How Do Housing Markets Affect Local Consumer Prices? - Evidence from U.S. Cities*

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Abstract

We investigate the relationship between house prices and local consumer prices across 41 cities in the U.S. by employing retail price data of a multitude of consumer goods. We find that changes in house prices tend to precede changes in consumer prices, rather than the other way around. The magnitude of the impacts of house price on consumer prices varies, depending on location and product types. It also hinges on the nature of housing market shocks; housing supply shocks affect prices temporarily through the cost-push channel, while housing demand shocks impact prices persistently through wealth and collateral effects. Our findings imply that the impact of the housing market fluctuations on local cost of living and consumer welfare could be greater than its representation in the Consumer Price Index (CPI).

Keywords: Housing market, Consumer price, U.S. cities, Pass-through, FAVAR model, VECM.

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"*[F]or many Americans, the rise in food and housing prices is a tough squeeze. That's because - even in an era with low overall inflation - low-income Americans spend a disproportionate share of their money on food and housing.*" - The Wall Street Journal (April 6, 2015)

1 Introduction

Housing is a central component in households' net wealth; well over 60 percent of the U.S. households own their home which represents most households' largest asset and their primary source of collateral for borrowing (Bhutta and Keys 2016).[1] Thus, any shifts in housing market conditions could significantly impact consumption expenditures (Abdallah and Lastrapes 2013, Campbell and Cocco 2007, Mian and Sufi 2011, 2014). Such changes, in turn, may affect consumer prices, as highlighted by Kaplan and Menzio (2016) and Stroebel and Vavra (2019), for instance.

Previous studies, however, have predominantly focused on the link between house prices (hereafter HP) and real economic activities, such as consumption spending and mortgage loan growth. This has been primarily done within the framework of the policy transmission mechanism, as in Berger et al. (2018), Guren et al. (2020), and Iacoviello and Neri (2010). Yet, little is known about the relationship between the housing market and consumer prices (hereafter CP), particularly at the disaggregated level, and the channels through which HP changes impact CP.[2] Theoretical frameworks suggest that HP can both positively and negatively affect CP. On the one hand, higher HP drive up CP by increasing consumption through the *wealth effect* or *collateral effect*, as homeowners' net wealth and collateral values increase (e.g., Campbell and Cocco 2007; Mian and Sufi 2011, 2014; Mian et al. 2013). On the other hand, consumers may need to reduce their consumption of other products due to higher housing and rent expenditures, leading to a *substitution effect* and a subsequent decrease in CP.[3] Therefore, it remains to be an empirical exercise to understand the actual linkages between HP and CP.

This study aims to investigate the impact of changes in housing markets on CP, as well as the mechanisms through which these changes are transmitted. It provides two distinctive contributions to the existing literature. First, the study quantifies the response of city-level retail CP to housing market shocks across a broad range of consumer products. While previous research has mainly focused on aggregate-level analysis, this study utilizes a data set containing 41 products ranging from food, manufacturing goods to services in 43 cities across the U.S. over 25 years. By analyzing the comprehensive

[1] In the U.S., real estate accounts for 30 percent of consumer net wealth and approximately 60 percent of the household portfolio (Yoshida 2015). Kuhn et al. (2020) highlight the dominant status of housing in the U.S. middle-class portfolio.

[2] Stroebel and Vavra (2019) is a notable exception, which is discussed in detail later in this section and in Section 4.3.

[3] Waxman et al. (2020) observe a significant substitution effect in China, where an increase in HP is associated with reduced consumption due to a rise in savings.

micro price data, the study can estimate the differential reactions of local CP to both aggregate and local housing market shocks, across locations and products. It also focuses on the dynamic relationship between HP and CP, which may differ substantially from short-term responses as previously noted by Ghent and Owyang (2010). Second, the study aims to shed light on the channels through which HP changes propagate. We seek to link the estimated CP responses to a range of geographical and product characteristics to pinpoint the underlying channels of transmission.

To examine how local CP respond to aggregate housing shocks, we employ a factor-augmented vector autoregressive (FAVAR) model in our empirical analysis. This approach offers the advantage of assessing the impulse responses of multiple variables within a single framework. We find that aggregate housing demand shocks have positive effects on CP of most products, whereas aggregate housing supply shocks have transitory negative effects. This highlights the importance of differentiating the source of HP changes and analyzing the dynamic responses of CP over a long horizon. To further investigate the pass-through at the city level, we use a Vector Error Correction Model (VECM), controlling for local fundamentals such as wage and labor market conditions. Our results indicate that local CP are highly responsive to local HP changes, but not the other way around. In other words, local HP changes have a leading or causal influence on local CP, but not vice versa. The estimated average *long-run* effect implies that a 10-percent increase in HP leads to about a 4.6-percent increase in CP over time.

More importantly, we find significant heterogeneity in the responses of CP to housing market shocks across cities and products. We investigate how the observed heterogeneity is related to various local economic conditions and product characteristics that are linked to underlying transmission channels predicted by theories. Our analysis reveals that the impacts of housing demand shocks are greater in cities with higher concentrations of skilled workers, while the effects of housing supply shocks are more pronounced in cities with greater regulation on housing supply or higher rates of homeownership. Additionally, housing demand shocks primarily affect flexibly-priced products, while the pass-through of housing supply shocks is more prominent in locally-produced product prices. This suggests that HP shocks of different types affect CP through distinct channels; housing demand shocks transmit through the wealth and income effects of the conventional demand-pull channel, and housing supply shocks propagating through the cost-push channel via the local cost and markup effects.

Our work is closely related to Strobel and Vavra (2019, henceforth SV) which examines how local retail prices respond to changes in local HP in selected U.S. cities. SV uses retailer scanner data for grocery and drugstore products and shows that retail prices grow significantly stronger in metropolitan statistical areas (MSAs) with higher HP growth. They conclude that firms raise markups and prices as households become less price-sensitive due to a rise in wealth driven by higher HP, with markup variation being the primary explanation for the empirical patterns. Our analysis differs in several dimensions including product diversity, methodology, and impact horizons, as detailed in Table 1. SV focuses on prices of 31 items such as processed food and beverages, cleaning, and personal hygiene products. These items are typically homogeneous nation-wide and sold in drugstore and mass-merchandise chains that charge nearly uniform prices across stores. Hence, their prices may reflect cross-city heterogeneity of a limited magnitude only. Another crucial difference is that we analyze the dynamic impacts on CP over time, whereas SV concentrates on cross-sectional elasticity. Finally, while SV show that the markup effect is a dominant channel, we find that diverse channels are at work depending on the nature of HP changes. Therefore, we extend and complement the analysis in SV, as further discussed in Section 4.3.

Our study also offers additional insights on the role of HP fluctuations in explaining consumer welfare. Our findings on the positive relationship between HP and CP suggest that HP may have a greater impact on the overall cost of living than what is typically reflected in its Consumer Price Index (CPI) weight. The methodology used by the Bureau of Labor Statistics (BLS) to construct its owner-occupied shelter index, which makes up 32 percent of CPI, only takes into account changes in the "user cost" or fair rental value of owner-occupied housing over a given period of time, while keeping the asset ownership constant. However, it overlooks the fact that owner-occupied housing is also an asset that forms a substantial portion of a typical household's portfolio. As highlighted by Cecchetti (2007), if the owner-equivalent rent or implicit rent aims to measure the opportunity cost of owning rather than renting, then CPI should be based on the price of the house rather than on the rental market. This implies that the user cost-based CPI may underestimate the effects of HP changes on CPI by disregarding its subsequent impacts on CP through various channels.

Moreover, our research is relevant to recent studies that identify changes in HP as a significant driver of increasing geographic price dispersions, such as Hsieh and Moretti (2015) and Strobel and Vavra (2019). It implies that the disproportionate effects of HP on home owners versus renters could be a factor for such dispersion, for example.[4]

The paper is structured as follows. Section 2 outlines the data set used in our study and presents descriptive analyses. Section 3 presents econometric analyses on how housing markets impact the CP of different products in various U.S. cities. The underlying transmission mechanism is discussed in Section 4, which examines the large variations observed in the impact on CP across locations and products. Finally, Section 5 concludes. The Appendix offers a detailed description of our data and a

[4]The empirical evidence regarding the impact of HP appreciation on consumption behavior among homeowners and renters, as well as its effect on CP, has yielded mixed results. Sheiner (1995) finds a positive effect of HP on the net worth of young renters using U.S. PSID data. In contrast, Campbell and Cocco (2007) find that the effect of HP changes on consumption is lowest and insignificant for young renters, and highest for old homeowners.

comparison with alternative data sets.

2 Data and preliminary analysis

We employ the quarterly retail price data provided by the Council for Community and Economic Research (C2ER) for certain U.S. MSAs from 1990Q1 to 2015Q4. This survey data set was initially created for comparing living expenses for mid-level managers in various cities and contains retail prices of individual goods and services that include sales taxes levied by all jurisdictions.

This data set is suitable for our study for several reasons. First, prices are measured for comparable items across different locations. This feature enables us to perform cross-city comparisons. CP are absolute prices in dollars and cents collected by a single agency for products of matching quality (brand) and quantity (package), such as gasoline (one gallon, regular unleaded) and beauty salon (service charges for woman's shampoo, trim, and blow dry). Included products range from basic food products, manufacturing goods, to services such as medical services and hair-styling, as shown in Appendix A.[5] Summary statistics for the 43 products used in our study are presented in Table A.3. Second, our data set covers a long sample period and wide geographic regions, as shown in Figure 1. Although the number of products is lower than that in the BLS micro-data, our data set covers more cities and has a longer time series, with which one can construct a comprehensive panel that is useful for analyzing the dynamic effects on CP. Third, our data set provides actual HP instead of index values, which enables us to investigate the long-run relationship between HP and CP within the framework of VECM (refer to footnote 14 for further details).

Our study focuses on MSAs, as housing markets are typically defined at this level. Workers likely consider jobs within the same MSA for commuting and form a single labor market (Sinai 2012). The 41 selected MSAs are diverse in terms of size, as measured by average per capita income and population (Figure 1).[6] They collectively represent a significant share of the nation's wealth, consumption, and investment. Table A.4 in the Appendix provides summary statistics for the 41 cities.

We have incorporated various sources of data on the local economic environment and housing market conditions as controls for our regression analysis. These city-level control variables include per capita income, population density, unemployment rate, homeownership rate, financial integration, share of skilled workers, and the measure of housing supply constraints by Guren et al. (2020). Table A.5 in the Appendix document a comprehensive list of these variables, their descriptions and sources.

Two control variables warrant detailed descriptions. First, we utilize the measure of housing supply

[5] The products analyzed in this study are everyday essentials that are frequently bought, rather than high-value items like electronics or cars that are purchased less often. For detailed descriptions on each product, please see Table A.2.

[6] Due to data insufficiency, major cities like New York, Chicago and San Francisco are not included in our dataset.

constraints at the city level, which is the inverse measure of housing supply elasticity ($\hat{\gamma}$) estimated by Guren et al. (2020) based on the historical sensitivity of local HP to regional housing market cycles.[7] Second, the share of skilled workers is measured by the educational attainment of adults over 25 years old with at least a bachelor's degree. Research has shown that higher educational attainment is associated with urban and metropolitan prosperity, where cities with a higher concentration of bachelor's degree holders have higher levels of income and HP. The reader is referred to Table A.5 in the Appendix for the descriptions of the remaining control variables.

Before moving forward, Figure 2 presents scatter plots of annualized HP and CP of two selected products (i.e., 'cornflakes' on the left and 'haircuts' on the right) in levels (top panel) and in growth rates (bottom panel).[8] As shown in the top panels, there is a strong positive correlation between HP and CP for both products. In other words, cities with higher HP (on the horizontal axis) generally have higher CP (on the vertical axis), in line with our expectations. However, as depicted in the bottom panels, the positive correlation between the growth rates of prices is less evident. Nonetheless, this outcome does not necessarily contradict the existence of a long-term relationship between CP and HP growth rates, as there may be a lagged relationship between the two variables. Therefore, our analysis focuses on the long-term relationship between HP and CP.

3 Empirical analysis

This section aims to quantify the impact of housing market shocks on local CP. More specifically, we utilize two different empirical approaches, a FAVAR model and VECM. The FAVAR model identifies structural *aggregate* housing market shocks using sign restrictions, following the methodology of Jarocinski and Smets (2008) and Abdallah and Lastrapes (2013), and provides a consistent and coherent framework for examining impulse responses. In addition, the VECM estimates the dynamic effects of *local* HP changes on local CP.

Both the FAVAR model and VECM are suitable for our study for a few reasons. First, unlike traditional structural models where HP is usually assumed to be exogenous, both approaches allow for possible interactions between HP and CP with fewer restrictions. This feature is particularly

[7] The housing supply elasticity data are obtained from Adam Guren's website (`http://people.bu.edu/guren/`). Differences in housing supply elasticities are often cited as a possible explanation for the wide variation in HP movements across cities (Aastveit et al., 2020; Green et al., 2005). However, the use of Saiz's (2010) housing supply elasticity estimates based on land-unavailability as an instrument has been criticized for its validity (Davidoff, 2013). Instead, Guren et al. (2020) propose a measure of housing supply elasticities at the city level that is based on the systematic historical sensitivity of local HP to regional housing cycles. This measure is claimed to address the major problems of the Saiz's measure. While the literature typically employs time-invariant measures of housing supply elasticities, Aastveit et al. (2020) demonstrate that these elasticities may vary over time.

[8] The findings are consistent across other products. A comprehensive version of Figure 2 will be available upon requests.

beneficial for our MSA data analysis, where distinguishing between purely endogenous and exogenous variables is challenging. Second, both approaches consider the likely dynamic interactions between HP and CP over time. Since housing market shocks may impact CP over time, it is essential to assess both the short- and long-term effects of housing markets on CP. Although these two approaches share attractive features, they capture different housing market shocks. While the FAVAR model focuses on the impact of *aggregate* housing market shocks affecting all MSAs, VECM enables us to track the impact of *local* housing market shocks, which is of growing interest in the literature. Hence, we employ both approaches to gain further insights into the topic at hand.

