin by exploring whether the main IV estimates are stable across specifications with different county-level controls. Results are reported in Table A.VII. Reassuringly, the coefficient associated with chain-linked percentage change in house prices in other counties remains stable across different specifications. This suggests that, once I control for county's house price growth, the instrument is not correlated with other county-level variables in the error term.

Table A.VII: Validity of identification assumption: Adding controls to IV estimations: (A)

Dep Variable: County's Δ Log Price Index						
	IV: WLRI instrument					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.063*	0.064*	0.066*	0.064*	0.063*	0.048
	(0.033)	(0.034)	(0.035)	(0.034)	(0.038)	(0.037)
Chain-linked Δ Log HP (other counties)	0.133***	0.132***	0.137***	0.139***	0.139***	0.150***
	(0.033)	(0.034)	(0.034)	(0.033)	(0.033)	(0.035)
ω_{cc}		-0.029	-0.034	-0.039	-0.037	-0.046*
		(0.028)	(0.028)	(0.028)	(0.027)	(0.026)
County's Δ Log Wages		-0.003	0.005	0.026*	0.026*	0.020
		(0.014)	(0.011)	(0.014)	(0.014)	(0.012)
County's Δ Log # Establishments			-0.038	-0.024	-0.025	-0.022
			(0.025)	(0.025)	(0.025)	(0.022)
County's Δ Log Employment				-0.022	-0.023*	-0.025*
				(0.014)	(0.014)	(0.013)
County's Log Retail Sales in 2007					-0.000	-0.000
					(0.001)	(0.001)
County's Log Market Access 2007						-0.007**
						(0.003)
Panel B: First Stage						
F-stat	14.984	15.059	13.523	13.665	12.578	12.573
Observations	924	924	924	924	924	922
R-squared	0.111	0.111	0.096	0.110	0.116	0.171

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. The dependent variable is the percentage change in the county price index between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (1) to (6) report results, after instrumenting county exposure to house price shocks through the network of retailer chains with county exposure to WLRI through the network of retailer chains. Panel A report the second stage coefficients. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008), Housing supply elasticity is obtained from Saiz (2010).

The next table incorporates additional controls to account for other potential local shock proxies. These include changes in employment shares across the grocery, retail, construction, and nontradable sectors, as well as the county's poverty rate, population and median household income. The coefficient remains remarkably stable across specifications, ranging from 0.126 to 0.139.

The fact that the coefficient remains stable across specifications that add different set of controls is suggestive evidence that the remaining covariates in the error are not correlated with the instruments.

Table A.VIII: Validity of identification assumption: Adding controls to IV estimations: (B)

Dep Variable: County's Δ Log Price Index						
	IV: WLRI instrument					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.064*	0.064*	0.062*	0.069*	0.071*	0.069*
	(0.034)	(0.034)	(0.034)	(0.036)	(0.038)	(0.037)
Chain-linked Δ Log HP (other counties)	0.139***	0.139***	0.139***	0.136***	0.135***	0.126***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.037)
ω_{cc}	-0.039	-0.039	-0.038	-0.039	-0.039	-0.036
	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)
County's Δ Log Wages	0.026*	0.026*	0.025*	0.037***	0.037***	0.035***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
County's Δ Log Establishments	-0.024	-0.024	-0.023	-0.012	-0.012	-0.016
	(0.025)	(0.025)	(0.026)	(0.023)	(0.023)	(0.021)
County's Δ Log Employment	-0.022	-0.022	-0.021	-0.021	-0.020	-0.019
	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)	(0.012)
County's Δ Log Population			-0.017	-0.013	-0.017	-0.019
			(0.030)	(0.032)	(0.033)	(0.033)
County's Δ Log Median HH Income				-0.058**	-0.052**	-0.039**
				(0.028)	(0.024)	(0.020)
County's Δ Log Construction					0.007	0.009
					(0.011)	(0.011)
County's Δ Log Non-Tradable L Share						0.018***
						(0.006)
County's Δ Log Construction L Share						-0.004
						(0.003)
County's Δ Log Grocery L Share						-0.003**
						(0.002)
Panel B: First Stage						
F-stat	13.665	13.665	13.462	18.622	17.837	19.995
Observations	924	924	924	924	924	863
R-squared	0.110	0.110	0.117	0.113	0.109	0.128

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. The dependent variable is the percentage change in the county price index between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (1) to (6) report results, after instrumenting county exposure to house price shocks through the network of retailer chains with county exposure to WLRI through the network of retailer chains. Panel A report the second stage coefficients. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008).

D.3.2. Test of Overidentifying assumptions: Saiz Housing Supply elasticity instrument: As a further check, I explore whether the main results change if I use another common instrument in the literature. In particular, I instrument county's percentage change in house price with housing supply elasticity (HSE, hereafter) constructed by Saiz (2010). Saiz (2010) uses geographic information of the metropolitan area to measure how easy is constructing new houses (e.g: areas with a flat topology are assigned with a higher elasticity). Naturally, I also use the Saiz HSE and the weights ω_{ck} to construct an instrument for network-weighted percentage change in house price in other counties.[26] Results are reported in Table A.IX. The first two columns present OLS coefficients. Column (3) and (4) reports results using the WRLI instrument, as in my main specification. Columns (5) and (6) instrument the endogeneous variables with the Saiz HSE. The main coefficient increases modestly. Columns (7) and (8) present results including the 4 instruments. Again, throughout specifications, the coefficient remains stable between 0.129 and 0.146. In addition, I cannot reject the hypothesis that the coefficients obtained by using the different instruments are different.

Table A.IX: Validity of identification assumption: Saiz housing supply elasticity instrument

	Dep Variable: County's Δ Log Price Index					
	IV: WLRI instrument		IV: HSE (Saiz) instrument		IV: All instruments	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.070**	0.064*	0.043**	0.039	0.052**	0.047*
	(0.029)	(0.034)	(0.022)	(0.025)	(0.025)	(0.028)
Chain-linked Δ Log HP (other counties)	0.130***	0.139***	0.126***	0.126***	0.137***	0.142***
	(0.031)	(0.033)	(0.034)	(0.034)	(0.030)	(0.030)
Panel B: First Stage						
First Stage F-stat	21.838	13.665	15.005	10.285	12.706	9.893
County controls	no	yes	no	yes	no	yes
Observations	924	924	922	922	922	922
R-squared	0.082	0.110	0.193	0.220	0.141	0.168

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retail chains distribution of stores: $\sum_{k \neq c} \omega_{c,k} \Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008), Housing supply elasticity is obtained from Saiz (2010).

[26] Saiz HSE is at the MSA level so I have less variability. In addition, it is available for a lower number of counties. For this reason, the WLRI instrument is my baseline specification.

D.3.3. Propagation of house price-induced shocks: higher frequency and alternative instruments: How do retail chains' prices react to higher frequency (yearly) changes in house prices? I extend the analysis period to the years between 2007-2015 and estimate a yearly version of the main equation at the county-level (Equation 4.3):

$$\Delta \log(P_{c,t}) = \beta_0 + \beta_1 \Delta \log(HP_{c,t}) + \beta_2 \sum_{k \neq c} \omega_{ck,t-1} \Delta \log(HP_{k,t}) + \gamma_c + \gamma_t + \Delta\epsilon_{c,t}, \quad \text{(D.1)}$$

where t denotes year, γ_c are county fixed effects, and γ_t are year fixed effects. I propose two different instruments that leverage identifying variation from different sources. The first instrument mimics the strategy in previous sections exploiting differences in the initial level of housing supply elasticity across counties. I combine the WLRI in 2006 with average national yearly changes in house prices, ΔHP_t^{US}, to construct a time-varying version of the instrument: $WLRI_{ct} = WLRI_c \times \Delta HP_t^{US}$. As in the main part of the paper, I use this to instrument the direct effect of house price changes. More importantly, I then construct the instrument for exposure to house price changes in other counties as exposure to this instrument, $\sum_{k \neq c} \omega_{ckt-1} WLRI_{kt}$.

As a second strategy, I use a Bartik-like instrument for house prices recently developed by Graham and Makridis (2023). The instrument, $Bartik_{ct}$, combines the historical county-level composition of housing characteristics (e.g., number of bathrooms, size, number of bedrooms) with national changes in the marginal prices of these characteristics. The idea is that if San Francisco's apartments historically had relatively more bathrooms, when national bathrooms prices increase, then house prices will increase relatively more in San Francisco. At the same time, this variable is plausibly exogenous with respect to the most likely determinants of household consumption, productivity, and local retailers' costs, which suggests that it should not directly affect retail prices. I use this instrument for the direct effect.[27] More importantly, I construct the instrument for exposure to house price changes in other counties as $\sum_{k \neq c} \omega_{ckt-1} Bartik_{kt}$.

[27] I am grateful to Graham and Makridis (2023) for generously sharing their code to construct the instrument.

Results are presented in Table A.X. Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap rk F-statistic for the first stage, while first stage coefficients are reported in Table A.VI of Appendix D. In columns (1) and (2), I report results using instruments based on WRLI. In columns (3) and (4), I report results using instruments based on $Bartik_{ct}$. Columns (2) and (4) also include county-fixed effects. Across specifications, we observe that yearly county-level consumer prices are sensitive to house price changes in distant locations connected by the retail chain's network. In fact, across specifications with a different set of instruments and fixed effects, the main coefficient is relatively stable. The elasticity ranges from 0.11 to 0.15. Notably, the main coefficient is almost identical after including county-fixed effects.

Table A.X: Beyond the Great Recession: Propagation of yearly house price changes: 2007-2015

	Dep Variable: County's Δ Log Price Index			
	IV: WLRI		IV: Bartik-type	
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
County's Δ Log HP	0.089**	0.082**	0.101**	0.068*
	(0.035)	(0.034)	(0.041)	(0.040)
Chain-linked Δ Log HP (other counties)	0.112***	0.111***	0.153***	0.153***
	(0.040)	(0.040)	(0.030)	(0.028)
Panel B: First Stage				
F-stat	23.644	21.535	38.502	36.514
County FE	no	yes	no	yes
Year FE	yes	yes	yes	yes
Observations	9,379	9,379	7,778	7,778
R-squared	0.511	0.618	0.428	0.596

A unit of observation is a county by year. The dependent variable is the percentage change in county-level price index between t and $t-1$. County's Δ Log HP is the county-level percentage change in house prices between t and $t-1$ and 2011. Chain-linked $\Delta \log HP(other counties)$ is the network-weighted percentage change in house prices in other counties. In Columns (1) to (2), I use the time-varying version of the WLRI to construct the two instruments. In Columns (3) and (4), I use the Bartik-type Graham and Makridis (2023) variable to construct the two instruments. Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap rk F-statistic for the first stage. Standard errors clustered at the county-level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively.

D.3.4. Robustness Checks: Different assumptions to construct the Price Index: In my baseline specification, I choose the CES exact price index for continuing varieties to construct the price index. In this section, I show that my main results remain qualitatively unchanged under different assumptions to construct the price indices. In particular, I repeat my main analysis with Laspeyers, a Paasche and a Fisher price index.

Results are reported in Table A.XI. We can observe that the main results hold under these alternative county-level price indices.

Table A.XI: Robustness Check: Other Price Indices

	Dep Variable: County's Δ Log Price Index			
	Exact CES	Laspeyeres	Pasche	Fischer
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
County Δ Log HP	0.064*	0.064*	0.071**	0.066*
	(0.034)	(0.037)	(0.033)	(0.035)
Chain-linked Δ Log HP (other counties)	0.139***	0.160***	0.122***	0.143***
	(0.033)	(0.033)	(0.034)	(0.033)
Panel B: First Stage				
F-stat	13.665	13.665	13.665	13.665
County controls	yes	yes	yes	yes
Observations	924	924	924	924
R-squared	0.110	0.081	0.167	0.128

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retailer chains distribution of stores: $\sum_{k \neq c} \omega_{c,k} \Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors clustered at the state level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008), Housing supply elasticity is obtained from Saiz (2010).