3.1 Transmission of aggregate housing market shocks

3.1.1 FAVAR model

We employ the following FAVAR model in which the joint dynamics of the factors and macroeconomic variables are modeled as

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = B_0 + B(L) \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + e_t, \tag{1}$$

$$X_t = \lambda F_t + \gamma Y_t + \delta U_t + \epsilon_t, \tag{2}$$

where Y_t and F_t respectively represent observable and unobservable factors, and X_t is a vector of city-level price changes of various goods and services. The factors (Y_t and F_t) are assumed to capture common dynamics in X_t. Following the setup in Abdallah and Lastrapes (2013), we include six macroeconomic indicators as observable factors (Y_t): (i) real private residential fixed investment, (ii) aggregate real HPs, (iii) 5-year U.S. Treasury-bond yield, (iv) GDP deflator, (v) real GDP, and (vi) real personal consumption expenditure. We control for the local labor market condition by including city-level unemployment rates (U_t) in eq.(2) which are related to local housing market.[9]

We use sign restrictions, as in Abdallah and Lastrapes (2013), to identify *aggregate* housing demand and supply shocks. Our strategy assumes that the housing *demand* shock will push both real aggregate HP and residential fixed investment in the same direction, while the housing *supply* shock will push them in opposite directions. The sign restrictions are imposed for three quarters following the impact. It is important to note that we do not restrict other macro variables in Y_t or F_t, and allow their dynamic responses to be determined by the data. Table 2 provides a summary of the imposed restrictions.

Shocks identified in our FAVAR model represent a wide range of unexpected changes in the aggregate housing market. For example, a housing demand shock may arise from the implementation

[9] Beraja et al. (2019) find that states with lower unemployment growth experienced faster price growth compared to those with higher unemployment growth, indicating that changes in the unemployment rate are associated with urban economic performance. This relationship has also been observed in other studies (e.g., Aastveit et al. 2020).

of macroprudential policies, such as loan-to-value or income-to-debt payment ratios. It could also be broad-based, driven by changes in monetary policy or productivity (e.g., Iacoviello and Neri 2010). Housing supply shocks, on the other hand, come from unexpected fluctuations in the costs of building homes and developing real estate, as well as changes in input prices and regulatory policies affecting housing supply. Similar to Abdallah and Lastrapes (2013), we do not attempt to further identify the sources of these shocks but rather focus on investigating their varying impacts on local CP.

As in Bernanke et al. (2005) and Boivin et al. (2009), our FAVAR model is estimated through a two-step principal component approach. In the first step, we extract principal components and rotate unobservable factors orthogonal to Y_t to estimate common unobservable factors from X_t. In the second step, we augment the common factors to Y_t for the estimation of eq.(1). To ensure stationarity, all variables except the 5-year T-bond yield are included in first-differenced logs. Consumer prices at the city level are also first-differenced logs to represent quarterly growth rates. After estimating impulse responses for variables and factors in the main VAR, we incorporate them into eq.(2) to examine how aggregate-level shocks affect city-level CP changes. We normalize the magnitude of shocks to reflect a demand or supply shock that increases aggregate housing construction by one percent at the impact. The impulse responses are estimated for 16 quarters (four years) after the impact so as to tell whether short-run dynamics resulting from specific shocks sustain for a longer term period.

3.1.2 The FAVAR results

We first assess whether aggregate housing market shocks are properly identified. Figure 3 displays the cumulative Impulse Response Functions (IRFs) of local HP in 41 cities to aggregate housing demand and supply shocks in the top and bottom panels, respectively. The IRFs are in line with our priors regarding the effects of aggregate housing market shocks, i.e., positive impacts of housing demand shocks and negative impacts of housing supply shocks. It is noteworthy that the responses exhibit significant differences in terms of persistence. After an aggregate housing demand shock, local HP steadily and persistently rises, reaching a peak response of more than 1.5 percent in the four-year horizon.[10] By contrast, in response to a supply shock, local HP displays a U-shaped response, declining for one year to a trough of about 0.3 percent before gradually returning to zero thereafter.

Table 3 summarizes the estimated IRFs, which are average peak/trough reponses across cities for each product. The left-hand side presents the average *peak* cumulative responses over the 16-quarter

[10] In Appendix B, we delve deeper into the effects of two different housing demand shocks: (i) a credit supply shock and (ii) a productivity shock. The results show that the IRF of the credit supply shock peaks at around 7 quarters and then gradually diminishes. In contrast, the impact of the productivity shock on HP persistently increases without decay over time, resembling the pattern of the IRFs of the housing demand shock estimated from the FAVAR model. Taken together, it appears that the housing demand shock identified in the FAVAR model reflects the productivity shock more closely than the credit supply shock.

horizon to an aggregate housing demand shock, while the right-hand side reports the average *trough* responses to an aggregate housing supply shock. The responses to the demand shock are predominantly positive in most products, with an average peak of 0.241 percentage points (p.p.). Conversely, the supply shock has negative effects in most cases, with an average trough impact of −0.145 p.p.[11]

Our findings demonstrate several key points. First, there is significant variation in the responses across products. In response to a housing demand shock, for instance, the price of 'wine' increases by only 0.005 p.p., whereas 'house price' rises by 1.674 p.p. As discussed further in Section 4, this wide cross-product variation in the response is informative about the transmission mechanism of housing market shocks to local CP. Second, sizable variations in the magnitudes of cross-city responses captured in the inter-quartile bands indicate substantial heterogeneity, likely driven by local factors such as distribution costs (Moretti, 2013; Diamond, 2016). Specifically, retail prices may include various elements of local costs, including rents paid by the retail establishment, wages of the retail workers, transportation, and warehousing, which contribute to the observed cross-city heterogeneity.[12] Lastly, our results reveal the stickiness of price responses in most products, with CP responding to housing demand shocks with some lags, consistent with the finding in Abdallah and Lastrapes (2013).

In summary, our FAVAR analysis results demonstrate that city-level CP generally responds positively to aggregate housing demand shocks and negatively to housing supply shocks, with the former having more significant and longer-lasting impacts. However, the size of these responses varies significantly across cities and products. As we discuss in more detail in Section 4, we use these variations to identify the channels through which housing markets affect local CP.

3.2 Spillovers of local house price changes

3.2.1 VECM model

This section employs a VECM framework to explore how *local* HP affects local CP. The VECM is similar to a vector autoregression (VAR) model, but includes an error correction term that captures deviations from a long-run relation between endogenous variables. By so doing, it enables us to identify the direction of causality between the variables of interest and control for other relevant factors.

As Figure 2 illustrates, higher HP is often associated with higher CP. Establishing the causality from HP growth to CP growth, however, is challenging due to the possibility of causal relationships

[11] It is worth noting that the average peak responses of CP to housing demand shocks exhibit an opposite sign in two products (Coffee and Hamburger), and housing supply shocks have an unexpected positive sign in Steak and Coffee, but they are statistically insignificant.

[12] Retail prices may also reflect a pass-through of local retail rents or land prices as part of marginal costs (along with labor costs). By contrast, SV find little evidence that the relationship between retail prices and house prices was driven by pass-through of local land prices or rents.

running from both sides over time. The VECM analysis helps us make formal inferences about the leading/causal relationship between HP growth and CP growth while controlling for other factors. Furthermore, this approach enables us to identify a long-run relationship between the variables of interest and estimate the long-run effect (LRE) of these variables.[13] Nonetheless, the VECM has yet been widely used in housing market research, primarily due to a lack of adequate HP data.[14]

Of note is an implicit assumption in our VECM analysis that local HP changes are exogenous, following much of the literature. To rephrase, we use HP changes as housing market shocks without identifying its origin, although they can be driven by either housing supply or demand shocks. Since local HP *per se* may be the transmission mechanism of housing demand or supply shocks rather than a source of fundamental shocks, an ideal approach would consider how CP and HP jointly respond to appropriately identified, exogenous shocks.[15] However, in the absence of identified shocks at the city level, exogenous HP changes can serve as a reasonable proxy for local housing market shocks.

To estimate the causal relationship between HP and CP, we use the following bivariate VECM in which HP and CP are simultaneously determined and determining,

$$\begin{bmatrix} \Delta HP_{i,t}^{m} \\ \Delta CP_{i,t}^{m} \end{bmatrix} = \begin{bmatrix} a_{H,i}^{m} \\ a_{C,i}^{m} \end{bmatrix} + \begin{bmatrix} \rho_{H}^{m} \\ \rho_{C}^{m} \end{bmatrix} \hat{\epsilon}_{i,t-1}^{m} + \sum_{j=1}^{k} \begin{bmatrix} \gamma_{11,j}^{m} & \gamma_{12,j}^{m} \\ \gamma_{21,j}^{m} & \gamma_{22,j}^{m} \end{bmatrix} \begin{bmatrix} \Delta HP_{i,t-j}^{m} \\ \Delta CP_{i,t-j}^{m} \end{bmatrix} + \sum_{h=0}^{k} \Delta X_{i,t-h}^{m} \delta_{h}^{m} + \begin{bmatrix} e_{H,t}^{m} \\ e_{C,t}^{m} \end{bmatrix}, \tag{3}$$

where $a_{H,i}^{m}$ and $a_{C,i}^{m}$ denote fixed effects for city i in product m and $\hat{\epsilon}_{i,t-1}^{m} = (CP_{i,t-1}^{m} - \hat{\beta} HP_{i,t-1}^{m})$ is the error correction term capturing the deviation from the long-run equilibrium relationship between HP and CP. The cointegrating vector $(1, -\beta)$ provides a consistent estimate of the long-run relationship between the two variables. If there is a deviation from the long-run equilibrium in the previous period (captured by the error correction term, $\hat{\epsilon}_{i,t-1}^{m}$), either HP or CP should adjust to correct for the deviation in the current period. The parameter ρ_{C}^{m} (or ρ_{H}^{m}) captures the speed at which CP (or HP) adjusts to the long-run equilibrium per period after a shock. A significant estimate of ρ_{C}^{m} (or ρ_{H}^{m}) therefore indicates that CP (or HP) in the current period moves to correct for the deviation. The VECM also allows for asymmetry of the convergence speed, i.e., $\rho_{C}^{m} \neq \rho_{H}^{m}$, which is useful for

[13] The FAVAR model is useful for determining the effect of housing market shocks over a long period, but it does not provide a summary of the long-term effect that the VECM approach can offer.

[14] Because most HP data is in index form, establishing the long-term cointegration relationship required in the error-correction terms has been proven challenging for researchers. For example, both HP and CP are indexed to 100 in the base year in CPI, resulting in a zero error correction term for the cointegrating vector (1,-1). Specifically, in eq.(3) below, $\hat{\epsilon}_{i,t-1} = 0$ in the base year in which $CP_{i,t-1} = HP_{i,t-1} = 100$ when $\beta = 1$. For an exception, see Gallin (2008) who studied the long-run relationship between HP and rent using a VECM.

[15] In studying the impact of HP changes on retail prices, SV adopted exclusion restrictions by using local housing supply constraints constructed by Gyourko et al. (2008) and Saiz (2010) as instruments for local HP movements. This IV approach, however, is subject to a couple of criticisms. First, the popular measures of MSA-level housing supply constraints are usually static variables (fixed over time) and hence cannot capture properly the time-varying behavior of the relationship between HP and CP. Second, housing supply constraints could be a valid but not necessarily exogenous instrument for HP growth (Davidoff 2013, Guren et al. 2020).

determining the direction of causality between HP and CP. City-fixed effects are included in both the cointegrating equation and the VECM to control for factors other than wage and labor market conditions that influence CP at the city level. Lagged terms of HP and CP capture short-run dynamics such as the cyclicality of HP. We also include current and lagged changes in city-level wage and unemployment rate as control variables ($X_{i,t} = [W_{i,t}, U_{i,t}]$) in eq.(3) in order to account for changes in local economic fundamentals, cyclicality in the local labor market, and labor mobility across cities.[16]

Before applying the VECM approach, it is essential to establish a cointegrating relationship between the variables as a prerequisite. Therefore, we begin by conducting the Dickey-Fuller-GLS test, a popular unit-root test that checks for unit-root nonstationarity in the city-level price series. The results, as shown in Table 4, indicate strong evidence of unit-root nonstationarity for most of the CP series and all of the HP series under study. To determine whether there is a long-run cointegrating relationship between HP and CP at the city level, we employ the Hausman-type cointegration test developed by Choi et al. (2008) on the 1,763 HP-CP combinations. The last column of Table 4 reports the results, which show that the null hypothesis of cointegration cannot be rejected in most cases at the 5 percent significance level. Therefore, our VECM is a valid approach for capturing such long-run cointegration relationships between HP and CP at the city level.

3.2.2 The VECM results

The results of the city-level VECM analysis are presented in Table 5. First, the analysis provides strong evidence that local CPs are affected by local HPs, but the reverse is not true. This is evident from the left panel of Table 5 (columns 1-2), where $\hat{\rho}_C$ is significant and positive for all products except one, while $\hat{\rho}_H$ is mostly negative and insignificant. In other words, deviations from the long-run equilibrium between HP and CP are primarily corrected by the adjustment of CP rather than HP. The cross-product average of $\hat{\rho}_C$ is approximately 0.194, indicating that almost 20 percent of the gap between HP and CP is reduced every quarter by the adjustment of CP. The adjustment speed ($\hat{\rho}_C$) varies widely across products, ranging from 0.012 ('auto maintenance') to 0.548 ('lettuce'). Interestingly, the adjustment speed of CP appears to be faster in perishable products.

The VECM presented in eq. (3) enables us to perform a Granger (non-)causality test to determine if changes in HP can predict changes in CP. This test involves checking if HP Granger causes CP ($H_0 : HP \not\Rightarrow CP$) using an F-test with the null hypothesis $\rho_H^m = \gamma_{21,j}^m = 0$ for $j = 1, ..., k$. Similarly,

[16] Local wage and labor market conditions can alleviate the issue of reverse causation from CP to HP. Previous studies have demonstrated that MSA-level wage dispersion, which reflects local labor productivity, has been substantial enough to explain the spatial distribution of HP (Van Nieuwerburgh and Weill, 2010), and local labor market conditions play a crucial role in determining prices (Beraja et al., 2019). However, Coibion et al. (2015) offer a contrasting perspective, finding that changes in retail prices are not significantly influenced by local unemployment rates in numerous U.S. metropolitan areas.

we can test the null hypothesis that CP does not Granger cause HP ($H_0 : CP \nRightarrow HP$) by setting $\rho_C^m = \gamma_{12,j}^m = 0$ for $j = 1, ..., k$. However, rejecting the null hypothesis of noncausality of HP to CP only suggests that changes in HP can help forecast changes in CP, without indicating the strength of the improvement in the forecast. Table 5 (columns 3 and 4) shows the rejection rates of the nominal 10-percent Granger causality test for each product. We observe that the rejection rate of $H_0 : HP \nRightarrow CP$ is generally high in most products studied, while that of $H_0 : CP \nRightarrow HP$ is relatively low. This result indicates a one-way Granger causality running from HP to CP, but not the other way around.[17]

However, the findings from the bivariate VECM that examines each HP-CP pair in each city separately, may be susceptible to fragility if the relationship is driven by unobservable common factors. Particularly in our case, local prices of a product may be correlated across cities, possibly through common national factors like national supply chains.[18] To further verify the robustness of our results, we apply the Panel VECM approach to all 41 cities for each product. Following Holly et al. (2010), we use the Common Correlated Effects (CCE) estimator in the Panel VECM to address issues of cross-sectional dependence and unobserved common factors, while still controlling for local wages and labor market conditions as before. The CCE estimator, based on a multifactor error structure, can control for both unobserved common factors and spatial effects of price changes.[19]

The Panel VECM results, reported in the right panel of Table 5, largely confirm the findings from the city-level bivariate VECM. We still find evidence of one-way causality from HP to CP, i.e., CP is responsive to HP, but not vice versa. The evidence is not as strong as before, which is expected as the CCE estimator effectively removes the influences of common national factors. This is especially relevant for products that are typically produced nationally, such as 'shortening'. The estimates of $\hat{\rho}_C^m$ are statistically significant in almost half of the products, while none of $\hat{\rho}_H^m$ is significant. Interestingly, the long-run causal relationship running from HP to CP is found more frequently in food- and rent-related products that are more influenced by local factors. The speed of adjustment ($\hat{\rho}_C^m$) varies widely across products, with non-durable products typically adjusting faster than nationally-produced manufacturing goods. The fastest adjustment speed is found in 'ground beef' (almost 39 percent per quarter), while the adjustment speed is very slow for 'men's shirt' (less than 1 percent per quarter).

The last column of Table 5 displays the varying LRE of a unit-shock of HP on CP, ranging from

[17] This finding is consistent with SV's research on the causal response of local retail prices to changes in local HPs based on different shock identifications.

[18] Additionally, HP is likely to be correlated across MSAs, not just through common macro factors such as interest rates, but also through spatial effects, i.e., HP changes in one MSA can affect those in other MSAs. In this context, CP in one MSA may also be affected by HP changes in other MSAs.

[19] The CCE estimators are generated using regressions that incorporate cross-sectional averages of all dependent and independent variables. As Pesaran (2006) demonstrates, these cross-sectional averages can effectively control for unobserved common factors.

0.024 for 'men's shirt' to 0.994 for 'gasoline'. This indicates that local gasoline prices are much more responsive to changes in local HP compared to other products. The average LRE across products is around 0.46, meaning that a 10-percent increase in HPs results in around a 4.6-percent increase in CP. This estimate is greater than the cross-sectional elasticity of CP to HP (0.15-0.20) reported in SV. In Section 4.3, we discuss possible reasons for the differences between the two studies, including variations in data coverage, shock identification, time horizons of shock impacts, and methodologies.

4 Transmission channels of housing market changes to CPs

Our findings so far demonstrated that the impact of housing market shocks on local CP is significant and enduring. Furthermore, the impact varies significantly across cities and products, providing valuable information on the underlying transmission mechanisms. Prior research has identified a range of channels through which these mechanisms operate, and we assess their empirical importance by utilizing the heterogeneity observed across cities and products. To achieve this goal, we perform another regression analysis that links the estimated impacts to different product- and city-specific characteristics, thereby identifying the relative importance of different transmission channels.

4.1 Transmission mechanisms of housing market shocks to CPs

The channels through which HP changes affect consumption has garnered significant attention from both policymakers and academic researchers. The existing literature identifies two primary channels through which HP changes affect consumption spending: the *wealth effect* and the *collateral effect*. The wealth effect posits that higher HP increases consumption spending by raising homeowners' wealth.[20] The collateral effect suggests that higher home values affect consumption by allowing credit-constrained households to borrow more against homes, thus enabling consumption smoothing over life cycle (e.g., Campbell and Cocco 2007, Iacoviello 2005). The strength of the latter effect therefore depends on the degree of friction in local financial markets, which can be a binding constraint for some individuals, such as young households who are first-time home buyers. Since these *demand-pull channels* imply higher demand for products upon HP appreciation, they further point to positive effects on CP.

On the supply side, recent work by SV highlights the mechanism through the pricing practices of firms and/or local retailers; an increase in HP leads to higher CP as firms raise their markups while taking advantage of homeowners' lower price sensitivity. This effect is called the *markup effect*. Another supply-side channel may work through the production costs that are directly affected by the

[20] However, Abdallah and Lastrapes (2013) argue that this "pure" wealth effect on aggregate spending may not be strong because the asset value of a home is generally offset by the implicit (or explicit) rental cost of using the home.

local housing market. This effect is called the *local cost effect*. The strength of the local cost effect likely hinges on the extent of overall housing supply constraints in the area (e.g., Gyourko et al. 2008). Both markup and local cost effects are related to the costs of firms, and thus called cost-push channels.

We examine how such various transmission mechanisms operate in our data. Specifically, we regress the estimated cumulative IRFs of CP, obtained from the FAVAR model in Section 3.1, on a set of observable city- and product-level characteristics drawn from the previous theoretical literature. Before getting into the estimation results, it is worthwhile to elaborate on those included in the analysis.

The city characteristics considered are per capita income, population density, the share of skilled workers, homeownership rate, unemployment rate, remoteness, financial integration, and housing supply constraints. First, the wealth effect is expected to be stronger in cities with lower per capita income or a smaller share of skilled workers; households in these cities are more likely to use HP appreciation to finance consumption expenditures, thereby increasing CP. It would also be stronger in cities with higher homeownership rates, as homeowners may respond more sensitively to HP changes than renters. Second, the collateral effect is likely weaker in cities with a higher share of skilled workers who are less financially constrained (e.g., Berger et al. 2018, Lustig and Van Nieuwerburg 2010), but stronger in cities with a tighter linkage to the national banking system, with which homeowners can easily access home equity.[21] Third, the markup effect would be less dominant in densely populated cities than in geographically and economically isolated cities; firms exhibit lower pricing power in more competitive markets which typically show higher population density (e.g., Handbury and Weinstein 2015). The markup effect would also be negatively related to local unemployment, as the markup rate is well-known to be cyclical (e.g., Nekarda and Ramey 2013). Finally, we expect stronger local cost effects in cities where housing supply constraints are more stringent, so HP changes result in larger impacts on local costs such as rents and eventually on CP.

For the product characteristics, we consider flexibility of price adjustment and production proximity, drawing on previous literature (e.g., Parsley and Wei 1996, O'Connell and Wei 2002). First, the price adjustment flexibility serves as a proxy for market competition. Prices are expected to be more flexible in competitive markets, leading to lower markup effects. We divide products into three groups based on their price flexibility, ranging from most flexible to least flexible.[22] Second, production proximity to the marketplace captures the markup rates and frictions in product markets. Locally-produced products are expected to have lower markup rates because consumers have lower brand loyalty, while the local cost channel is likely to be stronger for locally-produced products due to higher

[21] Similarly, Abdallah and Lastrapes (2013) argue that consumption spending is more sensitive to housing demand shocks in states with well-developed financial institutions.

[22] Price flexibility for products in our sample was obtained from the comprehensive data set created by Nakamura and Steinsson (2008). Further details on the categorization of products can be found in Table A.2.

susceptibility to local production costs such as rent. We again group products into three categories in terms of production proximity, following the framework proposed by O'Connell and Wei (2002): generally not locally-produced products (Category A), maybe locally-produced products (Category B), and always locally-produced products (Category C), as detailed in Table A.2.

It is important to note that the inferences made in this study regarding the transmission mechanisms of HP onto CP are hence indirect and based on theoretical guidance from the literature.[23] This is because direct inference, as done in SV, is infeasible due to the lack of relevant data at the city level, let alone the time series of those. Table 6 summarizes the relationship between each transmission mechanism and the city- and product-level variables discussed above. Table A.5 in the Appendix provides detailed definitions and sources.

4.2 Identifying transmission mechanisms using a regression analysis

We perform a cross-section regression analysis, where we regress the estimated cumulative responses of CP to aggregate housing market shocks on the city- and product-characteristic variables, as follows:

$$\widehat{IRF}^m_{i,h} = \alpha_m + \sum_{s=1}^{2} \gamma_s D_s + X_i^{'}\beta + \varepsilon^m_{i,h}, \quad \text{for } m = 1, ..., 43, i = 1, ..., 41, h = 0, ..., 4, \tag{4}$$

where $\widehat{IRF}^m_{i,h}$ represents the estimated median cumulative effect of housing market shocks on the price of the m_{th} product in city i after h years. We use product dummy variables to group products based on their price flexibility or production proximity, depending on the type of housing market shock being analyzed. The aforementioned set of city characteristics is denoted by X_i. Since error term ε^m_{ih} may have cross-sectional correlation and possible heteroskedasticity, we use robust clustered standard errors to account for clustering among city and product combinations.[24] We conduct two sets of regression analyses, one for the IRFs to housing demand shocks and the other for housing supply shocks.

The estimation results are presented in Table 7. The explanatory power of the variables differ significantly across the type of housing market shocks. For housing demand shocks, the city characteristics such as the share of skilled workers and remoteness are consistently significant in explaining the pass-through. The positive relationship between housing prices and the number of college graduates in a city is in line with the findings of Moretti (2013). However, these results do not align with the demand-pull channel; the insignificance of per capita income and financial integration, and the unexpected negative sign of the share of homeownership counter the wealth effect and collateral

[23] For example, our use of city characteristics such as the share of college graduates and population density is related to the theory of skill-biased economic growth (e.g., Card and DiNardo 2002, Giannoni 2018).

[24] The impacts of housing market shocks are likely more correlated across cities for a given product, rather than across products for a given location. So, standard errors are clustered by observations by cities rather than by products.

effect arguments.[25] Nonetheless, we find that housing demand shocks have significant impacts on consumer prices in products with higher price flexibility, which supports our prior that firms producing or selling such products would quickly respond to increased product demand. Our results partially support the demand-pull channel in the transmission of housing demand shocks across products, but not necessarily across space. However, these findings differ from Beraja et al. (2019), who argue that nominal wage rigidity plays an essential role in the transmission of local economic shocks during the Great Recession. The authors also claim that prices respond very quickly to changes in local economic conditions, but not to housing market shocks, which contrasts with the current study's findings.

Turing to housing supply shocks, the significance of the skilled worker share is no longer observed. Instead, the tightness of housing supply constraint and the homeownership rate consistently explain cross-city differences in the pass-through of housing supply shocks, consistent with the local cost and markup effect channels. The higher homeownership rate in smaller cities, where firms have stronger market power, further evidences the local cost effect. For the product characteristics, our findings indicate that locally-produced products are more affected by housing supply shocks compared to nationally-produced counterparts, further supporting the local cost effect but not the markup effect.

In conclusion, our study suggests that the nature of the housing market shocks matters for the transmission of HP to CP. Housing demand shocks transmit mainly through the demand-pull channel, while housing supply shocks primarily through the cost-push channel. It is unlikely that a single transmission mechanism can explain the impact of aggregate housing market changes on local CPs.

4.3 Further discussions on the empirical findings

As discussed in the introduction, our study is closely related to the recent work conducted by SV. Both studies arrive at similar conclusions regarding the impact of HP on CP. However, there are notable differences, particularly with regard to HP transmission mechanism. First, SV highlight the changes in markups as the primary propagation channel, while our study finds that the markup effect is only apparent in the case of housing supply shocks. Additionally, SV do not identify local retail rents or land prices as relevant factors, unlike our findings. Furthermore, while SV suggest that changes in homeownership are the main driver of the effect of HP on retail prices, we demonstrate that it mitigates the transmission of housing demand shocks but amplifies the effects of housing supply shocks. Finally, the two studies find differing implications on the role of price flexibility. Our results suggest that housing demand shocks spread more quickly to products whose prices adjust more frequently, where markup rates are likely smaller. In contrast, SV argue that pricing-to-market practices of firms are

[25] This outcome differs from Abdallah and Lastrapes (2013) who find supports for the collateral effect using the state-level consumption expenditure data.

the primary channel, as companies charge higher prices in locations with higher HP.

We first ensure that our results on the importance of price flexibility are not driven by specific empirical methods. We analyze the cross-product relationship between the degree of price flexibility and the adjustment speed of CP estimated from the VECM ($\hat{\rho}_C$ in eq.(3)). The speed of adjustment of CP to a shock may reflect how quickly deviations from the long-run equilibrium are corrected. Thus, a faster adjustment of CP would be expected for products with more frequent price adjustment. As shown in Figure 4-(a), we find a positive correlation between the adjustment speed ($\hat{\rho}_C$) and the degree of price flexibility across 41 products. The relationship between the price flexibility and the LRE estimates from the Panel VECM further provides strong evidence of a positive association between the two (the last column of Table 5 and Figure 4-(b)). These results corroborate our earlier findings from the FAVAR model that price flexibility plays a crucial role in the transmission mechanism.