D.3.5. Robustness Checks: Alternative period of analysis: 2007-2009: In my baseline specification, I choose the period between 2007 and 2011. In this section, I show that my main results remain qualitatively unchanged when I choose other period of analysis. Table A.XII replicates main table I for the period 2007 to 2009.

Table A.XII: Propagation of house price-induced local demand shocks across counties through the network of retailer chains: 2007-2009

	Dep Variable: County's Δ Log Price Index (2007-2009)					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.044	0.023	0.012	0.121***	0.073*	0.069
	(0.027)	(0.026)	(0.027)	(0.043)	(0.044)	(0.046)
Chain-linked Δ Log HP (other counties)		0.074**	0.081***		0.110***	0.117***
		(0.030)	(0.030)		(0.037)	(0.037)
Panel B: First Stage						
F-stat				20.757	14.378	13.437
Observations	910	910	910	910	910	910
County controls	no	no	yes	no	no	yes

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. The dependent variable is the percentage change in the county price index between 2007 and 2009. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2009, where the weights are defined as $\omega_{c,k}$ in the main text. Columns (1) to (3) report results for OLS estimations. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with WLRI. I instrument county exposure to house price shocks through the network of retailer chains with county exposure to WLRI through the network of retailer chains. Panel A report the second stage coefficients. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008), Housing supply elasticity is obtained from Saiz (2010).

D.3.6. Robustness Checks: Alternative market definitions: three digit Zip Code level: In my baseline specification, I choose the county as the relevant market. In this section, I check the robustness of my results to a different market definition. In particular, I define markets as a three digit zip code.

D.3.7. Robustness Checks: Region fixed effects: I explore the sensitivity of results to different combinations of region fixed effects. Throughout specifications, the main coefficient remains positive and significant. Note that once I include state fixed effects, the instrument becomes weak as reflected in the first stage F-statistic; so the coefficients in column (4) should be interpreted with caution.

Table A.XIII: Robustness Check: Region fixed effects

	County's Δ Log Price Index			
	(1)	(2)	(3)	(4)
County's Δ Log HP	0.064*	0.074*	0.117**	0.189***
	(0.034)	(0.041)	(0.047)	(0.070)
Chain-linked Δ Log HP (other counties)	0.139***	0.165***	0.125***	0.132***
	(0.033)	(0.031)	(0.033)	(0.021)
County controls	yes	yes	yes	yes
4-Regions FE	no	yes	-	-
9-Divisions FE	no	no	yes	-
State FE	no	no	no	yes
First Stage F-stat	13.665	13.278	10.829	9.253
Observations	924	924	924	924
R-squared	0.110	0.018	0.033	0.066

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2009, where the weights are defined as $\omega_{c,k}$ in the main text. Robust standard errors clustered at the state level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008), Housing supply elasticity is obtained from Saiz (2010).

D.3.8. Sample of counties with small house price changes: Arguably, counties where house prices did not fall substantially in the period are less likely to be hit by the same regional shocks that counties that were hit substantially. I restrict the sample to counties in which house prices fall or increase less than 5% during the Great Recession, but which are linked to counties hit hard by the house price slump and estimate the OLS equation. [28] Results are presented in Table A.XIV. Two things worth mentioning. First, in line with estimates in Table I, I find that the elasticity of local prices with respect to house price changes in distant locations is around 0.12. Second, it is interesting that the OLS estimates with the restricted sample in Column (3), 0.12, are higher than the OLS estimates in column (3) of Table I, 0.08, somehow converging to the IV estimates in column (6) of Table I (0.13). This constitutes additional evidence supporting that the instrument is addressing issues related to common regional shocks.

[28]Given that these are only 200 counties, I do not have enough variability to use the instruments

Table A.XIV: Robustness Check: Counties with small house price changes

	Dep variable: County's Δ Log Price Index		
	(1)	(2)	(3)
County Δ Log HP	0.083	0.071	0.078
	(0.053)	(0.045)	(0.046)
Chain-linked Δ Log HP (other counties)		0.117***	0.122***
		(0.035)	(0.032)
Observations	290	290	290
R-squared	0.007	0.221	0.254
County controls	no	no	yes
Sample:	$\lvert\Delta LogHP\rvert < 0.05$	$\lvert\Delta LogHP\rvert < 0.05$	$\lvert\Delta LogHP\rvert < 0.05$

County is the unit of observation. The sample is restricted with counties in which $|\Delta \log HP| < 0.05$. Clustered standard errors at the state-level in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

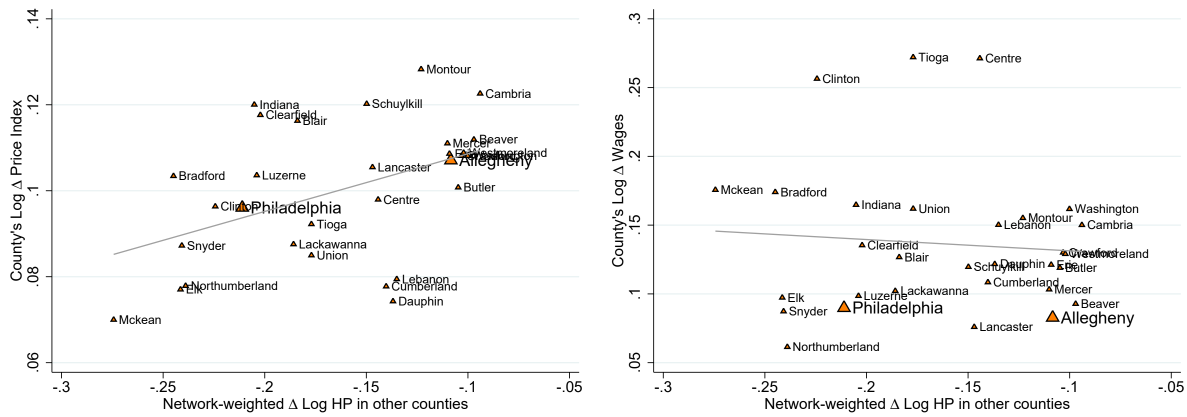
Illustrative Example: Pennsylvania

As an illustrative example that the network of retail chains affect prices, but now wages, in Figure A.IX I consider similar counties in Pennsylvania where house prices did not fall substantially. Panel A plots the relationship between network-weighted changes in house prices and county-level prices, while Panel B plots the relationship with county-level average wages. Focus, for instance, on the two largest counties: Philadelphia and Allegheny (home to Pittsburgh city). Philadelphia which was more connected to counties affected by the crisis experienced a 2 p.p lower food-at-home inflation rate. At the same time, the change in average wages was almost identical for both counties.

Figure A.IX: Example Pennsylvania

Panel a: Exposure and Price Index

Panel b: Exposure and average wages

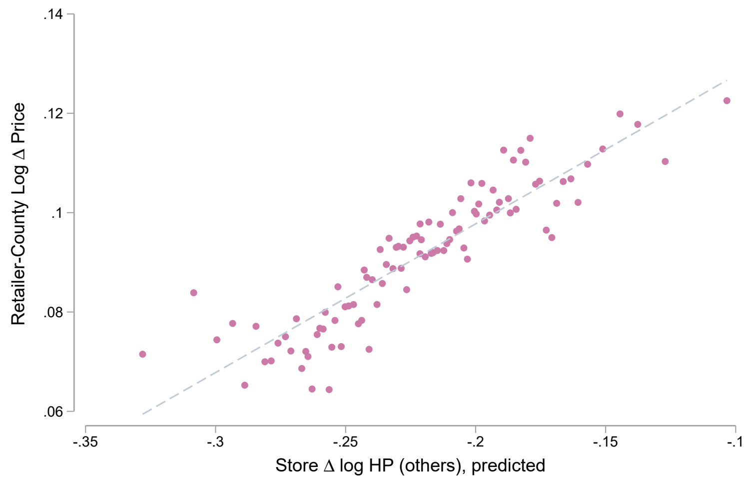


Note: Each observation is a county in Pennsylvania. I restrict to counties with $|\Delta HP| < 10\%$. Panel a plots the relationship between the network-weighted house price changes (x-axis) and county-level consumer prices (y-axis). Panel b reports the relationship network-weighted House Price changes (x-axis) and county-level change in average wages (y-axis).

D.3.9. Retail Chain by county level additional results:

1. Binscatter: Main results retail chain by county-level: Figure A.X provides a visual impression of the IV relationship between changes in the county-level retail price index and predicted changes in house prices in other counties as reported in Column (6) of Table VI. Specifically, the estimation of equation 4.4. Variables are residualized by county FE. The coefficient is 0.198.

Figure A.X: Network-weighted changes in house prices and county-level price changes



The binscatter plots the IV relationship between the network weighted house price changes in other counties and county-level retail prices. Counties are sorted into percentile bins based on their value on $\Delta \log(P_c)$. Each percentile bin represents 9 counties. I control for county fixed effects. Hence, the dot indicates the average value of (residual) $\Delta \log(P_c)$.

2.Retail chain by county-level: leave state out: I run my main equation at the retail chain by county-level, but only considering out-of-state shocks. I then estimate the leave-state-out version of Equation 4.4, while also instrumenting with leave-state-out WLRI. Results are reported in Table A.XV. Across a variety of specifications, I find that local prices are sensitive to shocks in distant counties (out-of-state) that are linked by the network of retail chains.

3.Clientele Effects: It is possible that common regional shocks bear different effects on different type of stores, even within a county. For example, a store of a retail chain that caters to richer consumers might be affected differently compared to a store of a retail chain that caters to poorer consumers. To account for this, I construct a variable at the retail chain level that captures whether the retail chain is mostly present in rich counties or in poor counties, based on county-level median household income.

I define the indicator variable, Clientele, that takes value one if the retail chain is above the median, and 0 otherwise. And then run the main specification at the county-by-store level, but now including County by Clientele fixed effects. Thus, I compare stores within a county, catering to similar demographic groups.

Table A.XV: Propagation of house price-induced local shocks to out-of-state counties

	Dep Variable: Retail chain by county Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County Δ Log HP	0.052***			0.123***		
	(0.015)			(0.025)		
Chain-linked Δ log HP (other state)	0.082**	0.089**	0.084**	0.153***	0.199***	0.206***
	(0.038)	(0.034)	(0.037)	(0.041)	(0.030)	(0.041)
Panel B: First Stage						
First Stage F-stat				12.426	38.675	38.947
Observations	3,666	3,666	3,666	3,666	3,666	3,666
R-squared	0.181	0.619	0.619	0.047	0.054	0.078
County controls	yes	-	-	yes	-	-
Retail chain controls	no	no	yes	no	no	yes
County FE	no	yes	yes	no	yes	yes

A unit of observation is a retail chain by county. The dependent variable is the percentage change in the price index of a retail chain in a county between 2007 and 2011 ($\Delta \log(P_rc)$). County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (out-of-state counties) is the network-weighted percentage change in house prices in other counties where the retail chain operates, excluding the state in which the county is located ($\sum_{k \neq State} S_{rk} \Delta \log(HP_k)$). Columns (1) to (3) report results for OLS estimations. County-level controls in columns (3) and (6) include changes in log wages, changes in log number of retail establishments, changes in log employment, and county's own weight ω_{cc}. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument network-weighted percentage change in house prices ($\sum_{k \neq State} S_{rk} \Delta \log(HP_k)$) in out-of-state counties with network-weighted WLRI in out-of-state counties ($\sum_{k \neq State} \omega_{rk} WLRI_k$). Panel A reports the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels. Source: Prices, quantities and sales are obtained from NielsenIQ Retail Scanner Data. Housing price data is obtained from from the Federal Housing Finance Agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008). County-level macroeconomic variables are obtained from the Bureau of Labor Statistics.

Results are presented in Table A.XVI. The main conclusions remain unchanged.