A variety of factors, such as data coverage, econometric framework, and time horizon of shock response, may contribute to differences in findings. While details are reported in Table 1, a couple of features are worthwhile to discuss. First, our data set encompasses a broad range of products including food, manufacturing goods, and services, whereas SV focus solely on tradable goods that are generally sold in grocery stores or drugstores. These are typically produced and marketed nationally and not likely much influenced by local factors. This might explain why the significant effect of the local cost channel is found in our study, but not in SV. Second, we note that the two studies focus on different time horizons. Our main interest is in the cumulative *long-run* effects that can differ significantly from the cross-sectional elasticity that SV focus on, particularly when shocks take time to propagate and their impacts display nonlinear patterns over time.

To better understand the contribution of different factors, we conduct an additional analysis following the approach of SV (eqs.(1)-(2) in p.1409), but employing our data set from C2ER. In doing so, we concentrate on 11 processed food-related products from our data to retain similarity with SV. We also trim our sample period to include 2001-2011 only, to match that in SV. Of note, we use the housing supply elasticity from Guren et al. (2020) as an instrument, instead of the Saiz's (2010) measure used by SV. The average elasticity of local CP obtained from this exercise is around 10.7 percent, which is significantly lower than the cumulative long-run effect found using our benchmark VECM, but closer to the range of 15-20 percent reported in SV.

The final exercise we conduct is a rolling window estimation to examine the stability of our findings over time. Figure 5 presents the mean and interquartile ranges of the LRE estimates from the Panel VECM using a 10-year rolling window for all 43 products. The mean estimates remain stable at around 0.4 during the period of 1998-2007, then starts to increase to approximately 0.6 before declining gradually toward zero.[26] The interquartile ranges of the estimates followe a similar pattern, suggesting that the variation of LRE over time is common across all products studied. Interestingly, such variation seems to coincide with the housing boom-bust cycle in the 2000s (e.g., Gelain et al., 2018); a strong pass-through is observed during the boom, while it becomes weaker during the bust. This finding supports Guren et al.'s (2020) claim that discerning between a cyclical pattern and a causal relationship between HP and CP based on a single cross-sectional regression is challenging. Overall, we believe that our study complements and extends the work by SV.

5 Concluding remarks

This paper investigated how housing markets affect local CP, using retail price data of selected U.S. cities over the past 25 years. Our empirical analysis revealed that most local CP are highly responsive to changes in local HP, but not vice versa. After controlling for city-level income and local labor market conditions, we found that a 10 percent increase in HP leads to an average increase of around 4.6 percent in CP in the long run. In addition, the nature of shocks would play a role; housing demand shocks have persistent positive effects on CP, while supply shocks exhibit transitory negative impacts. We also found significant heterogeneity in the size of effects across products and locations.

By exploiting the heterogeneity in responses of CP, we explored the potential transmission channels of HP pass-through. The CP responses were linked to a set of observables identified in the literature as reflecting underlying propagation mechanisms. CP responded more strongly to housing demand shocks in cities with higher shares of skilled workers and in products whose prices are adjusted more frequently. Responses to supply shocks are more noticeable in cities with tighter housing supply regulations and in locally-produced products. Our results pointed to the demand-pull and cost-push channel as the main pass-through mechanisms for housing demand and supply shocks, respectively.

Our findings had implications for the measurement of cost-of-living and consumer welfare. Housing market fluctuations would impact the CPI directly by affecting the shelter index (or user cost) and indirectly through spillover effects on local CP over time. Thus, HP might have a greater influence on overall cost-of-living and consumer welfare than implied by the CPI weight. Additionally, this paper provided useful insights into the geographic dispersions of cost-of-living and geographic economic inequality (e.g., Hsieh and Moretti 2015); our finding that homeownership mitigates the transmission

[26] The numbers on the horizontal axis in Figure 5 denote the ending point of ten-year rolling windows. 2000 represents the subsample period of 1991-2000, and so on. The decreasing responsiveness of CPs to HP in recent years could be due to reduced competition in many industries, which has given firms more pricing power, allowing them to time their pricing to maximize profits and absorb housing market shocks. A similar trend was observed by Heise et al. (2020) who attributed the decline in the pass-through of wages to goods prices to increased market concentration and import competition.

of a housing demand shock while intensifying the effects of a housing supply shock further highlighted the sources of the inequality across cities.

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Table 1: Comparison with the work by Stroebel and Vavra (2019)

	The current study	Stroebel and Vavra (2019)
Data coverage	Quarterly survey retail price in 41 cities for 43 products for food, manufacturing, and service over the period 1990-2015	Weekly IRI scanner data for 31 grocery and drugstore products over 2001-2011
Shock identification	Aggregate housing shocks identified in FAVAR model and HP changes in the VECM	IV approach using the Saiz's (2010) housing supply elasticity as an instrument
Time horizon	Both short-run and long-run effect of HP to CP	Cross-sectional elasticity of CP to HP
Transmission mechanism	Wealth effect and collateral effect for housing demand shock transmission; Markup effect and local cost effect for housing supply transmission	Markup effect No effect of local costs or rents
Quantitative effect effect of HP on CP	Average long-run effect of 0.46	Elasticity of 0.15-0.20
The role of price flexibility	Yes	No
Significance of homeownership	Yes for the transmission of housing supply shock, but not for housing demand shock	Yes for the cross-city difference in the elasticity of HP to CP
Econometric methodologies	FAVAR, VECM, and cross-sectional regression	Cross-sectional regression

Table 2: Sign Restrictions

Variables	Housing Demand Shock	Housing Supply Shock
Real residential investment	positive	positive
House prices	positive	negative
5-yr rate	–	–
GDP deflator	–	–
Real GDP	–	–
Real PCE	–	–
Unobservable factors (F_t)	–	–

Note: This table summarizes how we impose sign restrictions to identify housing demand ad supply shocks. The restrictions are imposed for three quarters after the impact on real residential investment and house prices only, while signs of other variables are left unrestricted (noted as "–" in the table).

Table 3: Peak responses of CPs to housing demand and supply shocks from FAVAR model

Product	Demand shock		Supply shock	
	Average	[25%,75%]	Average	[25%,75%]
Steak	0.416	[0.245, 0.512]	0.030	[-0.112, 0.225]
Ground beef	0.262	[0.077, 0.400]	-0.092	[-0.254, 0.115]
Whole chicken	0.234	[0.022, 0.327]	-0.168	[-0.441, 0.038]
Canned tuna	0.096	[0.048, 0.159]	-0.315	[-0.501, -0.135]
Milk	0.420	[0.185, 0.543]	0.093	[-0.055, 0.214]
Eggs	0.078	[0.005, 0.177]	0.059	[-0.006, 0.183]
Margarine	0.107	[0.005, 0.189]	-0.155	[-0.333, -0.057]
Cheese	0.081	[-0.134, 0.149]	-0.173	[-0.302, 0.037]
Potatoes	0.608	[0.478, 0.748]	-0.043	[-0.180, 0.047]
Bananas	0.077	[-0.081, 0.120]	-0.055	[-0.143, 0.065]
Lettuce	0.102	[0.050, 0.176]	-0.410	[-0.632, -0.261]
Bread	0.136	[-0.043, 0.209]	-0.037	[-0.258, 0.209]
Coffee	-0.133	[-0.252, 0.096]	0.093	[-0.090, 0.281]
Sugar	0.011	[-0.090, 0.041]	-0.268	[-0.392, -0.132]
Corn flakes	0.157	[-0.042, 0.255]	-0.104	[-0.249, 0.051]
Canned peas	0.191	[-0.016, 0.302]	-0.334	[-0.551, -0.053]
Canned peaches	0.182	[-0.050, 0.250]	-0.294	[-0.442, -0.162]
Tissue	0.254	[0.033, 0.498]	-0.314	[-0.557, -0.110]
Detergent	0.211	[0.092, 0.283]	-0.332	[-0.521, -0.152]
Shortening	0.566	[0.259, 0.682]	-0.490	[-0.655, -0.310]
Frozen corn	0.171	[-0.024, 0.322]	-0.084	[-0.222, 0.126]
Soft drink	0.182	[0.004, 0.227]	-0.249	[-0.443, -0.027]
Apartment rent	0.356	[0.022, 0.409]	-0.008	[-0.207, 0.146]
House price	1.674	[1.167, 1.954]	-0.363	[-0.607, -0.163]
Telephone	0.248	[-0.041, 0.322]	-0.286	[-0.525, -0.134]
Auto maintenance	0.150	[0.070, 0.227]	-0.322	[-0.399, -0.243]
Gas	0.204	[0.129, 0.247]	-0.580	[-0.652, -0.532]
Doctor visit	0.137	[-0.009, 0.285]	-0.118	[-0.328, 0.066]
Dentist visit	0.072	[-0.059, 0.068]	-0.194	[-0.378, -0.004]
Hamburger	-0.008	[-0.121, 0.013]	-0.253	[-0.466, -0.013]
Pizza	0.575	[0.170, 0.911]	-0.251	[-0.530, 0.022]
Fried chicken	0.225	[-0.036, 0.339]	-0.269	[-0.528, -0.011]
Man's haircut	0.213	[-0.015, 0.337]	-0.222	[-0.500, 0.098]
Beauty salon	0.193	[0.000, 0.370]	-0.171	[-0.481, 0.027]
Toothpaste	0.208	[0.054, 0.354]	-0.028	[-0.069, 0.147]
Dry cleaning	0.164	[-0.096, 0.271]	-0.197	[-0.386, 0.067]
Man's shirt	0.139	[0.032, 0.201]	0.098	[-0.066, 0.258]
Appliance repair	0.252	[0.025, 0.386]	-0.119	[-0.346, 0.025]
Newspaper	0.144	[-0.031, 0.219]	-0.191	[-0.473, -0.045]
Movie	0.075	[-0.048, 0.141]	-0.404	[-0.578, -0.171]
Bowling	0.174	[-0.032, 0.268]	-0.095	[-0.284, 0.036]
Tennis balls	0.183	[-0.030, 0.402]	-0.095	[-0.252, 0.103]
Beer	0.634	[0.469, 0.815]	-0.434	[-0.525, -0.330]
Wine	0.005	[-0.109, 0.057]	-0.358	[-0.550, -0.205]

Note: Entries represent the average peak (for demand shock) and trough (for supply shock) responses of CPs to housing market shock and the corresponding intercity quartile (25^{th}- and 75^{th}-percentiles) across cities. Impulse responses are normalized responses to each shock that increases private residential fixed investment by 1% at the impact.

Table 4: Rejection rates of unit-root and cointegration tests

Significance level	DF-GLS test		Hausman-type cointegration test
	CP (1,763 series)	HP (41 series)	
1%	0.019	0.000	0.221
5%	0.061	0.000	0.175
10%	0.103	0.000	0.119

Note: See Choi et al. (2008) for the Hausman-type cointegration test under the null hypothesis of cointegration between CP and HP. The rejection rates refer to the frequency of cases out of 1,763 (=43×41) combinations of CP and HP in which the null of cointegration is rejected. The critical values of the DF-GLS (Hausman-type cointegration test) are -1.62 (4.61), -1.95 (5.99), and -2.58 (9.21) for 10%, 5%, and 1% significance levels.

Table 5: Bivariate VECM and the Granger-causality test results

Product	Bivariate VECM				Panel VECM		
	Average adjustment speed		Granger-test rejection rates		Average adjustment speed		Long-run
	$\hat{\rho}_C$	$\hat{\rho}_H$	$HP \nRightarrow CP$	$CP \nRightarrow HP$	$\hat{\rho}_C$	$\hat{\rho}_H$	effect (LRE)
Steak	0.224‡[0.93]	-0.035 [0.05]	0.146	1.000	0.299‡(0.130)	-0.061 (0.047)	0.633‡(0.118)
Ground beef	0.089* [0.46]	0.008 [0.00]	0.146	0.951	0.387‡(0.164)	-0.077 (0.061)	0.755‡(0.155)
Whole chicken	0.309†[0.93]	-0.015 [0.00]	0.195	1.000	0.325* (0.176)	-0.041 (0.044)	0.395‡(0.124)
Canned tuna	0.174* [0.85]	0.020 [0.00]	0.244	0.878	0.257 (0.205)	-0.059 (0.053)	0.223* (0.120)
Milk	0.201‡[0.93]	-0.046 [0.12]	0.239	1.000	0.135 (0.095)	-0.048 (0.056)	0.446‡(0.144)
Eggs	0.214‡[0.98]	0.013 [0.00]	0.171	0.976	0.338* (0.201)	-0.085 (0.062)	0.557‡(0.125)
Margarine	0.302‡[0.93]	-0.022 [0.00]	0.195	1.000	0.267 (0.180)	-0.036 (0.049)	0.414‡(0.190)
Cheese	0.163‡[0.93]	-0.060 [0.17]	0.293	0.634	0.067 (0.099)	-0.043 (0.066)	0.103 (0.121)
Potatoes	0.463‡[1.00]	0.001 [0.00]	0.244	0.976	0.378‡(0.124)	-0.031 (0.050)	0.462‡(0.165)
Bananas	0.351‡[1.00]	-0.008 [0.00]	0.171	0.756	0.241 (0.161)	-0.046 (0.052)	0.171* (0.094)
Lettuce	0.548‡[0.98]	-0.038 [0.00]	0.171	0.927	0.349‡(0.167)	-0.046 (0.053)	0.383‡(0.158)
Bread	0.214‡[0.98]	-0.005 [0.00]	0.098	1.000	0.327‡(0.120)	-0.049 (0.045)	0.631‡(0.174)
Coffee	0.127‡[1.00]	0.010 [0.00]	0.146	0.902	0.212* (0.127)	-0.061 (0.069)	0.393‡(0.093)
Sugar	0.139‡[0.93]	0.023 [0.00]	0.024	0.951	0.234* (0.142)	-0.066 (0.062)	0.270‡(0.091)
Corn flakes	0.153‡[0.93]	-0.030 [0.05]	0.293	1.000	0.188* (0.108)	-0.038 (0.050)	0.476‡(0.138)
Canned peas	0.250‡[0.98]	-0.011 [0.00]	0.220	0.951	0.276‡(0.108)	-0.047 (0.055)	0.484‡(0.155)
Canned peaches	0.132* [0.85]	-0.023 [0.02]	0.073	1.000	0.177 (0.124)	-0.051 (0.055)	0.436‡(0.122)
Tissue	0.228‡[1.00]	0.010 [0.00]	0.098	1.000	0.248†(0.125)	-0.046 (0.056)	0.505‡(0.118)
Detergent	0.162‡[1.00]	0.010 [0.00]	0.024	0.976	0.231* (0.134)	-0.060 (0.071)	0.522‡(0.140)
Shortening	0.198‡[0.95]	-0.021 [0.07]	0.190	0.561	0.096 (0.069)	-0.035 (0.047)	0.340‡(0.107)
Frozen corn	0.184‡[0.83]	-0.051 [0.00]	0.266	0.951	0.293‡(0.136)	-0.045 (0.052)	0.572‡(0.212)
Soft drink	0.219* [0.80]	0.049 [0.02]	0.220	0.854	0.259 (0.182)	-0.046 (0.057)	0.222 (0.140)
Apartment rent	0.071* [0.59]	-0.061 [0.54]	0.439	0.732	0.092* (0.053)	-0.051 (0.056)	0.499‡(0.122)
Telephone	0.163* [0.93]	-0.016 [0.12]	0.122	0.927	0.101 (0.070)	-0.036 (0.031)	0.356* (0.203)
Auto maintenance	0.012 [0.07]	-0.017 [0.00]	0.171	0.341	0.152 (0.146)	-0.093 (0.076)	0.588‡(0.148)
Gas	0.180‡[1.00]	0.016 [0.00]	0.000	1.000	0.104 (0.128)	-0.143 (0.150)	0.994‡(0.129)
Doctor visit	0.084* [0.54]	-0.051 [0.34]	0.190	0.780	0.221 (0.140)	-0.081 (0.067)	0.893‡(0.202)
Dentist visit	0.079* [0.59]	-0.051 [0.27]	0.361	0.634	0.169 (0.121)	-0.056 (0.058)	0.549‡(0.176)
McDonald's	0.055* [0.63]	-0.006 [0.05]	0.049	0.927	0.136 (0.109)	-0.116 (0.100)	0.551‡(0.095)
Pizza	0.212* [0.95]	-0.053 [0.07]	0.195	0.683	0.118 (0.073)	-0.035 (0.040)	0.181‡(0.089)
Fried chicken	0.177* [0.76]	-0.035 [0.05]	0.195	0.927	0.183 (0.141)	-0.044 (0.045)	0.444‡(0.110)
Man's haircut	0.155* [0.85]	-0.043 [0.12]	0.220	0.976	0.187* (0.102)	-0.061 (0.061)	0.551‡(0.113)
Beauty salon	0.201* [0.76]	-0.033 [0.05]	0.293	0.927	0.197* (0.121)	-0.029 (0.042)	0.555‡(0.166)
Toothpaste	0.319‡[0.98]	-0.063 [0.05]	0.217	0.780	0.134 (0.198)	-0.035 (0.052)	0.181 (0.152)
Dry cleaning	0.103* [0.73]	-0.035 [0.22]	0.195	0.829	0.140* (0.072)	-0.059 (0.058)	0.513‡(0.112)
Man's shirt	0.183‡[0.90]	-0.036 [0.00]	0.317	0.488	0.008 (0.285)	-0.068 (0.092)	0.024 (0.162)
Appliance repair	0.150†[0.83]	-0.026 [0.00]	0.146	0.951	0.195 (0.157)	-0.056 (0.054)	0.634‡(0.186)
Newspaper	0.124* [0.76]	-0.037 [0.15]	0.195	0.707	0.155 (0.131)	-0.045 (0.047)	0.445‡(0.217)
Movie	0.113* [0.76]	-0.059 [0.39]	0.122	0.854	0.095 (0.062)	-0.086 (0.053)	0.462‡(0.101)
Bowling	0.169* [0.88]	-0.052 [0.10]	0.293	0.976	0.215 (0.141)	-0.048 (0.049)	0.726‡(0.136)
Tennis balls	0.335‡[0.95]	0.015 [0.05]	0.195	0.732	-0.028 (0.222)	-0.037 (0.050)	0.033 (0.146)
Beer	0.137‡[0.73]	-0.066 [0.17]	0.293	0.780	0.103 (0.077)	-0.107 (0.092)	0.839‡(0.130)
Wine	0.256‡[0.93]	-0.021 [0.02]	0.146	0.976	0.185 (0.123)	-0.039 (0.046)	0.316‡(0.118)

Note: Entries represent cross-city (left panel) and cross-product (right panel) average of the convergence speed coefficients estimated from the bivariate vector error correction model (VECM) in eq.(3). Entries inside the square brackets represent the portion of cities in each product where the coefficient of convergence speed is statistically significant at 10%. Rejection rate denotes the frequency that the null hypothesis of no Granger causality is rejected at the 10% significance level. ‡, † and asterisk (*) respectively indicate the statistical significance at the 1%, 5% and 10% significance levels.

Table 6: Transmission mechanisms and the related variables

	Transmission mechanism	Variables (expected signs)	
		City characteristics	Product characteristics
Demand-pull channel	Wealth effect	Per capita income (−)	Price flexibility (+)
		Share of college graduates (−)	
		Homeownership rate (+)	
	Collateral effect	Financial integration (+)	Price flexibility (+)
		Share of college graduates (−)	
		Homeownership rate (+)	
Cost-push channel	Markup effect	Population density (−)	Production proximity (−)
		Remoteness (+)	Price flexibility (−)
		Unemployment rate (−)	
		Homeownership rate (+)	
	Local cost effect	Housing supply constraint (+)	Production proximity (+)

Note: Signs inside the parenthesis represent the expected signs of variables to support the corresponding effect.

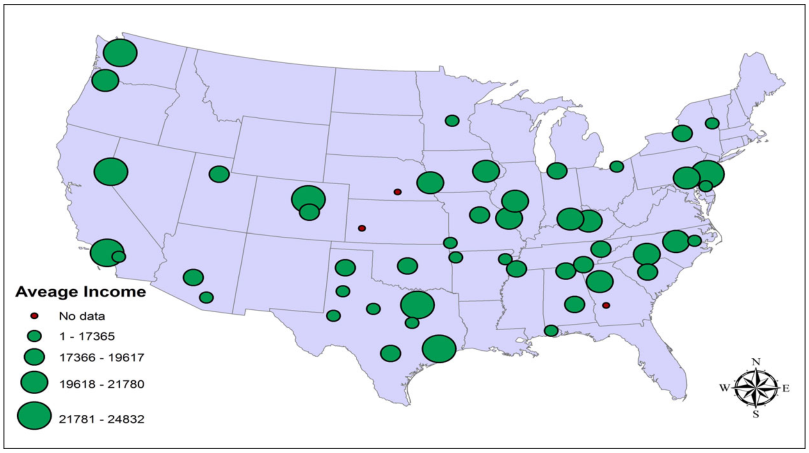
Table 7: Regression results for the transmission mechanism of aggregate housing demand and supply shocks

Explanatory Variables	contemporaneous	After 1 year	After 2 years	After 3 years	After 4 years
	Housing demand shock				
Constant	-0.053 [0.064]	-0.190 [0.169]	-0.001 [0.198]	0.164 [0.244]	0.257 [0.274]
Dummy for Most FLEX gp	0.024‡[0.011]	0.079* [0.042]	0.123†[0.061]	0.153†[0.073]	0.166‡[0.078]
Dummy for Med FLEX gp	0.011 [0.015]	0.030 [0.044]	0.046 [0.059]	0.070 [0.072]	0.084 [0.079]
Per capita income	0.001 [0.001]	0.000 [0.003]	-0.005 [0.004]	-0.007 [0.005]	-0.009 [0.006]
Population Density	0.001 [0.001]	0.002 [0.003]	0.004 [0.005]	0.008 [0.006]	0.010 [0.007]
Share of skilled worker	0.001* [0.001]	0.004†[0.002]	0.005†[0.002]	0.005‡[0.002]	0.005‡[0.002]
Remoteness	-0.007 [0.014]	0.005 [0.040]	0.044 [0.054]	0.075 [0.067]	0.093 [0.075]
Unemployment rate	0.005 [0.004]	0.012 [0.010]	0.004 [0.013]	-0.006 [0.015]	-0.013 [0.017]
Financial integration	0.015 [0.011]	0.028 [0.031]	0.051 [0.040]	0.055 [0.048]	0.053 [0.054]
Homeownership rate	-0.111* [0.057]	-0.188 [0.169]	-0.312 [0.195]	-0.425* [0.225]	-0.441* [0.247]
Housing supply constraint	0.034†[0.015]	0.094‡[0.033]	0.094 [0.043]	0.088* [0.052]	0.085 [0.059]
	Housing supply shock				
Constant	-0.158 [0.175]	-0.586‡[0.287]	-0.632‡[0.273]	-0.619‡[0.279]	-0.595‡[0.275]
Dummy for LOCAL group	0.106‡[0.047]	0.119* [0.066]	0.133* [0.076]	0.151* [0.078]	0.161†[0.077]
Dummy for MAYBE LOCAL	0.017 [0.030]	0.084* [0.050]	0.093 [0.059]	0.104* [0.062]	0.113* [0.064]
Per capita income	-0.008‡[0.004]	-0.003 [0.005]	-0.004 [0.005]	-0.004 [0.005]	-0.005 [0.005]
Population Density	-0.004 [0.004]	-0.002 [0.006]	-0.003 [0.007]	-0.002 [0.007]	-0.001 [0.007]
Share of skilled worker	0.001 [0.002]	0.004 [0.003]	0.005 [0.003]	0.005* [0.003]	0.005* [0.003]
Remoteness	-0.006 [0.042]	-0.087‡[0.053]	-0.098 [0.067]	-0.092 [0.067]	-0.085 [0.065]
Unemployment rate	0.000 [0.011]	0.016 [0.015]	0.018 [0.017]	0.016 [0.018]	0.015 [0.017]
Financial integration	-0.013 [0.041]	-0.041 [0.053]	-0.033 [0.063]	-0.030 [0.064]	-0.028 [0.062]
Homeownership rate	0.456‡[0.162]	0.541‡[0.368]	0.568†[0.284]	0.534* [0.291]	0.521* [0.290]
Housing supply constraint	0.065* [0.039]	0.187‡[0.058]	0.214‡[0.062]	0.221‡[0.061]	0.225‡[0.060]

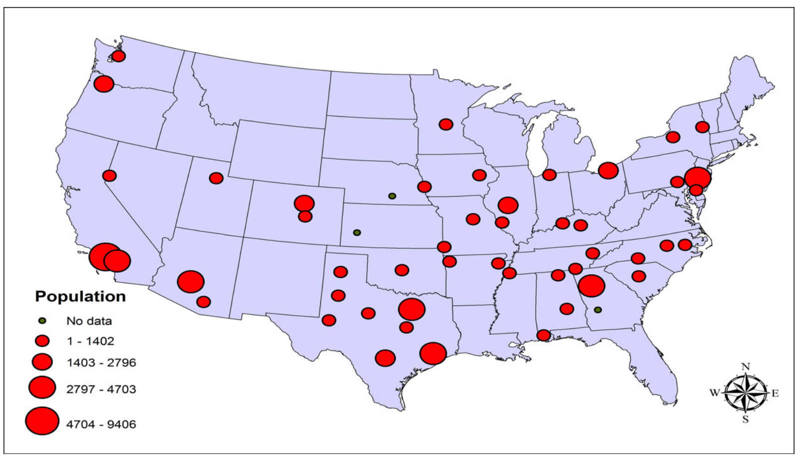
Note: The regression equation is

$$IRF_{i,h}^{m} = \alpha_m + \sum_{s=1}^{2} \gamma_s D_s + X_i^{'}\beta + \varepsilon_{i,h}^{m}, \quad \text{for } m = 1, ..., 43, i = 1, ..., 41, h = 0, ..., 4,$$

where $IRF_{i,h}^{m}$ represents the h-year *median* cumulative effect of housing market shocks on the price of the m_{th} product in city i. D_s denotes a product dummy variable. For the house demand shock, D_{1i} and D_{2i} respectively represent dummy variables for the most flexible price group (Most FLEX) and less-flexible price group (Med FLEX) by setting the least flexible price group as the base group. For the house supply shock, D_{1i} and D_{2i} respectively denote dummy variables for the locally produced product group (LOCAL) and maybe locally produced product group (MAYBE LOCAL) by setting the not locally produced product group as the base group. X_i is a set of city-level characteristics including per capita income, population density, share of college graduates, remoteness, unemployment rate, financial integration, homeownership and the housing supply constraint by Guren et al. (2020). Clustered standard errors are used by clustering observations by cities rather than by products. ‡, † and asterisk (*) respectively indicate the statistical significance at the 1%, 5% and 10% significance levels.