Table A.XVI: Robustness Check: Clientele effects at the retail chain by county-level

	Dep Variable: Chain's Δ Log Price in county c			
	OLS		IV: WLRI instrument	
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
Store $\Delta \log HP(others)_{rc}$	0.094***	0.079***	0.183***	0.191***
	(0.032)	(0.033)	(0.037)	(0.061)
Panel B: First Stage				
F-statistic			19.932	16.221
Retail chain controls	yes	yes	yes	yes
County FE	yes	-	yes	-
County-Clientele FE	no	yes	no	yes
Observations	3,747	3,747	3,747	3,747
R-squared	0.612	0.738	0.497	0.568
# retailers	84	84	84	84
# counties	910	910	910	910

Clustered standard errors at the state-level in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

D.3.10. Robustness check: Only more representative counties: Figure A.III of section 2 demonstrates that the price index constructed using NielsenIQ's sample of retail chains closely tracks the behavior of the BLS food-at-home CPI. As a result, the paper's findings could be considered a reliable representation of the food-at-home inflation rate. Nevertheless, since the NielsenIQ data is not a census, it is possible that for some counties, NielsenIQ's retail chain sales data may not accurately reflect local retail sales.

To address this issue, I perform two exercises. In the first exercise, I consider only those counties where county-level observable covariates are good predictors of sales figures within NielsenIQ's data. To do this exercise I proceed in two steps. The first step consists on estimating for the year 2007 the following equation:

$$\ln(Nielsensales_c) = \beta_0 + \beta_1 \ln Employment_c + \beta_2 Establishments_c + \beta_3 \ln Wages_c + FE_s + u_c$$

The regression model has an R^2 value of 0.89. In a second step, I remove the 20% of observations with the highest residuals (in absolute terms) and re-run the main Equation 4.3 using the remaining sample. The results of this restricted sample are reported in columns (1) and (2) of Table A.XVII. Reassuringly, the main estimate remains almost unchanged.

In a second exercise, I restrict the sample to counties where NielsenIQ firms are large relative to the population size of the county. The idea is to restrict the sample to counties where NielsenIQ firms are a large share of total retail revenues. I exclude counties observations for which the ratio of $Nielsensales_c$ with respect to $population_c$ is at the bottom 10% of the distribution. Results are reported in columns (3) and (4) of Table A.XVII.

Table A.XVII: Propagation of house price-induced local shocks: Restricting to most representative counties in NielsenIQ Data

	Dep Variable: County's Δ Log Price Index					
	IV: Benchmark		IV: Exercise 1		IV: Exercise 2	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.070**	0.064*	0.064**	0.060*	0.066**	0.056
	(0.029)	(0.034)	(0.029)	(0.035)	(0.030)	(0.034)
Chain-linked Δ Log HP (other counties)	0.130***	0.139***	0.133***	0.143***	0.137***	0.146***
	(0.031)	(0.033)	(0.032)	(0.035)	(0.033)	(0.034)
First Stage F-stat	21.838	13.665	19.414	13.048	23.934	16.054
County controls	no	yes	no	yes	no	yes
Observations	924	924	739	739	832	832
R-squared	0.082	0.110	0.089	0.110	0.124	0.160

This table repeats Table I, but excluding counties where NielsenIQ retail sales might not be representative. Column (1) and (2) report benchmark estimates including all counties. Columns (3) and (4) exclude those counties where county-level covariates are not a good predictor of NielsenIQ retail sales. Column (5) and (6) excludes counties for which retail sales in NielsenIQ are too small relative to the county population. Clustered standard errors at the state-level in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

D.3.11. Robustness check: Excluding California: I check the robustness of my results to excluding the largest state in the sample, California.

Table A.XVIII: Robustness Check: excluding CA

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.047***	0.029**	0.019	0.126***	0.072*	0.078
	(0.014)	(0.013)	(0.014)	(0.034)	(0.041)	(0.050)
Chain-linked Δ Log HP (other counties)		0.077**	0.079***		0.165***	0.174***
		(0.030)	(0.029)		(0.038)	(0.037)
Panel B: First Stage						
F-stat				20.527	16.695	11.933
Observations	881	881	881	881	881	881
County controls	no	no	yes	no	no	yes

This table repeats Table I, but excluding Caliornia (the largest state) from the analysis. Clustered standard errors at the state-level in parenthesis. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

D.3.12. Robustness check: Sample of 924 counties versus full sample: In the main analysis, I focus on the 924 counties for which there is information on the WLRI. These counties represent more than 70% of US population. In order to check whether the effect obtained in this sample is comparable to a larger sample of counties, I compare the results of my OLS estimations with the 924 counties and with the full NielsenIQ sample of 2300 counties. Reassuringly, the estimates are almost identical.

Table A.XIX: OLS estimations with the whole NielsenIQ sample

	Dep Variable: County's Δ Log Price Index	
County's Δ Log HP	0.028**	0.016
	(0.014)	(0.011)
Chain-linked Δ Log HP	0.089***	0.093***
(other counties)	(0.027)	(0.022)
Observations	910	2,186
R-squared	0.247	0.178
Sample	Counties with non-missing WLRI	All counties

D.3.13. Robustness check: Trade Flows: Alternatively, I construct a variable that accounts for the trade flows between county c and county k:

$$\text{trade-weighted}\Delta\log(HP)_c^{others} = \sum_{k\neq c}\gamma_{ck}^{trade}\Delta\log(HP)_k^{07-11},$$

where

$$\gamma_{ck}^{trade} = \frac{tradeflow_{ck}}{\sum_k tradeflow_{ck}}$$

where $trade_{ck}$ is the trade flow (exports and imports) between the county c's state and the county's k state. [29] Intuitively, the more county c and county k trade, the more their prices correlate.

I add this term to my main Equation 4.3 and estimate it. Results are reported in Table A.XX.

Table A.XX: Channels of propagation of shocks: retail chains versus trade channel

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instruments		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
Tradeflows-linked Δ Log HP (other counties)	0.095***	0.059***	0.007	0.153***	-0.115	-0.106
	(0.007)	(0.012)	(0.012)	(0.044)	(0.087)	(0.089)
County's Δ Log HP		0.026***	0.027***		0.183***	0.130***
		(0.007)	(0.007)		(0.050)	(0.049)
Chain-linked Δ Log HP (other counties)			0.083***			0.159***
			(0.008)			(0.034)
Panel B: First Stage						
F-stat				12.572	11.510	10.447
Observations	910	910	910	910	910	910
R-squared	0.154	0.167	0.250	0.096	0.082	0.042

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta\log(P_c)$). County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the network-weighted percentage change in house prices in other counties ($\sum_{k\neq c}\omega_{ck}\Delta\log(HP_k)$) as defined in Equation 4.2. Trade flows-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, where the weights proportional to trade flows between states. Columns (1) to (3) report results for OLS estimations. Columns (4) to (6) report results, after instrumenting the three main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument Chain-Linked Δ Log HP (other counties) with Chain-Linked WLRI in other counties ($\sum_{k\neq c}\omega_{ck}WLRI_k$). I instrument Trade-Linked Δ Log HP (other counties) with Trade-Linked WLRI in other counties ($\sum_{k\neq c}\delta_{ck}^{prox}WLRI_k$). Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Retail Scanner Data. Housing price data is obtained from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008).

D.3.14. Robustness check: All similarity controls: Here I incrementally add similarity-weighted shocks as controls across the columns, culminating in column (7), which includes all variables simultaneously. Although this approach introduces some collinear-

[29] This data was obtained from Bureau of Transportation Statistics, Office of Secretary And Federal Highway Administration U.S. Department of Transportation combining data from the 2012 Commodity Flow Survey(CFS) and other trade data from the Census Bureau.

ity, complicating the separate interpretation of coefficients, it is reassuring to observe that the main coefficient remains stable when all variables are included.

Table A.XXI: Similarity-weighted shocks: all controls

	Dep Variable: County's Δ Log Price Index						
	IV: WLRI instrument						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Second Stage							
Δ Log HP	0.064*	0.062*	0.060*	0.060*	0.060*	0.095*	0.020
	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)	(0.052)	(0.018)
Chain-linked Δ Log HP (others)	0.139***	0.140***	0.139***	0.140***	0.139***	0.131***	0.174***
	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)	(0.036)	(0.031)
Income-weighted Δ Log HP (others)		0.029***	0.027**	0.027**	0.027**	0.019	0.022**
		(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
Employment-weighted Δ Log HP (others)			0.016	0.017	0.017	0.009	0.024
			(0.015)	(0.014)	(0.015)	(0.016)	(0.015)
Population-weighted Δ Log HP (others)				-0.003	-0.004	-0.010	0.003
				(0.017)	(0.017)	(0.017)	(0.015)
Education-weighted Δ Log HP (others)					0.011	0.012	0.012
					(0.009)	(0.009)	(0.009)
HH debt-weighted Δ Log HP (others)						-0.072*	0.002
						(0.037)	(0.013)
Social-weighted Δ Log HP (others)							0.063***
							(0.023)
Observations	924	924	924	924	924	924	924
County controls	yes	yes	yes	yes	yes	yes	yes
First Stage F-stat	13.665	13.809	13.884	13.803	13.698	8.233	11.153

A unit of observation is a county. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in counties linked by retail chains. Columns (2) to (4) control for similarity-weighted changes in house prices. Similarity is based on median age of the county and on share of Democratic Party votes in the 2008 presidential election. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: NielsenIQ Scanner Data, FHFA.

D.3.15. Robustness check: Shocks in similar counties in terms of age and voting patterns: To account for similarities in consumer preferences across connected counties, I also control for shocks originating from counties that are similar in terms of median age demographics or voting patterns, as proxied by the share of votes for the Democratic Party in the 2008 presidential election. Reassuringly, the results remain largely unchanged.

Table A.XXII: Control similarity in demographics: age and voting patterns

Dep Variable: County's Δ Log Price Index			
County Δ Log HP	0.064*	0.064*	0.065*
	(0.034)	(0.034)	(0.034)
Chain-weighted Δ Log HP (others)	0.139***	0.139***	0.138***
	(0.033)	(0.033)	(0.033)
Voting-weighted Δ Log HP (others)		0.001	
		(0.012)	
Age-weighted Δ Log HP (others)			-0.013
			(0.018)
Observations	924	924	924
R-squared	0.110	0.110	0.110
County controls	yes	yes	yes
First Stage F-stat	13.665	12.918	13.545

A unit of observation is a county. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in counties linked by retail chains. Columns (2) to (4) control for similarity-weighted changes in house prices. Similarity is based on median age of the county and on share of Democratic Party votes in the 2008 presidential election. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: NielsenIQ Scanner Data, FHFA.

D.3.16. Inference with correlated errors in shift-share design: In a recent paper, Adao et al. (2019) shows that in shift-share designs, regression residuals can be correlated across regions with similar shares, independent of their geographic location. This implies that even though I cluster at the state-level in my main analysis, there could still be remaining issues with the standard errors.

In this section, I follow Adao et al. (2019) methodology to take this into account. In particular, their methodology provides inference methods that are valid under arbitrary cross-regional correlation in the regression residuals. I present results in table A.XXIII.

Table A.XXIII: Adao et al. (2019) Robust Standard Errors

	Dep Variable: County's Δ Log Price Index			
	OLS		IV: WLRI instrument	
	(2)	(3)	(5)	(6)
Panel A: Second Stage				
Chain-linked Δ Log HP (other counties)	0.085***	0.091***	0.130***	0.139***
	(0.035)	(0.036)	(0.051)	(0.056)
Panel B: First Stage				
F-stat			17.122	12.431
Observations	924	924	924	924
County controls	no	yes	no	yes
Demeaned by $\Delta LogHP_c$	yes	yes	yes	yes

This table repeats Columns (1), (2), (3) and (4) of Table I using shift-share robust standard errors proposed by Adao et al. (2019) to conduct valid inference under arbitrary cross-regional correlation in the residuals. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

D.4 Extensive Margin Adjustments

In the main analysis, we have focused on the propagation of shocks to prices of continuing varieties. However, retail chains might also adjust their extensive margin in response to shocks. For instance, they might close stores or discontinue products.