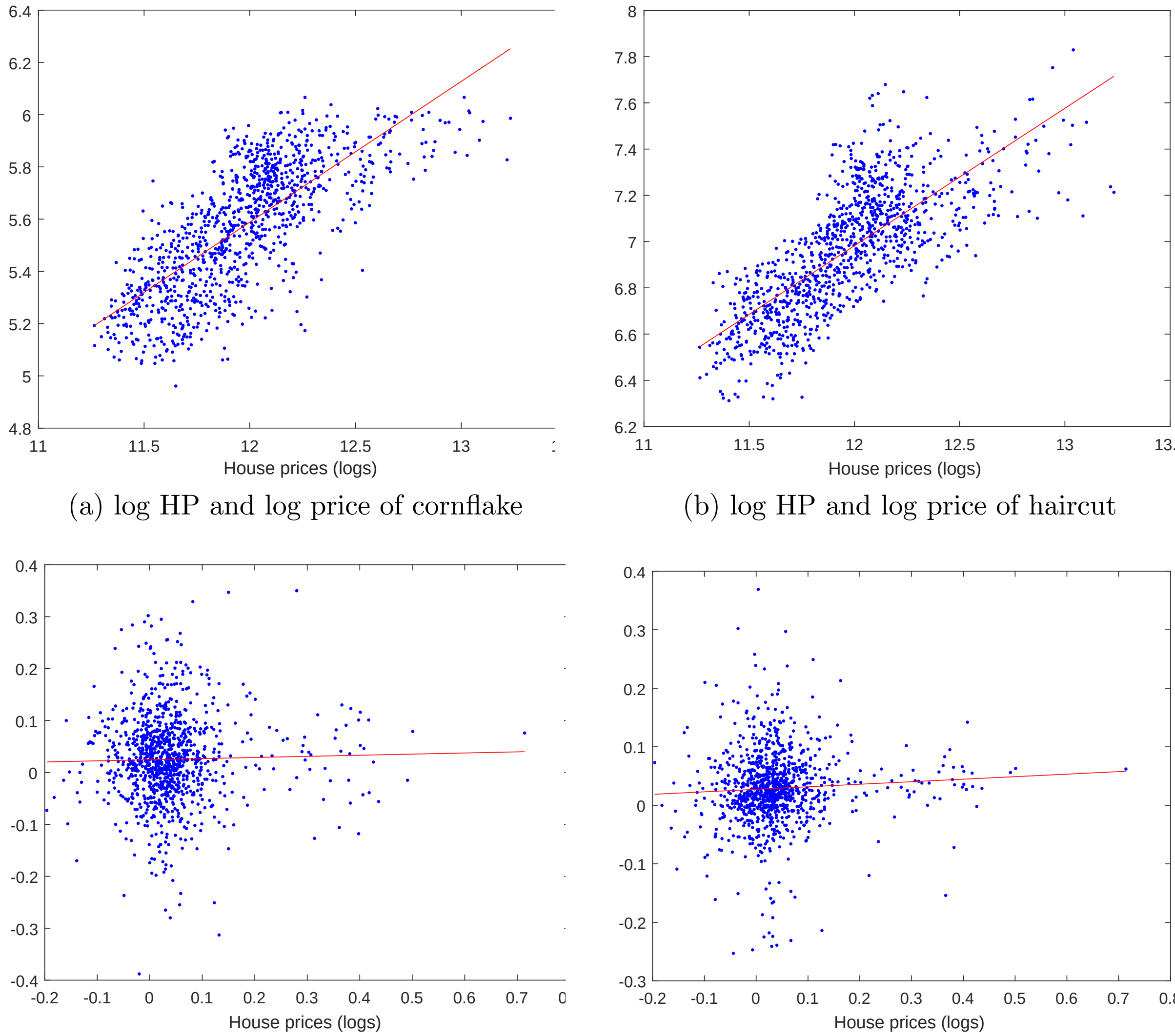
(a) Nominal per capita income



(b) Population

Figure 1: Income and population of the U.S. Cities

Note: The figure maps the location of each city and the size of the circle denotes the size of the city in terms of per capita income (top) and population (bottom).



(a) log HP and log price of cornflake

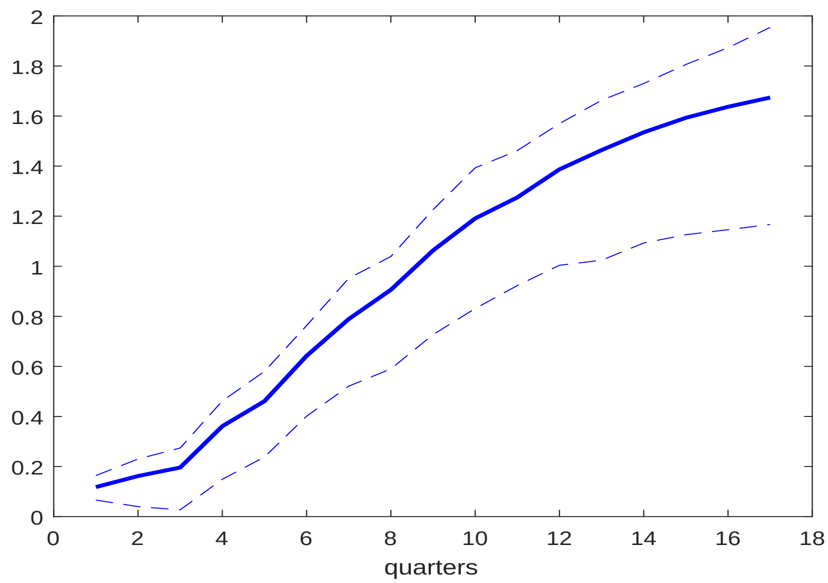
(b) log HP and log price of haircut

(c) growth rates of HP and cornflake price

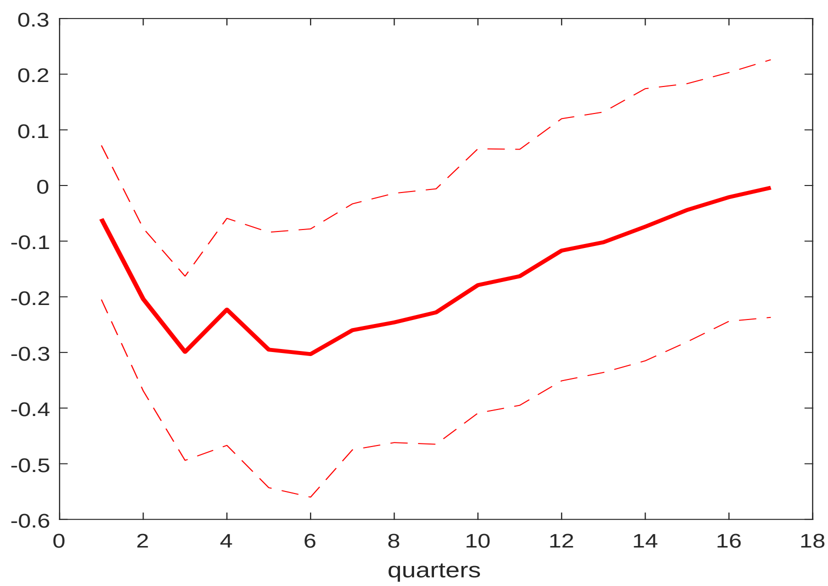
(d) growth rates of HP and haircut price

Figure 2: Relationship between annual average HP and CP (on the top panel) and relationship between growth rates of HP and CP (on the bottom panel)

Note: This figure displays the relationship between annualized HP and the price of 'conflake' (top-left panel) and price of 'haircut' (top-right panel), and the relationship between annualized HP growth and the growth rates of 'cornflake' (bottom-left panel) and growth rates of 'haircut' (bottom-right panel).



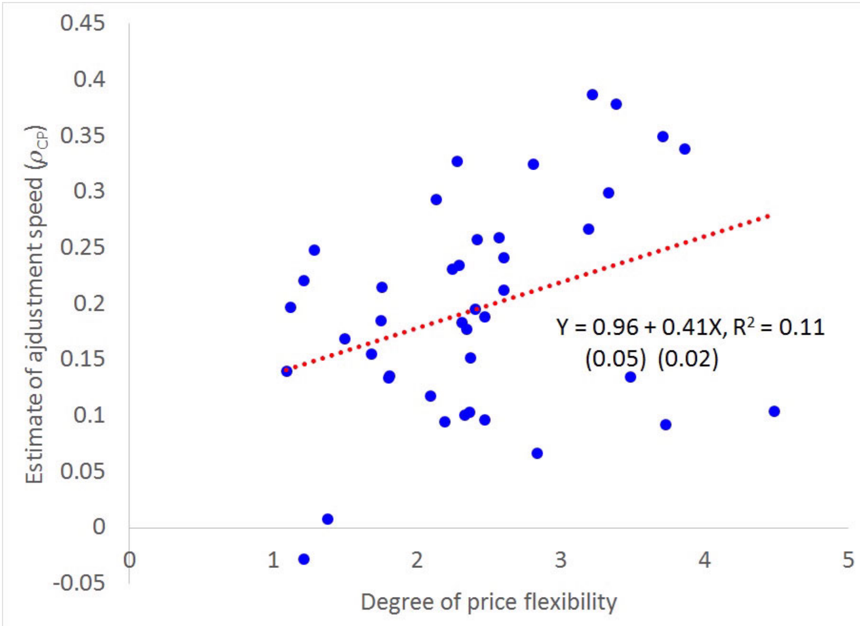
(a) Response of local HP to the aggregate housing demand shock



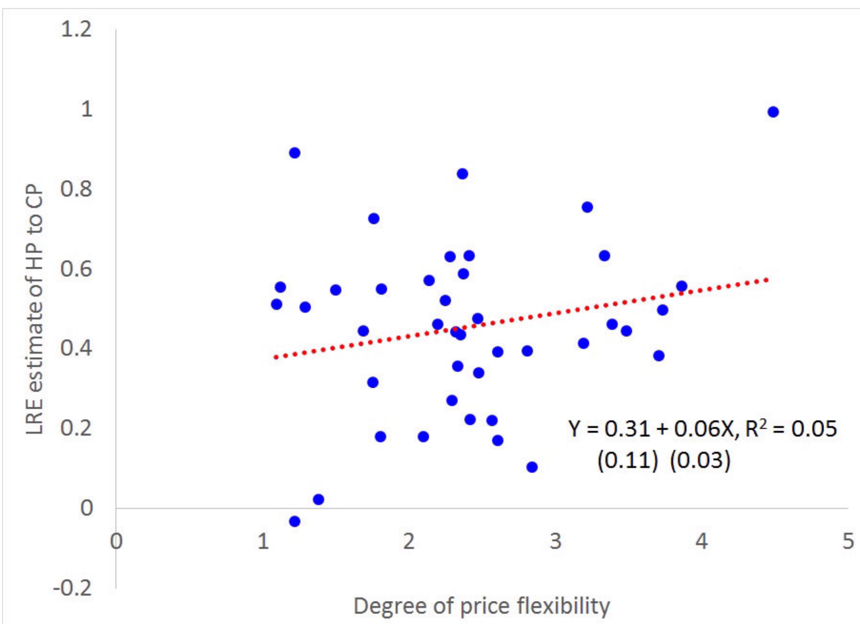
(b) Response of local HP to the aggregate housing supply shock

Figure 3: Responses of local HP to aggregate housing market shocks

Note: This figure plots the cumulative IRFs of local HP in 41 cities to aggregate housing demand and supply shocks on the top and bottom panes, respectively. The solid line represents the *median* response among the 41 cities, and the dashed lines are the inter-city quartile (25^{th}- and 75^{th}-percentile) bands.



(a) Relationship between price flexibility and adjustment speed



(b) Relationship between price flexibility and long-run effect

Figure 4: Degree of price flexibility and average adjustment speed and long-run effect estimated from the (P)VECM

Note: The top panel shows the relationship between price flexibility and the adjustment speed of CP to the deviation from long-run equilibrium across 43 products, estimated from VECM. The top panel plots the relationship between price flexibility and the long-run effects of HP to CP among 43 products, estimated from the panel VECM.

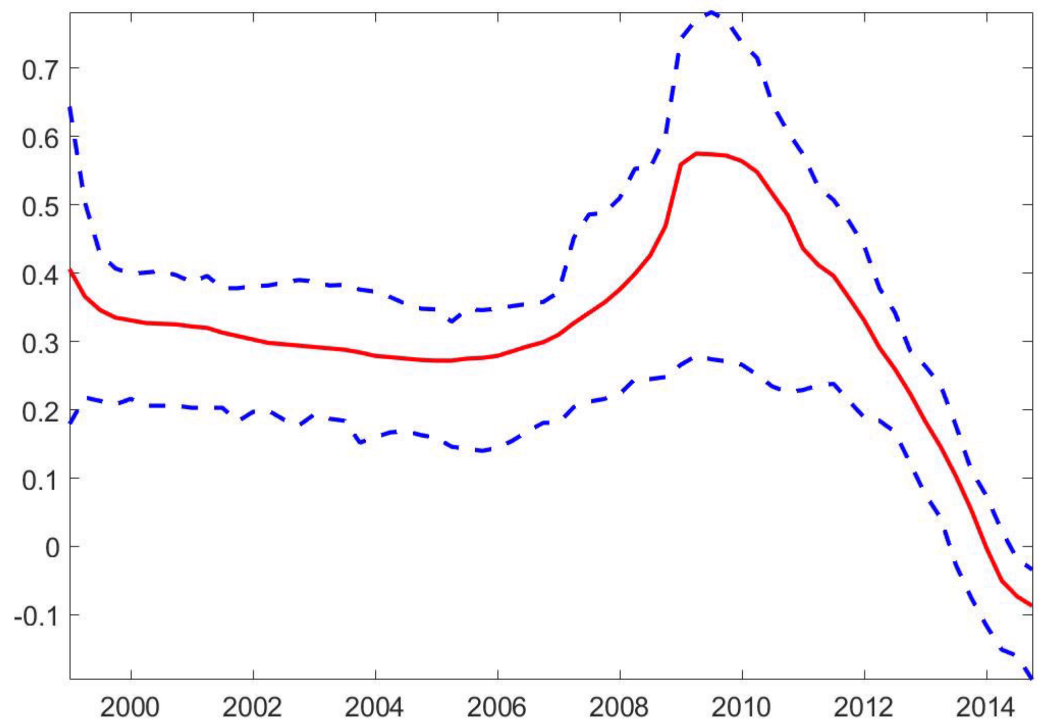


Figure 5: The mean (solid line) and inter-quartiles (dotted lines) of long-run effect (LRE) estimates of HP to CP for 10-year rolling window

Note: This figure plots the mean (solid line) and interquartile ranges (dotted lines) of the long-run effects among 43 products, estimated from the Panel VECM using a 10-year rolling window. The numbers on the horizontal axis in Figure 5 denote the ending point of ten-year rolling windows. 2000 represents the subsample period of 1991-2000, and so on.