In this section of the appendix, I explore this possibility. In my previous analysis, I showed that county level prices are sensitive to shocks in distant regions linked by the retail chains' network. This can imply changes in average markups of the county, leading to entry or exit of stores. For example, a county exposed to negative shocks in other county will experience a drop in its retail prices. This, in turn, will make competition tougher in the county. Therefore, we may observe more exit of stores due to tougher competition in counties that were linked to counties more affected by the house price drops.

In order to study the effect on the extensive margin at the county level, I begin by running my main specification with counties' percentage changes in number of stores, barcodes and varieties as dependent variable. I present results in Table A.XXIV. Although significant only at 10%, there is some suggestive evidence of exit of stores and barcodes in counties served by retail chains more exposed to drops in house prices in other counties.

Table A.XXIV: Retailer chain's extensive margin responses

VARIABLES	(1) $\Delta Stores$	(2) $\Delta Stores$	(3) $\Delta Products$	(4) $\Delta Products$	(5) $\Delta Varieties$	(6) $\Delta Varieties$
County's Δ Log HP	0.024	-0.095	0.271	0.135	0.093	-0.122
	(0.151)	(0.187)	(0.175)	(0.230)	(0.246)	(0.296)
Chain-linked Δ Log HP (other counties)		0.316*		0.361		0.570*
		(0.179)		(0.297)		(0.317)
Observations	910	910	910	910	910	910
R-squared	0.001	0.030	0.006	0.003	0.004	0.026
County controls	yes	yes	yes	yes	yes	yes
First Stage F-stat	13.358	13.862	13.358	13.862	13.358	13.862

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retailer chains distribution of stores: $\sum_{k \neq c} \omega_{c,k} \Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008), Housing supply elasticity is obtained from Saiz (2010).

Previous table shows how the Great Recession and the geographic distribution of retailer chain's stores affected the varieties available for consumers. Given that consumers have a taste for variety, an increase in the range of available varieties should lead to a decrease in the price index. Translating the increase in product variety into welfare gains requires structural assumptions. Following Feenstra 1994 I assume a CES utility function to infer the infra-marginal consumer surplus created or destroyed by changes in product variety from the observed spending shares on new and exiting products. I also decompose entry and exit of barcode-stores into two terms:[30] In particular, I decompose the Feenstra Ratio into two margins of adjustments:

1. Store-level Feenstra Ratio: captures consumer surplus by changes in stores available. 2. Barcode-level Feenstra Ratio: captures consumer surplus created by entry or exit of barcodes in existing stores.

I then construct an exact CES price index that considers entry and exit of new varieties:

[30]To do so, I assume that consumers first choose the store in which they will shop and then choose the barcodes.

$$\left[\Pi_{bs\in I_{mc}}\left(\frac{P_{bsmct}}{P_{bsmt-1}}\right)^{w_{bsmct}}\right]\left[\Pi_{s\in I_{mc}}\left(\frac{\lambda_{smct}}{\lambda_{smct-1}}\right)^{\frac{w_{smct}}{\sigma_s-1}}\right]\left(\frac{\lambda_{mct}}{\lambda_{mct-1}}\right)^{\frac{1}{\sigma_m-1}},with$$

The first multiplicative term in brackets is the the CES price index for continuing products between t and $t-1$, as described in the body of the paper. We refer to the second term as the barcode-level Feesntra Ratio. The higher the expenditure share of new varieties within a product module and store, the lower λ_{smct}, implying a lower adjusted inflation rate. Intuitively, conditional on the number of stores, the adjusted inflation rate is going to be lower if consumers spend more in new varieties. The third term is the store-level Feenstra Ratio. The higher the expenditure in new stores, the lower λ_{mct}, implying a lower adjusted inflation rate. The price index also depends on the module-specific elasticity of substitution σ_m between stores and module-store specific elasticity of substitution σ_s between barcodes in a product-module-store. As these elasticities grow, the additional terms converge to one and the bias in the price index goes to zero. The intuition is that when existing varieties are close substitutes to new or disappearing varieties, price changes in the set of existing products perfectly reflect price changes for exiting and new varieties.

Now, I estimate my main specification with each of the terms above as dependent variable. Table A.XXV report the results. Columnn (1) report results for the price index for continuing varities, as in the main analysis of the paper. Column (2), reports the effect of retailer chains networks on changes in product variety within existing stores. Column (3) report results for the effect on changes in available stores. Finally, column (4) provides the exact price index combining the three terms. We do not observe any effect of the network of retail chains on entry and exit of stores and barcodes. However, in column (4), we observe that the main conclusions of the paper remain when we adjust the price index to account for entry and exit of varieties.

Table A.XXV: County level Price Index adjusted for entry and exit of varieties

	Δ Log Price Index (continuers)	Feenstra Ratio (barcodes)	Feenstra Ratio (stores)	Δ Log Price Index (adjusted)
	(1)	(2)	(3)	(4)
Panel A: Second Stage				
County's Δ Log HP	0.069*	-0.034	0.035	0.071
	(0.040)	(0.025)	(0.034)	(0.067)
Chain-linked Δ Log HP (other counties)	0.119***	0.034	-0.008	0.147**
	(0.039)	(0.034)	(0.033)	(0.071)
Observations	922	922	922	922
County controls	yes	yes	yes	yes
First Stage F-stat	14.479	14.479	14.479	14.479

A unit of observation is a county. I define a chain to be a unique combination of two identifiers in the NielsenIQ data: parent code and retailer code. The dependent variable is the change in county price index between 2007 and 2011: $\Delta log(HP)_c^{07-11}$. The average of the dependent variable is 11.8%. Chain-linked Δ Log HP (other counties) refers to the weighted average percentage change in house prices in other counties, linked through retailer chains distribution of stores: $\sum_{k \neq c} \omega_{c,k} \Delta log(HP_k)^{07-11}$. Chain-linked Δ Log HP (other counties) is the percentage change in house prices between 2007 and 2011, where the weights are the county share of the chain national sales. Columns (2) to (8) report results, after instrumenting county exposure to house price shocks through the network of retailer chains. In column (3) to (4), I instrument with exposure to WLRI, as in the baseline specification. In columns (5) and (6), I instrument with exposure to Saiz Housing supply elasticity. Columns (7) and (8) use the 4 instruments. Panel A report the second stage coefficients. Robust standard errors are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008), Housing supply elasticity is obtained from Saiz (2010).

D.5 Costs or markups

In order to understand the cost structure of retail chains, I collect information from Form 10K official reports for the major US supermarkets and pharmacies in years for which a report is available. [31] These reports provide comprehensive annual financial statements for publicly traded companies in the US. I classify costs into wholesale costs of goods and operational expenses. Cost of goods is the wholesale cost of the goods acquired for sell. Operating expenses consist of employee-related costs such as wages, health care benefit costs and retirement plan costs, utilities, credit card fees, and rent expenses.

Table A.XXVI reports the cost structure of the thirteen major companies. The majority of supermarkets' and pharmacies' costs are wholesale costs. Wholesale costs of goods represent the majority of the retailers costs. Within the operating cost category, wages is the most important. For those supermarkets that report rent costs, this is marginal. For example, rental costs are 0.2% of the total costs for Kroger.

[31] Downloaded from `https://last10k.com/sec-filings/swy`, accessed on January, 2023.

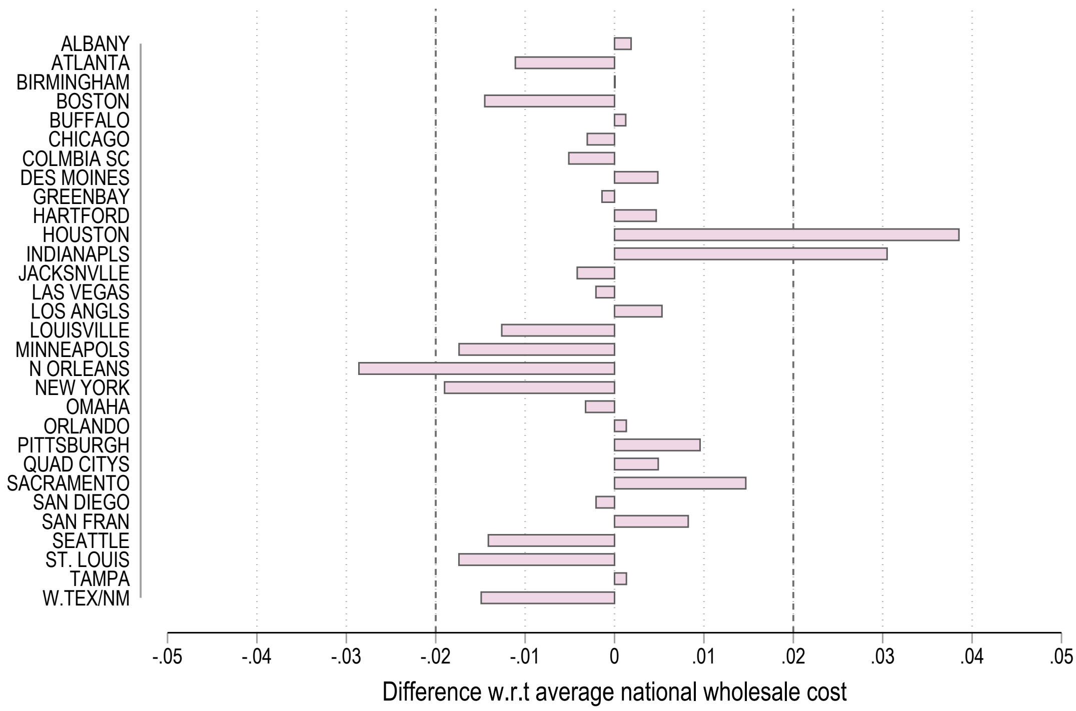
Table A.XXVI: Costs of major retail chains by category

Company (million US$)	Cost of goods sold	Selling, Operating and Administ. Expenses	Total Costs	% costs Goods sold	Year
Walmart	373859	105771	479629	77.95	2018
CVS Health	155539	33183	188721	82.42	2018
Kroger	78138	15696	93834	83.27	2014
Walgreens	54823	17992	72815	75.29	2014
Target	51278	14676	65954	77.75	2014
Albertson	46672	15660	62332	74.88	2015
Safeway	26645	8859	35504	75.05	2013
Publix	23460	6481	29941	78.35	2015
Whole Foods	15389	4627	20016	76.88	2015
Dollar General	12068	3670	15738	76.68	2014
Southeastern Groceries	8388	2721	11109	75.51	2015
Dollar Tree	5050	1820	6870	73.51	2014
Grocery Outlet	1271	561	1832	69.38	2016

Source: Form 10K official reports.

Wholesale costs: Figure A.XI provides insights into the degree of geographic variation of wholesale costs across markets. Each bar represents the percentage difference between the average wholesale cost in each market and the national average. Overall, 27 out 30 markets have average wholesale costs within 2 percent of the national average.

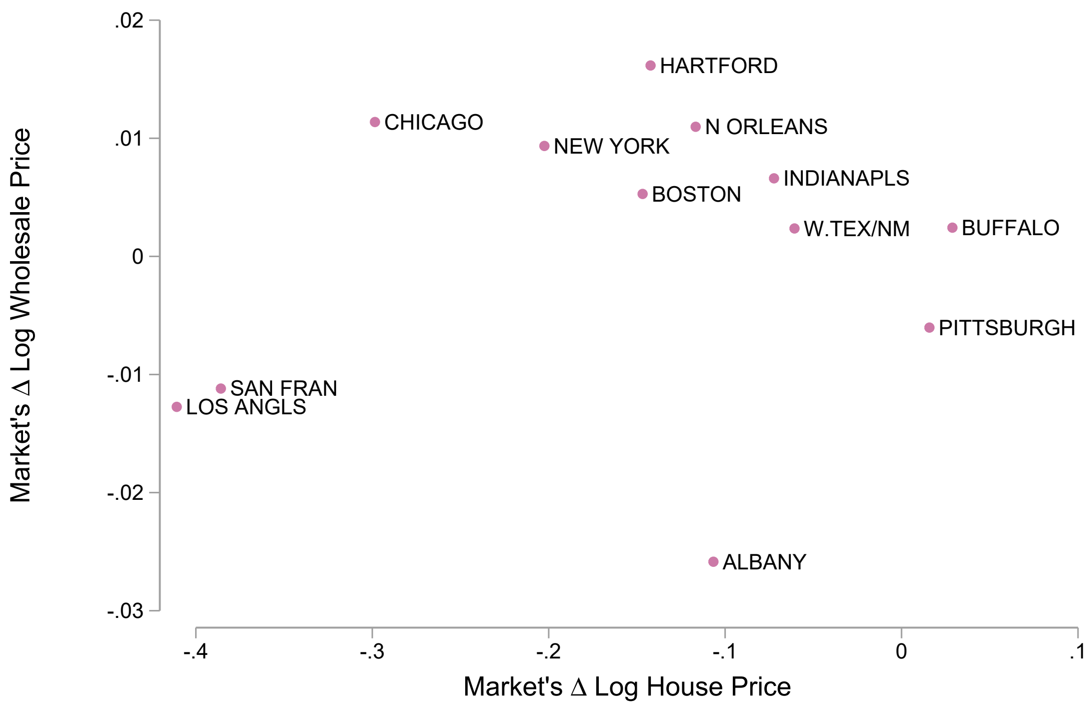
Figure A.XI: Wholesale costs do not vary geographically



Source: Promodata database.

For 12 metropolitan areas, we observe changes in wholesale costs between 2007 and 2011. Figure A.XII presents a scatter plot that shows the average change in wholesale prices relative to the national average (y-axis) against the change in house prices in each market (x-axis). The y-axis indicates minimal changes in wholesale costs relative to the national average, with most values within 2% (while the house price changes range between -40% and 5%). Additionally, there is no clear correlation between local changes in house prices and local wholesale costs. Notably, San Francisco and Los Angeles do exhibit slightly lower wholesale costs and are the most affected by the crisis. However, other markets, such as Chicago and New York, which were heavily impacted by the housing price slump, show similar wholesale cost changes to markets like Indianapolis, Texas, and Buffalo, which were much less affected.

Figure A.XII: Changes in wholesale costs between 2007 and 2011 do not vary geographically



Source: Promodata database.

Labor costs: To explore the role of labor costs as a mechanism for my findings, I augment my main Equations at the county and retail chain level to include controls for county-level wage changes and weighted average wage changes in counties connected by the retail chains networks. Results are reported in Table A.XXVII. In Columns (1) and Columns (2) I report results for the county-level regressions. In Column (3), I repeat the analysis with granular data at the retail chain by county-level and include county fixed effects. The main coefficient remains stable throughout specifications.

Table A.XXVII: Propagation of house price-induced local demand shocks: controlling for labor costs

Dep Variable:	Δ Log Price Index		Δ Log Price Index
	County-level		Retail by County-level
	(1)	(2)	(3)
Panel A: Second Stage			
County Δ Log HP	0.118***	0.063*	
	(0.026)	(0.034)	
Chain-linked Δ Log HP (others)		0.132***	0.222***
		(0.034)	(0.036)
County Δ Log Wages	0.024*	-0.003	
	(0.015)	(0.013)	
Chain-liked Δ Log Wages (others)		0.003	0.005**
		(0.003)	(0.002)
Panel B: First Stage			
F-stat	20.507	15.111	47.444
County FE	no	no	yes
Observations	924	924	3,666
R-squared	0.067	0.115	-0.084

In columns 1 and 2, the unit of observation is the county-time. In column 3, the unit of observervtion is retail chain by county. The dependent variable is the percentage change in the retail chain by county price index between 2007 and 2011 ($\Delta \log(P_c)$) or in county-by-retail chain price index (column 3). Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at both the retail-chain level and state-level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Retail Scanner Data. Housing price data is obtained from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008). County-level macroeconomic variables are obtained from the Bureau of Labor Statistics.

D.6 Retail chain decisions and Producers margin of adjustment

When analyzing retail chains' pricing behavior using the NielsenIQ database, two distinct margins of adjustment come into play. On one hand, there are the decisions made by retail chains, such as Carrefour.[32] On the other hand, there are decisions made by producers, such as Coca-Cola. Hyun and Kim (2019), henceforth referred

[32] I use the example of a French retail chain since NielsenIQ policy prohibits naming U.S.-based retail chains.

to as HK, examine producers' decisions and how these influence the propagation of shocks. They find that producers' adjustments predominantly occur through the entry and exit of varieties in distant markets, indicating that the extensive margin dominates producers' responses.

In this section, I (1) compare the qualitative theoretical differences between the HK mechanism for producers and my mechanism for retail chains, while also addressing the different implications of each mechanism for spillovers to regions unaffected by local shocks, and (2) provide a quantitative assessment of the impact of each mechanism.

D.6.1. Qualitative and Theoretical Differences between mechanisms: There are four key differences between HK's manufacturers' uniform product replacement propagation mechanism and the retail chains' centralized pricing propagation mechanism in my paper. Table A.XXVIII summarizes these distinctions.

First, HK focus on manufacturers that operate from a single location and distribute products across multiple U.S. markets (multi-market producers). In contrast, my paper focuses on retail chains with establishments located across various U.S. regions that sell products locally (multi-establishment firms).

Second, the propagation of shocks differs between the two mechanisms. HK's mechanism operates through the extensive margin, where manufacturers respond to negative local shocks by reducing the varieties they produce to sell in all their markets. In contrast, my mechanism works through the intensive margin, with retail chains lowering the prices of continuous products across all markets in response to local negative demand shocks. I do not observe significant effects of retail chains decisions on entry and exit of varieties in distant markets.

Third, the mechanisms result in opposing welfare effects in regions unaffected by the local negative demand shock. In HK's framework, negative shocks in distant markets harm unaffected regions, as producers reduce the availability of varieties even in regions not directly impacted by the shock. This is equivalent to an increase in the price index and a corresponding reduction in welfare. Conversely, in my framework, spillovers through retail chains result in lower prices in unaffected regions, effectively decreasing the price index and benefiting unaffected regions.

Fourth, the two mechanisms differ in terms of risk-sharing between regions. HK's mechanism increases inter-regional risk-sharing, as a negative shock in one region (A) reduces access to varieties in another region (B), distributing the negative effects. In contrast, centralized pricing decisions in my framework reduce inter-regional risk-sharing. Prices in region A, which experiences the shock, do not decrease as much, worsening the local crisis. Meanwhile, prices in region B, which is unaffected, decline, leading to better economic conditions and amplifying regional disparities.

Table A.XXVIII: Comparison between HK manufacturers replacement channel and Retail Chains Centralized Pricing channel

	Uniform Replacement Channel (HK)	**Centralized Pricing**
(1) Unit of analysis	Multi-market manufacturers	Multi-establishment Retail chains
Response to a negative local shock:		
(2) Firm Adjustment:	Extensive margin: reduce varieties everywhere	Continuing Varieties: lower prices everywhere
(3a.) Price index effect:	Unaffected regions higher price index (due to exit of varieties)	Unaffected regions lower price index (due to continuing varieties)
(3b.) Welfare Effect:	Unaffected regions worse off	Unaffected regions better off
(4) Inter-regional risk sharing	Higher	Lower

D.6.2. Quantitative Comparison of Manufacturers' and Retail Chains' Decisions:

To quantitatively compare the mechanisms, I developed two exercises. In both cases, I constructed a more granular version of the dataset, disaggregating the data by retail chain, product-module, and county level. The addition of the product dimension enables me to better proxy the decisions made by manufacturers as in HK, distinguishing them from those made by retail chains as in my paper.

(A) Controlling for Manufacturers' Decisions

The first exercise examines the robustness of my findings by controlling for the manufacturing dimension in the HK results. To isolate the impact of retail chain pricing decisions, I hold manufacturers' decisions regarding changes in product varieties constant by controlling for relevant variables at the product-module level. The results are presented in Table A.XXIX.

Column (1) presents the benchmark specification, which includes only the exposure of retail chains to shocks elsewhere, using the disaggregated data. The elasticity of local retail chain prices with respect to shocks in other counties is 0.184, consistent with the main findings of the paper. Columns (2) through (4) introduce controls for manufacturer-level shocks. In Column (2), I control for the entry and exit of varieties by including the Feenstra ratio at the retail chain-by-county-by-product-module level. The main coefficient remains largely unchanged, suggesting that spillovers through retail chains are not driven by changes in the availability of varieties. In Column (3), I include a measure of product-module exposure to shocks in other counties to directly control for shocks to manufacturers, finding that the elasticity of local prices remains stable at 0.179. Column (4) adds county-by-product fixed effects, further confirming that the observed spillovers through retail chains are not attributable to manufacturers' decisions.

Table A.XXIX: Robustness check: controlling for manufacturer level shocks

	(1)	(2)	(3)	(4)
		$\Delta LogP_{mrc}$		
Store $\Delta \log HP(others)_{rc}$	0.184***	0.187***	0.179***	0.144**
	(0.043)	(0.043)	(0.044)	(0.066)
Log Feenstra Ratio		0.039*		
		(0.022)		
Product exposure (others)			0.117	
			(0.079)	
First Stage				
F-stat	35.831	35.759	106.221	35.433
Observations	2,165,213	2,165,213	2,165,213	2,165,213
County FE	yes	yes	yes	yes
County by Product FE	no	no	no	yes

A unit of observation is a retail chain by product-module by county. The dependent variable is the percentage change in the retail chain by product module by county price index between 2007 and 2011. County's Δ Log HP is the county-level percentage change in house prices between 2007 and 2011. Store $\Delta \log HP(others)_{rc}$ is the store-level network-weighted percentage change in house prices in other counties. Product exposue is the exposure of the product module to shocks in other locations. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at both the retail-chain level and state-level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Retail Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008). County-level macroeconomic variables are obtained from the BLS.

(B) Comparing Effects on Prices of continuing products and extensive margin

In the second exercise, I directly compare the effects of HK's product replacement decisions and the retail chain pricing decisions on prices of continuing varieties and on the extensive margin. Specifically, I examine how each mechanism affects welfare through the intensive margin (price index of continuing varieties) and the extensive margin (availability of varieties). Following Feenstra (1994), I decompose a CES price index at the product by retail by county level between the price index of continuing varieties and the Feenstra ratio which allows to infer the infra-marginal consumer surplus created or destroyed by changes in product variety from the observed spending shares on new and exiting products. Specifically, defining I_{rmc} as the set of barcodes b in retail chain r, product m, county c available both in 2007 and 2011, the CES price index is:

$$P_{mrct} = \left[\Pi_{b \in I_{mrc}} \left(\frac{P_{bmrct}}{P_{bmrt-1}} \right)^{w_{bmrct}} \right] \times \left(\frac{\lambda_{mrct}}{\lambda_{mrct-1}} \right)^{\frac{1}{\sigma_m - 1}}, \quad \text{where}$$

$$\lambda_{mrct} = \frac{\sum_{b \in I_{mrc}} Sales_{bmrct}}{\sum_b Sales_{brmct}}$$

Define the Feenstra Ratio as: $F_{mrc} = \left(\frac{\lambda_{mrct}}{\lambda_{mrct-1}} \right)^{\frac{1}{\sigma_m - 1}}$

The first multiplicative term in brackets is the the CES price index for continuing products between t and $t-1$, which I emphasize in the paper. The second term is the Feenstra ratio between the two periods which infers the change in price index due to changes in product variety. The higher the sales of new products in t, the lower the Feenstra ratio and, therefore, a lower implied price index due to the entry of varieties.