Appendix

Appendix A: Data Description

The present study utilizes a quarterly retail price dataset, known as the C2ER dataset, which was originally created by the Council for Community and Economic Research (formerly known as the American Chamber of Commerce Researchers Association (ACCRA)) to compare the cost of living across various US cities. The dataset contains retail prices for specific goods and services typically purchased by mid-management executive households. The dataset is highly specific, with each product including brand name, weight, model, and other identifying information, making it easier to compare prices across different locations. The dataset has been used in prior studies (e.g., Card and Krueger 1995, Parsley and Wei 1996, Crucini et al. 2012, Choi et al. 2020) and allows for comparisons over time due to its consistent collection by a single organization from a survey of mid-level managers.

In this study, cities and products were chosen based on the availability of continuous data observations since 1990. Specifically, products were chosen if data existed for them over a reasonably long period, while cities were selected if they appeared in the dataset for a sufficiently long time. The resulting balanced panel includes retail prices for 44 products in 41 cities, which were surveyed quarterly between 1990.Q1 and 2015.Q4. While a trade-off exists between data span and coverage, this balanced panel dataset is suitable for analyzing the dynamic relationship between HP and CPs across different locations over time. The 41 selected cities are diverse in terms of relative size, as measured by average per capita income and population, and account for a significant share of the nation's consumption, investment, and wealth. Table A.2 provides summary statistics for the 44 products included in the study.

As summarized in Table A.1, the C2ER price dataset has several advantages over alternative micro price datasets, such as the (confidential) BLS data and the grocery store scanner data sets, in terms of product diversity, coverage of cities, and data span. First, the C2ER dataset has a broad coverage of consumer products, both goods and services, ranging from basic food products such as *Bread* and *Eggs*, to manufacturing goods like *Detergents* and *Tissues*, and to services including *Medical Service* and *Hairstyling*. While the C2ER data cover a narrower set of products than the BLS micro-data, its coverage is much broader than the grocery store scanner data, such as the Nielsen or IRI data, which concentrate mostly on grocery items like soup and toilet paper.

Of particular value to the C2ER dataset must be a more extensive geographical coverage than other datasets that were popularly used in the literature, such as the BLS micro-data and grocery store scanner data. The wide geographic distribution of 41 cities around the U.S. (as displayed in Figure 1) allows a meaningful cross-city analysis in identifying potential transmission mechanisms of house prices to consumer prices by utilizing nontrivial heterogeneity across city characteristics. By contrast, the BLS price data are available for at most 28 metropolitan areas with different data frequencies (in semi-annual frequency for many areas) and the Nielsen dataset covers mostly 32 markets only after 2006. Although the Nielsen data set contains data for 52 markets, many of these have very little consistent data observations over time. This rendered SV to use Nielsen PromoData (use Homescan data from AC Nielsen), which collects information from one confidential grocery wholesaler in each of 32 markets for the period 2006-12. As noted by SV (in footnote 13), while the raw data set contains information on more than 32 markets, many of these have very little data, so they concentrate on the largest 32 markets.

A long data span is another notable merit of the C2ER dataset, especially compared to the grocery scan data like the Nielsen dataset. The relatively long data span is crucial for reliable time series analysis of the short-run and long-run relationship between house price and consumer prices. This allows us to construct a long and wide panel that is useful for analyzing the dynamic impacts on CP.

Notwithstanding the attractive features, the C2ER data have some limitations. One disadvantage of the dataset, especially compared to the BLS data, is that the product coverage is not as comprehensive as disaggregated BLS data. In addition, the quarterly frequency of the data observation is relatively lower than the alternative micro price data sets, especially the grocery store scanner data. Empirical evidence from the micro-data literature (e.g., Bils and Klenow, 2004; Nakamura and Steinsson, 2008) shows that many retail prices tend to be set weekly or monthly, while prices in the C2ER data are observed and collected at a quarterly frequency. But, the quarterly frequency of the C2ER data is not much consequential to the main theme of the present study because the transmission from housing prices to consumer prices turned out to take over relatively long time. Moreover, comparing an C2ER based price index to an index based on BLS data for 23 cities, Schoeni (1996) concludes that the two indices agree fairly closely, with a correlation of 0.715. Similarly, Card and Krueger (1995) also used the C2ER data (previously called ACCRA data) in their research on the minimum wage and found that using ACCRA data and the (limited) BLS data on city price indices produces very similar results.

Table A.1: Comparison of the micro price datasets

	C2ER data	BLS data	Nielsen data
Product coverage	Extensive from food to manufacturing goods to service products	Extensive from food to transportation to recreation and education	Limited mainly to items sold in grocery chain stores like soup, soda and toilet paper
Location coverage	Up to 756 cities in U.S. (focus on 41 cities)	28 U.S. MSAs	52 markets (but consistent data are available in 32 cities)
Data span	From 1968.Q1 (focus on after 1990.Q1)	From 1950s in many MSAs (after 1998 for some MSAs)	Only after 2006
Data Frequency	Quarterly	Monthly for many MSAs (semi-annual for some MSAs)	Weekly

Although not perfect, the C2ER data set arguably has an edge over the increasingly used micro data from BLS or the grocery scan data. The dataset is particularly well suited for analyzing the central topic of this study with a clear edge over the alternative datasets in terms of the extensive coverage of location and products. The resulting large balanced panel data for a relatively long time series makes meaningful time series and cross-sectional regression analysis possible in identifying potential transmission mechanisms of housing markets to consumer prices. The long data span and more extensive geographic coverage is more consequential to short of alternative data sources in terms of the locational coverage for homogeneous quality for many cities scattered around the country renders us to stick to this data set.

City-level personal income and population data are obtained from the websites of BEA (*https://www.bea.gov/data*) and the Census Bureau (*https://www.census.gov/*), respectively. City-level unemployment rates are seasonally adjusted observations and are downloaded from the BLS website (*https://www.bls.gov/web/metro/laummtrk.htm*). The share of skilled workers is measured by the proportion of adults over 25 years old with at least a bachelor's degree. The data for educational attainment are obtained from the decennial census (for 1990 and 2010) and from American Community Survey one-year 2010 estimates.

Remoteness for city i from city j is calculated by $\sum_{k=1,k<>j}^{41} \frac{D_{ik}}{Y_k}$ where D_{ik} denotes the distance between cities i and k and Y_k represents the per capita income of city k. It captures an output weighted average distance vis-à-vis all other cities. In general, cities on both coasts are among the more remote, while the cities in the central time zone are less remote. See Wolf (2000, p.556) for a further discussion on the remoteness measure.

The city-level financial integration is measured by the co-Herfindahl index of bank deposits borrowed from Choi and Hansz (2021). It captures the sum of deposit market shares of multimarket banks operating across the nation, with the higher co-Herfindahl index representing a stronger financial linkage to the rest of the nation via the nationwide banking system. Intuitively, cities with stronger financial integration are likely to have lower financial frictions and thus less susceptible to the collateral constraints. City deposit also controls for local credit supply in the sense that availability of deposits is known to be an important determinant of credit provision (e.g., Jayaratne and Morgan 2000). The co-Herfindahl index for city-pair i and j at time t ($H_{ij,t}$), which is given by $H_{ij,t} = \sum_{k=1}^{m} s_{i,t}^{k} \times s_{j,t}^{k}$, where $s_{h,t}^{k}$ denotes the market share of bank k in city h, in terms of outstanding deposits at t. This index therefore captures the sum of deposit market share of banks ($k = 1, ..., m$) operating in both cities i and j at time t. The basic idea of this measure is that if the deposit share of a bank is high in one city (i) but low in another (j), then the co-Herfindahl index will be low because the two cities are not much connected each other through common banks running business in both cities. Intuitively, cities with a higher market concentration of the common banks are likely to experience less constraints in mortgage borrowing. We exploit the information on total deposits, location, and ownership of all bank branches obtained from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD), available online ($https://www5.fdic.gov/sod/$) annually from 1994 onward.

For the measure of price flexibility, we utilize part of the extensive data set constructed by Nakamura and Steinsson (2008) for the infrequency of price changes measured by the duration of unchanged prices. Nakamura and Steinsson (2008) document the frequency of price changes for non-shelter CPs for some 270 entry-level items for the period 1998-2005. All of the products in our list can be matched directly to one of the prices that are compiled by Nakamura and Steinsson, except for the two products, CANNED PEAS and MAN'S HAIRCUT, which are dropped from our regression analysis. As shown by Nakamura and Steinsson (2008), the frequency of price change can be transformed to the degree of price stickiness using the formula for implied duration, $d = \frac{-1}{ln(1-f)}$, where f denotes the frequency of price change. Throughout the paper, we stick to the frequency of price change as our measure of price flexibility. Using Table 17 of a supplement to their paper as a guide, where the correspondence between the entry-level items (ELI's) and major product groups are documented, we match the relevant ELI's to 43 products in our study. We then use their data on the frequency of price changes and expenditure weights to calculate a measure of price flexibility for each of these 43 items based on the weighted mean of the frequency of price changes.

Appendix B: Impacts of credit supply and productivity shocks

In the standard macroeconomic models, housing demand shocks are popular reduced-form shocks used to study the linkage between the house price and the macroeconomic activity. (e.g., Liu et al. 2019). The housing market shocks identified in the FAVAR model reflect a broad range of unexpected changes in the aggregate housing market, without further identifying the origins of the shocks as in Abdallah and Lastrapes (2013). A housing demand shock therefore can arise from many underlying sources, from the implementation of macroprudential policy measures or more broad-based monetary policy changes or productivity changes. For example, income changes, which are driven by a productivity shock, can affect CP directly as well as indirectly through changes in housing demand. To investigate what constitutes or drives the housing demand shock identified in the FAVAR model that shows a long momentum, we consider a couple of shocks related to housing demand: (i) credit supply shock and (ii) productivity shock. In the literature housing demand shocks were often proxied by shifts in the representative agent's tastes for housing, but Liu et al. (2019) show that a credit supply shock can better capture the observed empirical regularities (see also Justiniano et al. (2019) and Greenwald and Guren (2021) for studies that emphasize the importance of credit supply shocks for house prices, and refer to the survey of Mian and Sufi (2018) and the references therein for empirical studies that point to the importance of credit supply shocks for the boom-bust cycle in the housing market).

We estimate the dynamic responses of the local house price to a credit supply shock within the framework of the instrumental-variable local projections (IV-LP) model.

$$\log HP_{i,t+h} - \log HP_{it} = \alpha_0^h + \sum_{j=0}^{p} \beta_j^h \Delta C_{i,t-j} + \sum_{k=0}^{q} X_{i,t-k}\delta_k^h + \gamma_i^h + \varepsilon_{i,t+h}^h, \tag{5}$$

where HP_{it} denotes house price in city i at time t and $h = 1, ..., 16$ represents horizons. So, the dependent variable is the percentage change in the local HP h periods (quarters) after shock. Following the approach of Mian et al. (2017) and Liu et al. (2019), we identify a credit supply shock as an acceleration in credit growth during periods with low mortgage spreads, where the mortgage spread is measured by the difference between the mortgage interest rate and the 10-year sovereign bond yield. $\Delta C_{i,t-j}$ in eq.(5) denotes the credit growth rate measured by city-level LTV ratio, which is then instrumented by a dummy variable that equals one if the mortgage spread is below the median and zero otherwise (refer to Mian et al. (2017) and Liu et al. (2019)). Due to the lack of quarterly data for city-level MTV ratio and mortgage rates in many MSAs under study, we use national data for our analysis. Again, X_{it} is a vector of control variables with parameters δ_k^h.

The upper panel of Figure A.1 plots the estimated dynamic responses of the house price following a credit supply expansion. As shown in Figure A.1, a credit supply shock generates dynamic responses of HP, such that an increase in credit supply is followed by significant and persistent increase in local HP over time. Unlike the IRFs of housing demand shock estimated from the FAVAR model, however, the IRF of credit supply shock is peaked around 7 quarters and hitherto dwindles gradually, indicating a mean reversion and thus transitory shock.

The debate, however, has been far from settled on the nature of housing market shock. There could be a myriad of other shocks that affect housing demand. Kiyotaki et al. (2007), for instance, claim that the role of credit supply shock in HP movements could be of limited relevance if credit market frictions primarily affect homeownership decisions rather than house prices. In fact, it is frequently documented in the literature that changes in productivity are the main driver behind HP movements (e.g., Kahn 2008, Iacoviello and Neri 2010). Studies in this regard often show that housing market responds positively to aggregate productivity shocks which explain a substantial share of HP movements. Studying the relationship between productivity growth and home price appreciation, Kahn (2008) finds that productivity growth is a key driver of medium- to long-term movements in HP. The author further shows that the downturn in productivity precedes the downturn in HP. Iacoviello (2005) and Iacoviello and Neri (2010) also document positive effects of productivity shock on housing markets. As noted by Iacoviello and Neri (2010), the increase in HP is resulted from technological progress in the housing sector and the dynamics of HP movements are driven largely by productivity shock. Given the influence of productivity shocks on labor productivity and thus income (Gali, 1999), it is conceivable that housing demand and house price are (positively) responsive to the productivity shock. We then consider a productivity shock for $\Delta C_{i,t-j}$ in eq.(5). For the productivity shock, we use the quarterly TFP shock series downloaded from the website of the San Francisco Fed (*https://www.frbsf.org/economic-research/indicators-data/*).

The lower panel of Figure A.1 displays the estimated dynamic responses of the HP following a positive productivity shock. Like the IRFs from credit supply shock in the upper panel of Figure A.1, a positive credit supply shock leads to increases in the local house prices. The pattern of the IRF estimates, however, appears to be quite different from that of credit supply shock. The impact of productivity shock to HP persistently increases without decaying over time. This mirrors the pattern of the IRFs of housing demand shock estimated from the FAVAR model. Taken together, it is likely that the housing demand shock identified in the FAVAR model picks up the productivity shock more than credit supply shock.