Using each of these multiplicative terms in logs as dependent variable, I estimate regressions including the exposure of retail chains and the exposure of product modules to shocks in other counties. All regressions include county fixed effects. I then compare the resulting coefficients across specifications. Results are reported in Table A.XXX. Columns (1) and (2) present the estimates for the price index of continuing varieties. The results confirm that retail chain networks play a significant role in transmitting shocks, with an elasticity of 0.179 in Column (2), significant at the 1% level.

Columns (3) and (4) present the estimates for the Feenstra ratio, which captures the extensive margin. While the retail chain exposure coefficient is not significant, product-module exposure to shocks in other counties is associated with a 13.7% increase in the Feenstra ratio, suggesting that variety reductions are more pronounced under the HK mechanism. In summary, both mechanisms are importing. The retail chain channel affects the price index of distant markets by affecting the prices of continuing varieties, with an elasticity of 14.1%, while the HK mechanism operates through the extensive margin, with an elasticity of -13.7%. Both results align with the theoretical predictions of each paper. Retail chains' uniform pricing strategies cause them to lower prices for continuing products across all markets in response to a local shock. In contrast, the HK mechanism leads producers to reduce the number of varieties sold in each market, which is equivalent to an implied increase in the price index due to access to a lower set of products.

Table A.XXX: Comparison: Retail chains centralized pricing decisions and Manufacturers uniform replacement decisions

	$\Delta LogP_{mrc}$		$Log(Feenstra)_{mrc}$	
	(1)	(2)	(3)	(4)
Store $\Delta \log HP(others)_{rc}$	0.184***	0.179***	-0.046	-0.043
	(0.043)	(0.044)	(0.050)	(0.051)
Product exposure (others)		0.117		-0.137**
		(0.079)		(0.042)
First Stage				
F-stat	35.831	106.221	35.831	106.221
Observations	2,165,213	2,165,213	2,165,213	2,165,213
County FE	yes	yes	yes	yes

A unit of observation is a retail chain by product-module by county. The dependent variable is the percentage change in the retail chain by product module by county price index between 2007 and 2011. County's Δ Log HP is the county-level percentage change in house prices between 2007 and 2011. Store $\Delta \log HP(others)_{rc}$ is the store-level network-weighted percentage change in house prices in other counties. Product exposue is the exposure of the product module to shocks in other locations. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at both the retail-chain level and state-level in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively. Source: Prices, quantities and sales are obtained from NielsenIQ Retail Scanner Data. Housing price data is obtained from from the Federal Housing Finance agency (FHFA). Wharton Land Regulation Index from Gyourko et al. (2008). County-level macroeconomic variables are obtained from the BLS.

E Model

E.1 Implications Uniform pricing at retail chain level

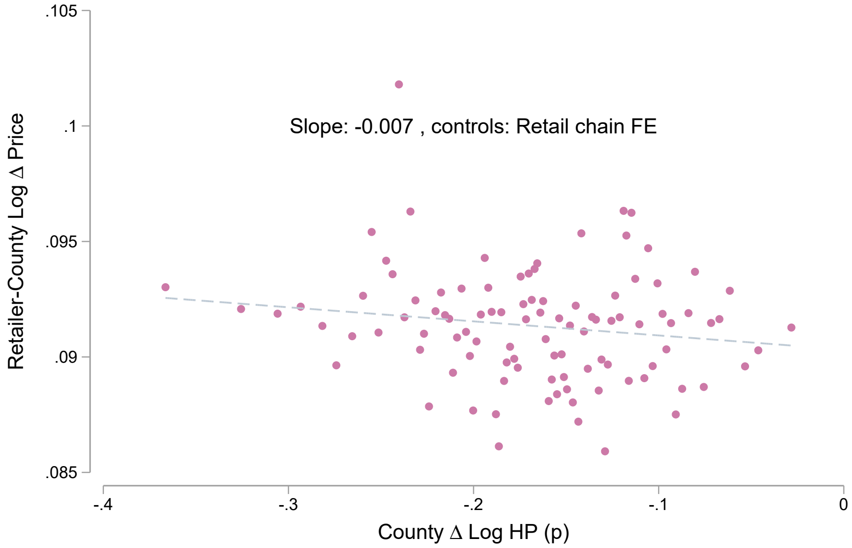
Testing Implication (II): No local effect of shocks when comparing Within retail chain

Implication (I) establishes that once retail chain fixed effects are included, we should observe no direct effect of the local shocks on local retailer prices as the retailer is adjusting in all its locations. Figure A.XIII plots the binscatter of the relationship between retail chain-centered predicted house price change (x-axis), and the the retail chain-centered change in retail by county-level price index (y-axis). That is, the relationship β_1 of estimating the following equation with retail chain fixed effects.

$$\Delta \log(P_{rc})^{07-11} = \beta_1 \Delta \log(HP_c)^{07-11} + \gamma_r + \epsilon_{rc}, \tag{E.1}$$

This regression compares price responses of a given retail chain across its locations. As expected the figure confirms that once we include retail chain fixed effects, local shocks have no effect on retail chain prices in that location (e.g: the retailer is increasing its prices in all its locations). Therefore, this constitutes further evidence in favor of a model with uniform pricing responses of the retail chains.

Figure A.XIII: Binscatter: Relationship between retail-by-county price changes and house price changes retail chains: *within retail chain effects*



Note: The figure plots the binscatter of the relationship between instrumented house price changes (x-axis) and retail chain by county-level consumer prices (y-axis). Both variables are residualized with retail-chain fixed effects, hence the effect is comparing within retail chains.

Also note that this Figure is consistent and resembles Panel A, Figure IV in DellaVigna and Gentzkow (2019). They shows that within a retail chain, in the cross-section, prices are similar across locations with different levels of income. Here we show that within a retail chain, its prices adjust uniformly in all its locations.

E.2 Proof of Equation 5.2

Aggregate county-level prices under uniform prices are:

$$P_c^U = \prod_r \left(\frac{\sum_k \sigma_k S_{rk}}{\sum_k S_{rk}(\sigma_k - 1)} c_r \right)^{l_{rc}}$$

Taking logs in both sides,

$$\log P_c^U = \sum_r l_{rc} \log \left(\sum_k \sigma_k S_{rk} \right) - \sum_r l_{rc} \log \left(\sum_k (\sigma_k - 1) S_{rk} \right) + \sum_r l_{rc} \log c_r$$

To analyze the impact of changes in elasticities σ_m and retail chain costs c_r, we total differentiate the logarithm of P_c^U, around the initial equilibrium shares in 2007 (l_{rc}^{07} , S_{rk}^{07}, σ_c^{07}). We proceed in partial equilibrium while maintaining shares S_{rk} constant at the initial year.

$$d \log P_c^U = \sum_r l_{rc}^{07} \sum_m \frac{S_{rm}^{07}}{\sum_k \sigma_k^{07} S_{rk}^{07}} \mathrm{d}\sigma_m - \sum_r l_{rc}^{07} \sum_m \frac{S_{rm}^{07}}{\sum_k (\sigma_k^{07} - 1) S_{rk}^{07}} \mathrm{d}\sigma_m + \sum_r l_{rc}^{07} \mathrm{d} \log c_r$$

Combining the first and second term yields:

$$\mathrm{d} \log P_c^U = \sum_r l_{rc}^{07} \sum_m \frac{S_{rm}^{07} \left[\sum_k (\sigma_k^{07} - 1) S_{rk}^{07} - \sum_k \sigma_k^{07} S_{rk}^{07}\right]}{\left(\sum_k \sigma_k^{07} S_{rk}^{07}\right) \left(\sum_k (\sigma_k^{07} - 1) S_{rk}^{07}\right)} \mathrm{d}\sigma_m + \sum_r l_{rc}^{07} \mathrm{d} \log c_r$$

$\sum_k S_{rk}^{07} = 1$ by definition. So,

$$\mathrm{d} \log P_c^U = \sum_r l_{rc}^{07} \sum_m \frac{-S_{rm}^{07}}{\left(\sum_k \sigma_k^{07} S_{rk}^{07}\right) \left(\sum_k (\sigma_k^{07} - 1) S_{rk}^{07}\right)} \mathrm{d}\sigma_m + \sum_r l_{rc}^{07} \mathrm{d} \log c_r$$

Changing the order of summation, multiplying and dividing each term in the summation by σ_m^{07} and using $d \log \sigma = d\sigma / \sigma$,

$$\mathrm{d} \log P_c^U = \sum_r \sum_m l_{rc}^{07} \frac{-S_{rm}^{07} \sigma_m^{07}}{\left(\sum_k \sigma_k^{07} S_{rk}^{07}\right) \left(\sum_k (\sigma_k^{07} - 1) S_{rk}^{07}\right)} \mathrm{d} \log \sigma_m + \sum_r l_{rc}^{07} \mathrm{d} \log c_r$$

Defining θ_{rm}^{07} as:

$$\theta_{rm}^{07} = \left[\frac{S_{rm}^{07} \sigma_m^{07}}{\sum_k \sigma_k^{07} S_{rk}^{07} \left(\sum_k S_{rk}^{07} (\sigma_k^{07} - 1)\right)} \right]$$

Thus, the differential log of P_c^U becomes:

$$\mathrm{d} \log P_c^U = - \sum_r \sum_m l_{rc}^{07} \theta_{rm}^{07} \mathrm{d} \log \sigma_m + \sum_r l_{rc}^{07} \mathrm{d} \log c_r$$

By decomposing the first term of the summation into the own county effect and the spillovers, we reach the formulation presented in Equation 5.2, thereby concluding the proof:

$$\mathrm{d}\log P_c^U = -l_{rc}^{07}\theta_{rc}^{07}\mathrm{d}\log\sigma_c - \sum_r \sum_{m\neq c} l_{rc}^{07}\theta_{rm}^{07}\mathrm{d}\log\sigma_m + \sum_r l_{rc}^{07}\mathrm{d}\log c_r$$

E.3 Proof of Equation 6.1

From Equation 5.2, we have:

$$\mathrm{d}\log P_c^U = -l_{rc}^{07}\theta_{rc}^{07}\log\sigma_c - \sum_r \sum_{m\neq c} l_{rc}^{07}\theta_{rm}^{07}\mathrm{d}\log\sigma_m + \sum_r l_{rc}^{07}\mathrm{d}\log c_r$$

By definition β^H is:

$$\beta^H = -\frac{\mathrm{d}\log\sigma_c}{\mathrm{d}\log HP_c}$$

and replacing,

$$\mathrm{d}\log P_c^U = \beta^H l_{rc}^{07}\theta_{rc}^{07}\mathrm{dd}\log HP_c + \beta^H \sum_r \sum_{m\neq c} l_{rc}^{07}\theta_{rm}^{07}\mathrm{d}\log HP_c + \sum_r l_{rc}^{07}\mathrm{d}\log c_r$$

E.4 Recovering β^H

I estimate Equation 6.1 to recover β^H, reporting results for various specifications in Appendix Table A.XXXI. Preferred specification in Column (6) shows $\hat{\beta}_2 = 0.16$, which, scaled by $\bar{\sigma} - 1 = 3.1$, implies an average demand elasticity response of $\hat{\beta}_H = 0.48$. In addition, I cannot reject that direct and indirect effect coefficients are equal, which is indicative that the uniform pricing model can explain county-level price co-movements. Although this conclusion needs to be interpreted with caution as it depends on assuming constant β^H (see appendix E.5.2).

Table A.XXXI: Recovering β^H

	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP (adjusted)	0.314***	0.108*	0.106*	0.609***	0.168	0.179
	(0.095)	(0.059)	(0.058)	(0.116)	(0.112)	(0.114)
Chain-linked Log Δ HP (other counties)		0.109***	0.108***		0.155***	0.155***
		(0.027)	(0.028)		(0.047)	(0.049)
Observations	910	910	910	910	910	910
R-squared	0.035	0.235	0.249	0.006	0.118	0.132
County controls	no	no	yes	no	no	yes
p-value $\beta_1 = \beta_2$	-	0.989	0.979	-	0.830	0.922
Panel B: First Stage						
First Stage F-stat				13.340	11.348	11.127

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta \log(P_c)$). The table reports results of estimating the empirical counterpart of Equation 6.1. County's $\Delta LogHP$ is adjusted by κ_{cc}. Columns (1) to (3) report results for OLS estimations. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument $(\sum_{k \neq c} \theta_{ck} \Delta \log(HP_k))$ with network-weighted WLRI in other counties $(\sum_{k \neq c} \theta_{ck} WLRI_k)$. Panel A reports the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively.

E.5 Heterogeneous β^H

E.5.1. Interpretation of coefficients and extension:: When taking the model to the data, I assume that β^H is constant across counties. Formally, $\beta^H_k = \frac{d \log \sigma_k}{d \log HP_k} = \beta^H$.[33] This assumption states that all counties will respond similarly to the same percentage change in house prices. Therefore, with this approach, β_1 captures the average direct effect and β_2 the average spillovers from connected regions, while abstracting for heterogeneous effects depending on, for example, county characteristics.

It is straight-forward to extend the framework to allow for heterogeneous β^H_k, which could be captured empirically as interaction terms between the house price changes, network-weighted house prices changes with county-level characteristics. In that case, the structural equation would become:

$$d \log P_c = \beta^H_c \kappa^{07}_{cc} d \log HP_c + \sum_{k \neq c} \kappa^{07}_{ck} \beta^H_k d \log HP_k + \sum_r l^{07}_{rc} d \log c_r,$$

The extension of this framework to capture heterogeneous effects and evaluating how county-characteristics combined with shock shape the propagation of shocks is

[33] It is important to note that this does not imply that the demand elasticity is identical across counties, but rather that the response of this elasticity to shocks is equal across them.

an interesting line of research that might be worth exploring in future work.

E.5.2. Constant β^H assumption and indirect test for uniform pricing: Under the assumption of constant β^H, the structural model provides a clear test for uniform pricing responses at the county-level by noting that the coefficient $\beta_1 = \beta_2 = \beta^H$.

However, if β^H differs by county, caution is needed when interpreting this test. If β^H varies across counties, it could be the case that even with uniform pricing, there are conditions under which these two coefficients might differ because of the heterogeneous responses of demand elasticities in the different regions.

To explore the cases in which the test is useful and the cases in which it might be interpreted with caution, suppose that there are N^A counties with β^H_A and N^B counties with β^H_B. Define $\mathcal{K}_A$ as the set containing counties in A and $\mathcal{K}_B$ as the set containing counties in B. Then, the structural equation that would capture heterogeneous effects would be:

$$d\log P_c = \beta_c^H \kappa_{cc}^{07} d\log HP_c + \beta_A^H \sum_{k\in\mathcal{K}^A, k\neq c} \kappa_{ck}^{07} d\log HP_k + \beta_B^H \sum_{k\in\mathcal{K}^B, k\neq c} \kappa_{ck}^{07} d\log HP_k + \sum_r l_{rc}^{07} d\log c_r,$$

Imagine we assume constant β^H and estimate the empirical analogous of the structural equation as I do in the paper.

$$d\log P_c = \beta_1 \kappa_{cc}^{07} d\log HP_c + \beta_2 \sum_{k\neq c} \kappa_{ck}^{07} d\log HP_k + \sum_r l_{rc}^{07} d\log c_r, \quad \forall c = 1, \dots, N$$

The question is what are β_1 and β_2 going to capture?

Case 1: Simple average: If both independent variables have the same variability, then each OLS coefficient will capture a simple average of the heterogeneous β_c. In particular, it can be shown that:

$$\beta_1 = \frac{1}{N} \sum_k \beta_k^H = \frac{1}{N} \left(N_A \beta_A^H + N_B \beta_B^H \right),$$

$$\beta_2 = \frac{1}{N}\left(N_A\beta_A^H + N_B\beta_B^H\right).$$

As a result, β_1 and β_2 are simple averages of the heterogeneous effects β_k^H. Therefore, the comparison between these coefficients is still informative about how close we are to uniform pricing responses. The intuition is that if a county's demand elasticity reacts more strongly to the shock, it will produce a higher effect both through its spillovers (captured in the average of β_2) and also locally, captured through its direct effect in the own county (entering to the average of β_1).

Case 2: Weighted average:

Now consider the more general case. Define $X_c = \kappa_{cc}^{07} d\log HP_c$ and $W_c = \sum_{k\neq c}\kappa_{ck}^{07} d\log HP_k$ and center the variables around 0 for exposition. The OLS estimates β_1 and β_2 will capture a weighted average of the β_k^H coefficients, where the weights are determined by the variability of the independent variables X_c and W_c. So we will have:

$$\beta_1 = \frac{\sum_k \beta_k^H X_k^2}{\sum_k X_k^2} = \beta_A^H \frac{\sum_{k\in\mathcal{K}^A} X_k^2}{\sum_k X_k^2} + \beta_B^H \frac{\sum_{k\in\mathcal{K}^B} X_k^2}{\sum_k X_k^2},$$

$$\beta_2 = \frac{\sum_k \beta_k^H W_k^2}{\sum_k W_k^2} = \beta_A^H \frac{\sum_{k\in\mathcal{K}^A} W_k^2}{\sum_k W_k^2} + \beta_B^H \frac{\sum_{k\in\mathcal{K}^B} W_k^2}{\sum_k W_k^2}.$$

By comparing the coefficients above, we can see that:

(A) In the constant β^H case, $\beta_A^H = \beta_B^H = \beta^H$, these two coefficients must be equal.

(B) If the terms capturing the variability of X_c and W_c are equal across all counties, then β_1 and β_2 will still be equal under uniform pricing responses.

(C) However, in the more general case, where these terms might differ, then it might be the case that even under uniform pricing, we could obtain $\beta_1 \neq \beta_2$. This discrepancy arises because the differing distributions of X_c and W_c lead to coefficients capturing different weighted averages of the same parameters.

Empirically, we find that the two coefficients are similar. We cannot reject the hypothesis that this coefficients are equal. This is suggestive evidence in favor of uniform pricing responses, but this has to be taken with caution as we might be in case (2.C).

E.6 National costs and error term

In this section, I discuss the the implication for identification in the model, when costs are at the retail level.

$$dlogP_{ct} = \beta^H \left[\sum_{r \in \Omega_c} \theta_{rc} S_{rc} \right] dlogHP_c + \beta^H \sum_{k \neq c \in \Omega_r} \sum_{r \in \Omega_c} l_{rc} \theta_{rk} dlogHP_k + \sum_{r \in \Omega_c} l_{rc} dlogC_r \quad \text{(E.2)}$$

As the cost of retail chain is not observed, it lies in the error term. Hence, the exogeneity assumption to identify β^H is given by,

$$E\Big[\sum_{r \in \Omega_c} l_{rc} dlogC_r \Big| \Big(\sum_{k \neq c \in \Omega_r} \sum_{r \in \Omega_c} l_{rc} \theta_{rk} dlogHP_k \Big) \Big] = 0 \quad \text{(E.3)}$$

This simply reflects that, conditional on own house price changes, the evolution of the marginal cost in county c cannot be correlated with the weighted average of the change in house prices in other counties k. For exposition, define $\Delta C_r = \sum_c \lambda_{rc} \Delta A_c$ as a weighted average of unit costs (A_c) across counties in the U.S; where λ_{rc} are the share of costs of retail r that comes from county c (e.g.: wholesale products that buys in c). The threat is common shocks to costs to regions in which the retail chain operates that also correlate with house price changes. Then there are a couple of intuitive *Sufficient conditions* to satisfy Condition E.3.

1. If $Cov(\Delta A_k, \Delta log(HP)_k) = 0$, then Condition E.3 is satisfied. *However, house price shocks could be correlated with productivity shocks in the county.*

2. If $Cov(\lambda_{rc}, \theta_{rc}) = 0$, then Condition E.3 is satisfied. Stroebel and Vavra (2019) present a range of evidence suggesting that the location where retail sell their products (θ_{rk}) differ from the locations where the retail buy their products from wholesales. In line with this, Hyun and Kim (2019), show that most of sales of manufacturing firms come from markets that are not where they have their plants.

In case sufficient conditions (1) and (2) do not hold, I rely on the housing supply elasticity instrument. The assumption then becomes:

$$E\Big[\sum_{r\in\Omega_c} l_{rc} dlog C_r \Big| \Big(\sum_{k\neq c\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\theta_{rk} WLRI_k\Big)\Big] = 0 \tag{E.4}$$

Note that now a sufficient condition for E.4 to hold is that: $Cov(\Delta A_k, WLRI_k) = 0$. This assumption mimics the identification assumption of papers that analyzed the local effect of the house price slump (e.g: Mian and Sufi (2011), Stroebel and Vavra (2019)). Hence, given that this condition is sufficient (but not necessary), my empirical design relies on milder assumptions.

E.7 Alternative assumptions for costs: local costs

In the main analysis, I solved the model for the case in which the retail chain has national costs $c_{rc} = c_r$. Here, I explore the case in which retail chain has local costs in each market (c_{rc}).

Solving the optimization problem, we get the optimal price in the situation where the retail chains' costs are local:

$$P_{rc} = \bar{p}_r = \frac{\sum_k \mu_k c_{rk}(\sigma_k - 1) S_{rk}}{\sum_k S_{rk}(\sigma_k - 1)} \tag{E.5}$$

where $\mu_k = \frac{\sigma_k}{\sigma_k - 1}$ is the markup in market k. From equation E.5 it is clear that the price under uniform pricing is a weighted average of the conditions (costs and markups) in the different markets that a retail chain serve.

Following the steps in the main section to aggregate the price index and total differentiate the aggregate price index to observe the sources of variation, we get:

$$dlog P^U_{ct} = -\left[\sum_{r\in\Omega_c} l_{rc}\tilde{\theta}_{rc}\psi_{rc}\right] dlog\sigma_c - \sum_{k\neq c\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\tilde{\theta}_{rk}\psi_{rk} dlog\sigma_k + \sum_{k\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\frac{S_{rk}\sigma_k c_{rk}}{\sum_k \sigma_k S_{rk} c_{rk}} dlog c_{rk} \tag{E.6}$$

where I define θ as in the main analysis

$$\tilde{\theta}_{rk} = \frac{S_{rk}\sigma_k}{\left[\sum\limits_{k\in\Omega_r} S_{rk}\sigma_k c_{rk}\right]\left[\sum\limits_{k\in\Omega_r} S_{rk}(\sigma_k - 1)\right]},$$

and,

$$\psi_{rc} = c_{rc}\sum_k S_{rk}\left(\sigma_k \frac{c_{rc} - c_{rk}}{c_{rc}} - 1\right)$$

Compared with the case of national costs in the main analysis, now the weights also adjust for initial differences in costs across markets (ψ_{rk}). In addition, local shocks can affect the cost term of the equation.

In the next section, I explore how propagation of cost shocks would look like.

E.8 Propagation of local cost shocks

In order to be consistent with previous papers that emphasize the demand channel of the house price shock, in the main analysis I assumed that the the house price shock affected the elasticity of demand. However, to study propagation of shocks through the network of retail chains, one could be agnostic about whether the shock is demand-driven or cost-driven.

In this section, I discuss theoretically the propagation of local shocks through the network of retail chains. Assume that σ_k is constant and the shocks are to the local costs of the firm. That is $\beta^{H-Costs} = \frac{\partial log c_{rc}}{\partial log HP_c}$. Then, Equation E.7 becomes:

$$dlogP^U_{ct} = \beta^{H-Costs}\sum_{r\in\Omega_c} l_{rc}\frac{S_{rc}\sigma_c c_{rc}}{\sum_k \sigma_k S_{rk} c_{rk}} dlog c_{rc} + \beta^{H-Costs}\sum_{k\neq c\in\Omega_r}\sum_{r\in\Omega_c} l_{rc}\frac{S_{rk}\sigma_k c_{rk}}{\sum_k \sigma_k S_{rk} c_{rk}} dlog c_{rk} \tag{E.7}$$

The last term corresponds to the propagation of local shocks through the network of retail chains. Note that the importance of a market is also increasing on S_{rk}. This makes more meaningful the weights ω_{ck} in the reduced form that can be used to proxy weights for both cost shocks and demand shocks.

E.9 Quantitative analysis

Table A.XXXII: σ by quartile of population (From Hottman, 2014)

City Size Dist:	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
σ_c	3.9	3.9	4.5	4.8

Table A.XXXIII: Propagation of local shocks through the network of retails chains (weights adjusted by σ)

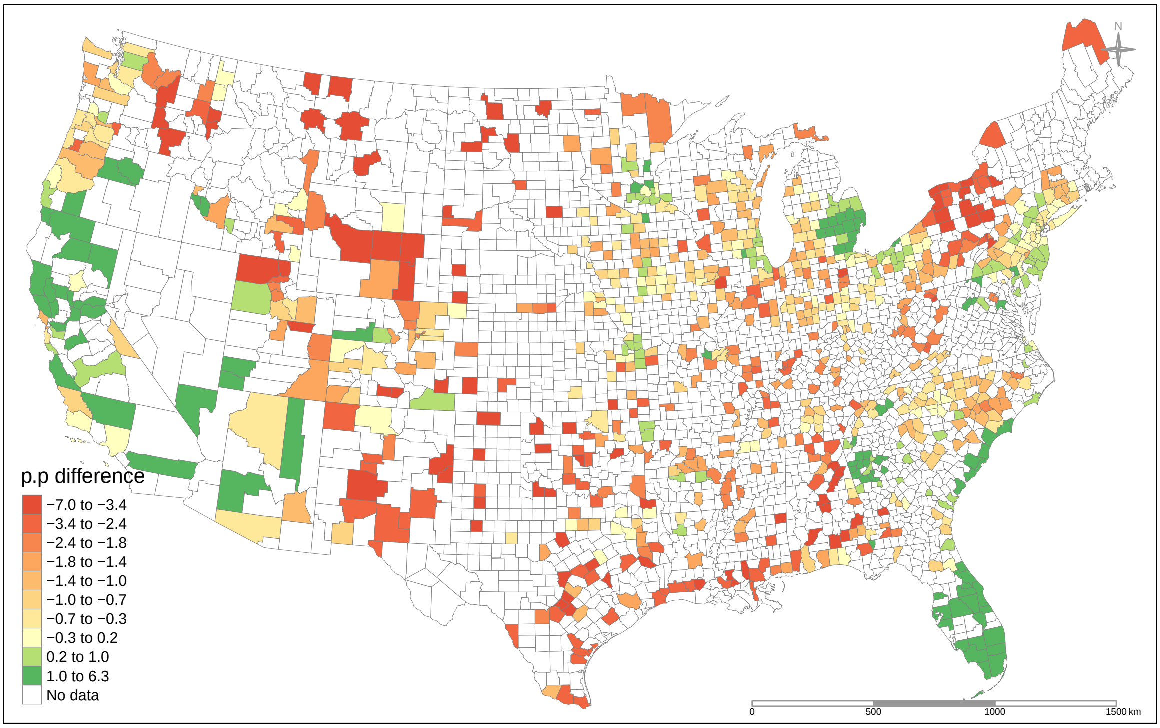
	Dep Variable: County's Δ Log Price Index					
	OLS			IV: WLRI instrument		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Second Stage						
County's Δ Log HP	0.056***	0.050***	0.050***	0.125***	0.093**	0.096**
	(0.014)	(0.013)	(0.015)	(0.027)	(0.034)	(0.037)
Chain-linked Δ Log HP (other counties)		0.049***	0.048***		0.116**	0.126**
($\sigma_{adjusted}$)		(0.017)	(0.017)		(0.050)	(0.054)
Panel B: First Stage						
F-stat				21.358	11.660	10.810
Observations	910	910	910	910	910	910
County controls	no	no	yes	no	no	yes

A unit of observation is a county. The dependent variable is the percentage change in the county price index between 2007 and 2011 ($\Delta log(P_c)$). County's Δ Log HP is the percentage change in house prices between 2007 and 2011. Chain-linked Δ Log HP (other counties) is the network-weighted percentage change in house prices in other counties ($\sum_{k \neq c} \theta_{ck} \Delta log(HP_k)$) as defined in Equation 6.1. Columns (1) to (3) report results for OLS estimations. County-level controls in columns (3) and (6) include changes in log wages, changes in log number of retail establishments and changes in log employment. Columns (4) to (6) report results, after instrumenting the two main endogeneous variables. I instrument local percentage change in house prices with local WLRI. I instrument network-weighted percentage change in house prices ($\sum_{k \neq c} \theta_{ck} \Delta log(HP_k)$) in other counties with network-weighted WLRI in other counties ($\sum_{k \neq c} \omega_{ck} WLRI_k$).Panel A report the second stage coefficients. Panel B reports the Kleibergen-Paap (2006) rk F-statistic for the first stage. Robust standard errors clustered at the state level are in parenthesis. ***,**,* denotes statistical significance at the 1, 5, and 10 percent levels, respectively.

F Counterfactuals

F.1 Distributive effects of uniform pricing

Figure A.XIV: Regional Redistribution of shocks: $\Delta \log(P_c^U) - \Delta \log(P_c^{flex})$



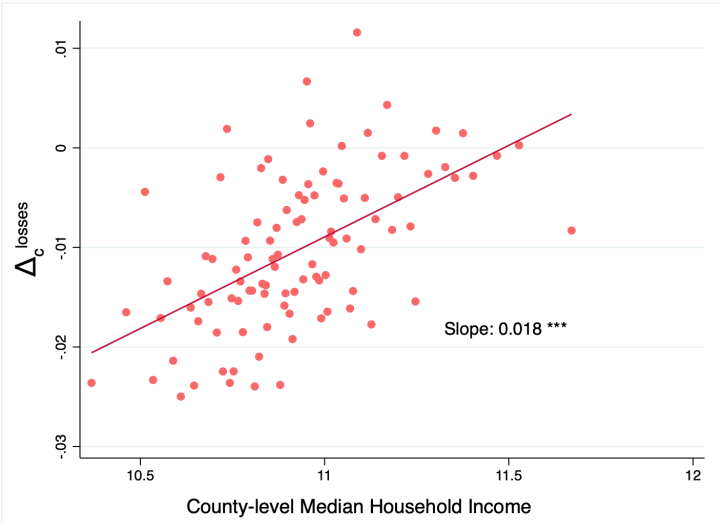
Note: Heat map for the difference between inflation rate under uniform pricing and inflation rate under flexible pricing for each county ($\Delta \log(P_c^U) - \Delta \log(P_c^{flex})$). The numbers are in %. The map is divided into deciles of $\Delta \log(P_c^U) - \Delta \log(P_c^{flex})$ (losses from uniform pricing) in percent points. Positive values (in green) are counties that lost from uniform pricing. As the heat goes from yellow to red, it indicates counties that gain more from uniform pricing compared to flexible pricing.

F.2 Distributive consequences of uniform pricing during the Great Recession

The effect of uniform pricing on real income inequality In the cross-section, uniform pricing exacerbates inequality as long as the demand elasticity is higher for poorer consumers. However, it is less clear how uniform pricing affects real income inequality in response to a shock. It will depend on the magnitude, sign, and location of the shocks, as well as on the geographic distribution of retail chains.

Define the losses in purchasing power from uniform pricing relative to flexible prices as $\Delta_c^{Losses} = \Delta \log(P_c^u) - \Delta \log(P_c^{flex})$. In Figure A.XV, I plot the binscatter of the relationship between Δ^{Losses} and the log county-level median household income. The pattern is clear. Compared to a scenario in which prices are flexible, low-income counties benefited most from uniform pricing. Intuitively, low-income counties were less affected by drops in local house prices, but still benefited from decreases in local consumer prices due to their dominant retail chains were affected in other counties. It's important to note that these redistributive consequences were specific to the Great Recession, and uniform pricing could have favored high-income counties during periods of increasing house prices.

Figure A.XV: Uniform pricing benefited low-income counties during the Great Recession



Note: Binscatter of the relationship between the logarithm of county-level median household income (x-axis) and $\Delta_c^{losses} = (\Delta \log(P_c^U) - \Delta \log(P_c^{flex})$ (y-axis). The elasticity is 0.018 and is statistically significant at 1% level.

F.3 Counterfactual 2: Mergers or acquisitions

Mergers have been one of the most important public policy concerns in the design of antitrust laws. A salient feature of the retail sector is that oftentimes firms expand their network of stores by merging with (or acquiring) firms that operate in different regions. For example, in 1998, Kroger merged with the then fifth-largest grocery company Fred Meyer, along with its subsidiaries, Ralphs, QFC, and Smith's.[34] This type of merger changes the spatial networks of retail chains, affecting the linkages between

[34] https://www.nytimes.com/1998/10/20/business/kroger-to-buy-fred-meyer-creating-country-s-biggest-grocer.html

counties and, thus, the propagation of shocks.

In this counterfactual, I study what would have been the cross-county dispersion of inflation rates during the Great Recession if the ownership structure of the major retail chains had been different. Note that in the extreme scenario in which there is only one retail chain, then the cross-county dispersion of inflation after a shock would be zero. Alternatively, if all retail chains split up into local stores, the cross-county dispersion of inflation will tend to the dispersion under flexible pricing. I explore two other scenarios:

(a) *De-merger:* the largest retail chain splits up into four different retail chains, each corresponding to one of the four Census regions: West, Midwest, Northeast, South.

(b) *Merger:* merger between the largest retail chain in each of the four Census regions of the U.S. (West, Midwest, Northeast, South).

Results are presented in Table A.XXXIV. First, notice that the average inflation rate is very similar in the three scenarios. However, the cross-county dispersion of inflation would have been considerably different under the alternative scenarios. As expected, when the largest firm split up into regions, the cross-county dispersion of inflation increases 5%. The reason for this is that the largest chain now only propagates shocks within regions, but not across them. In contrast, when the four largest chains in each region merge, the cross-county dispersion of inflation rates declines 12%. Intuitively, this merger expands the retail chains' spatial networks, which makes counties more economically connected. This, in turn, indicates that, under uniform pricing, mergers between retail chains in different regions would have synchronized even further the county-level consumer prices in the aftermath of the Great Recession, intensifying the local shocks (as prices react less) and benefiting counties not affected by the crisis.

Mergers might also have re-distributive consequences in the event of a shock. For example, during the Great Recession, I find that low-income counties would have been made better off had there been a merger between the largest retail chains in each region. Specifically, in the scenario of a merger, the poorest quintile would have experi-

Table A.XXXIV: Changes in the distribution of firms: Mergers and Partitions

$\Delta \log(P_c)$	Empirical	De-merger	Merger
Mean	-3.42 %	-3.42%	-3.45%
SD	1.52%	1.59%	1.36%
CV	0.44	0.46	0.39

Note: Counties are weighted by population.

enced a 0.18 p.p lower inflation (6%) than under the benchmark case. In contrast, the richest quintile, would have experienced a 0.13 p.p. higher inflation rate (4%). The reason for this pattern is that high-income counties were more affected by shocks during that period than low-income counties were. Therefore, as mergers between retail chains in different regions intensify the linkages between those regions, the effect of the shock in high-income counties spreads to low-income counties which benefit from reduction in their retail prices.

It is important to highlight that the counterfactual is done under the assumption that the uniform pricing is taken as a constraint, and do not take into account potential optimal retailer responses to the merger/de-merger exercises, other than the changes in its sales share. Naturally, those response may change the quantative conclusions regarding the effects of a merger.