Table A.2: Data Description (by product)

No.	Item	G1	G2	Descriptions
1	Steak	H	B	Pound, USDA Choice
2	Ground beef	H	B	Pound, lowest price
3	Whole chicken	H	B	Pound, whole fryer
4	Canned tuna	M	B	Starkist or Chicken of the Sea; 6.5 oz.(85.1-91.3),6.125 oz.(91.4-95.3), 6-6.125 oz.(95.3-99.4), 6.0 oz. (00.1-09.4)
5	Milk	H	B	1/2 gal. carton
6	Eggs	H	B	One Dozen, Grade A, Large
7	Margarine	H	B	One Pound, Blue Bonnet or Parkay
8	Cheese	H	A	Parmesan, grated 8 oz. canister, Kraft
9	Potatoes	H	B	10 lbs. white or red
10	Bananas	M	A	One pound
11	Lettuce	H	B	Head, approximately 1.25 pounds
12	Bread	M	B	24 oz loaf
13	Coffee	M	A	Can, Maxwell House, Hills Brothers, or Folgers; 1 lb. (85.1-88.3); 13 oz. (88.4-99.4); 11.5 oz. (00.1-09.4)
14	Sugar	M	B	Cane or beet; 5 lbs. (85.1-92.3); 4 lbs. (92.4-09.4)
15	Corn flakes	M	A	18 oz, Kellog's or Post Toasties
16	Canned peas	-	A	Can, Del Monte or Green Giant; 17 oz can, 15-17 oz. (85.1-85.4), 17 oz. (86.1-91.4), 15-15.25 oz. (92.1-09.4)
17	Canned peaches	M	A	1/2 can approx. 29 oz.; Hunt's, Del Monte, or Libby's or Lady Alberta
18	Tissue	L	A	175-count box (85.1-02.3), 200-count box (02.4-09.4); Kleenex brand
19	Detergent	M	A	42 oz, Tide, Bold, or Cheer (85.1-96.3); 50 oz. (96.4-00.4), 60 oz (01.1-02.3), 75 oz (02.4-09.4), Cascade dishwashing powder
20	Shortening	M	A	3 lbs. can, all-vegetable, Crisco brand
21	Frozen corn	M	A	10 oz. (85.1-95.3), 16 oz. (95.4-09.4); Whole Kernel
22	Soft drink	M	A	2 liter Coca Cola
23	Apartment rent	H	C	2-Bedroom, unfurnished, excld. all utilities except water, 1.2 or 2 baths, approx. 950 sqft
24	Home price	-	C	1,800 sqft, new house, 8,000 sqft lot, (85.1-99.4); 2,400 sqft, new house, 8,000 sqft lot, 4 bedrooms, 2 baths (00.1-09.4)
25	Telephone	M	C	Private residential line, basic monthly rate, fees and taxes
26	Auto maintenance	M	C	average price to balance one front wheel (85.1-88.3); average price to computer or spin balance one front wheel (88.4-09.4)
27	Gas	H	A	One gallon regular unleaded, national brand, including all taxes
28	Doctor visit	L	C	General practitioner's routine examination of established patient
29	Dentist visit	L	C	Adult teeth cleaning and periodic oral exam (85.1-04.4); Adult teeth cleaning (05.1-09.1)
30	McDonald's	L	C	McDonald's Quarter-Pounder with Cheese
31	Pizza	M	C	12"-13" (85.1-94.3), 11"-12" (94.4-09.4) thin crust cheese pizza, Pizza Hut or Pizza Inn from 1990Q1 to 1994Q3
32	Fried chicken	M	C	Thigh and Drumstick, KFC or Church's where available
33	Man's haircut	L	C	Man's barber shop haircut, no styling
34	Beauty salon	L	C	Woman's shampoo, trim, and blow dry
35	Toothpaste	L	A	6 to 7 oz. tube (85.1-06.2), 6 oz-6.4oz tube (06.3-09.4); Crest, or Colgate
36	Dry cleaning	L	C	Man's two-piece suit
37	Man's shirt	L	A	Arrow, Enro, Van Huesen, or JC Penny's Stafford, White, cotton/polyester blend (at least 55% cotton) long sleeves (85.1-94.3); 100% cotton pinpoint Oxford, Long sleeves (94.4-99.4)Cotton/Polyester, pinpoint weave, long sleeves (00.1-09.4)
38	Appliance repair	M	C	Home service call, washing machine, excluding parts
39	Newspaper	L	C	Daily and Sunday home delivery, large-city newspaper, monthly rate
40	Movie	M	C	First-run, indoor, evening, no discount
41	Bowling	L	C	Price per line, evening rate (85.1-98.2); Saturday evening non-league rate (98.3-09.4)
42	Tennis balls	L	A	Can of three extra duty, yellow, Wilson or Penn Brand
43	Beer	M	A	6-pack, 12 oz containers, excluding deposit; Budweiser or Miller Lite, (85.1-99.4), Heineken's (00.1-09.4)
44	Wine	L	A	1.5-liter bottle; Paul Masson Chablis (85.1-90.3) Gallo sauvignon blanc (90.4-91.3), Gallo chablis blanc (91.4-97.3) Livingston Cellars or Gallo chablis blanc (97.1-00.1) Livingston Cellars or Gallo chablis or Chenin blanc (00.2-09.4)

Notes: 'G1' denotes three product groups based on the degree of price flexibility: highly flexible (H), medium flexible (M), and less flexible (L). 'G2' denotes three product groups based on the proximity of production to the market place: not locally produced (A), maybe locally produced (B), and locally produced goods and services (C).

Table A.3: Summary statistics

Product	Price level mean	min	max	ratio(%)	Dispersion (CV)	Moran's I	% deviation from city average price [min,max]
Steak	6.22	5.45	7.20	32.1	0.07	0.175	[-0.12, 0.16]
Ground beef	1.71	1.37	2.05	49.6	0.08	0.056	[-0.21, 0.17]
Whole chicken	0.90	0.76	1.16	52.6	0.13	0.074	[-0.17, 0.23]
Canned tuna	0.71	0.60	0.93	55.0	0.10	0.066	[-0.16, 0.26]
Milk	1.57	1.33	1.82	36.8	0.08	0.145	[-0.14, 0.13]
Eggs	1.04	0.84	1.81	115.5	0.18	0.377	[-0.15, 0.52]
Margarine	0.70	0.60	1.12	86.7	0.14	0.071	[-0.17, 0.41]
Cheese	3.34	2.94	4.09	39.1	0.08	0.100	[-0.11, 0.17]
Potatoes	2.71	1.92	3.47	80.7	0.14	0.289	[-0.29, 0.24]
Bananas	0.48	0.39	0.61	56.4	0.10	0.172	[-0.21, 0.21]
Lettuce	1.01	0.86	1.27	47.7	0.09	0.278	[-0.19, 0.24]
Bread	0.86	0.65	1.14	75.4	0.13	0.036	[-0.25, 0.26]
Coffee	2.83	2.51	3.56	41.8	0.10	0.274	[-0.13, 0.22]
Sugar	1.63	1.37	1.92	40.1	0.06	0.083	[-0.15, 0.15]
Corn flakes	2.28	1.95	2.67	36.9	0.09	0.061	[-0.10, 0.12]
Canned peas	0.68	0.57	0.84	47.4	0.10	0.174	[-0.19, 0.20]
Canned peaches	1.50	1.34	1.84	37.3	0.07	0.063	[-0.13, 0.13]
Tissue	1.26	1.12	1.52	35.7	0.07	0.134	[-0.10, 0.17]
Detergent	3.21	2.89	3.78	30.8	0.07	0.128	[-0.11, 0.13]
Shortening	2.90	2.49	3.37	35.3	0.07	0.141	[-0.14, 0.14]
Frozen corn	0.92	0.80	1.11	38.8	0.08	0.051	[-0.15, 0.17]
Soft drink	1.23	1.05	1.45	38.1	0.08	0.023	[-0.15, 0.13]
Apartment rent	580.38	432.97	1,067.89	146.6	0.19	0.097	[-0.30, 0.62]
Home Price	165.17	133.56	371.55	178.2	0.23	0.119	[-0.16, 0.70]
Telephone	20.85	15.55	29.88	92.2	0.15	0.069	[-0.28, 0.22]
Auto maintenance	7.44	5.41	8.89	64.3	0.09	0.016	[-0.29, 0.11]
Gas	1.45	1.35	1.61	19.3	0.04	0.659	[-0.07, 0.10]
Doctor visit	50.95	42.15	61.43	45.7	0.09	0.073	[-0.18, 0.16]
Dentist visit	58.65	47.78	93.69	96.1	0.14	0.079	[-0.22, 0.41]
McDonald's	2.05	1.91	2.20	15.2	0.03	0.147	[-0.06, 0.07]
Pizza	8.84	8.12	10.27	26.5	0.05	0.042	[-0.08, 0.10]
Fried chicken	2.37	1.98	2.77	39.9	0.08	0.030	[-0.19, 0.16]
Man's haircut	9.18	7.31	11.64	59.2	0.11	0.013	[-0.21, 0.23]
Beauty salon	23.14	16.78	31.36	86.9	0.14	0.017	[-0.36, 0.27]
Toothpaste	2.07	1.71	2.42	41.5	0.07	0.041	[-0.17, 0.17]
Dry cleaning	6.98	5.64	8.42	49.3	0.11	0.058	[-0.23, 0.19]
Man's shirt	24.78	22.69	30.05	32.4	0.06	0.049	[-0.16, 0.20]
Appliance repair	37.80	25.95	48.14	85.5	0.11	0.030	[-0.40, 0.22]
Newspaper	12.00	7.13	16.75	134.9	0.18	0.039	[-0.36, 0.27]
Movie	6.39	5.72	7.95	39.0	0.07	0.117	[-0.09, 0.24]
Bowling	2.54	1.82	3.22	76.9	0.13	0.060	[-0.28, 0.23]
Tennis balls	2.34	2.02	2.96	46.5	0.08	0.010	[-0.14, 0.26]
Beer	5.28	4.83	6.33	31.1	0.05	0.048	[-0.10, 0.15]
Wine	5.56	4.40	6.79	54.3	0.10	0.050	[-0.21, 0.17]

Note: Entries represent mean, volatiltiy (CV), minimum, and maximum of average annual prices in dollar, except for "Home Price" which is in thousand dollars. 'Ratio' denotes the ratio of the highest price to the lowest price in percent. 'affordability' represents CP divided by annual wage or income. 'Moran's I statistics is a measure of the co-movements of city-level price series using the following modified Moran's I statistic.

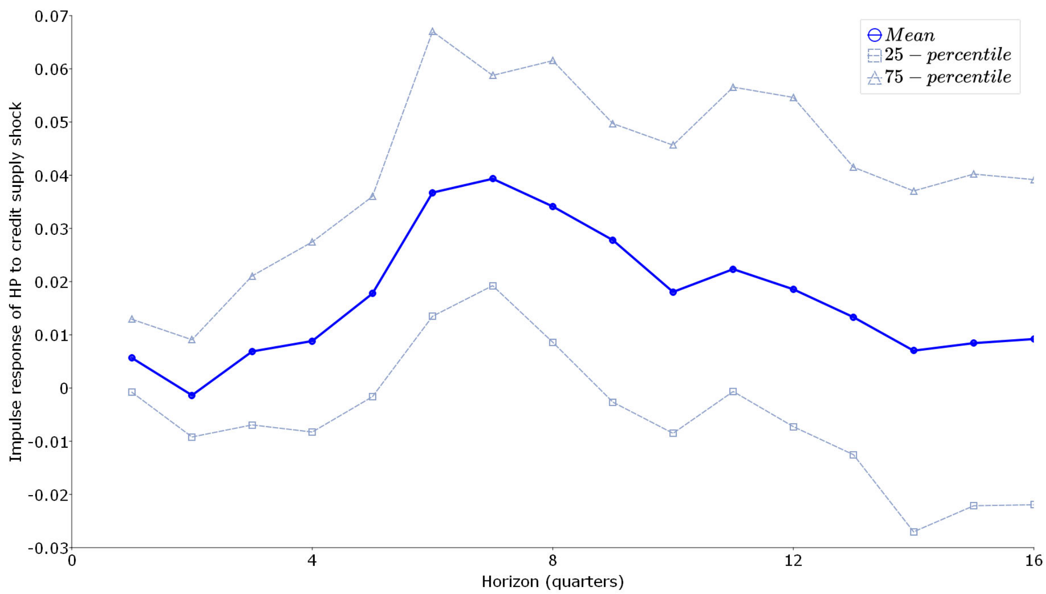
Table A.4: Summary statistics at the city level

city code	City name (CODE)	Income ($)	Population (1,000 ppl)	Share of skilled	Home price ($1,000)	House supply elasticity	Homeowner-ship rate (%)
1	AMARILLO, TX (AMA)	24,933	225.7	21.9	166.9	0.489	64.1
2	ATLANTA, GA (ATL)	29,895	4,124.2	34.0	189.0	1.049	63.3
3	CEDAR RAPIDS, IA (CID)	28,688	234.0	26.6	174.4	0.681	74.7
4	CHARLOTTE, NC (CLT)	28,281	1,720.9	31.7	175.2	0.619	65.3
5	CHATTANOOGA, TN (CHA)	25,707	476.7	22.4	170.6	0.525	67.2
6	CLEVELAND, OH (CLE)	30,168	2,116.9	26.3	186.4	0.533	65.1
7	COLORADO SPRINGS, CO (COS)	28,253	525.7	34.8	190.3	0.288	63.5
8	COLUMBIA, MO (COU)	26,777	135.4	43.3	173.0	0.594	55.5
9	COLUMBIA, SC (CAE)	25,843	646.1	29.9	164.9	0.490	67.2
10	DALLAS, TX (DAL)	30,870	5,122.2	30.1	157.7	0.652	59.9
11	DENVER, CO (DEN)	34,063	2,099.7	37.1	231.4	0.410	63.4
12	DOVER, DE (DOV)	24,721	131.6	19.4	184.2	-	70.0
13	HOUSTON, TX (HOU)	31,677	4,724.4	28.1	155.6	0.738	60.4
14	HUNTSVILLE, AL (HSV)	27,952	346.3	34.1	164.3	0.350	69.5
15	JONESBORO, AR (JBR)	21,746	106.2	19.6	156.7	0.312	58.7
16	JOPLIN, MO (JLN)	22,405	154.4	18.1	156.8	0.527	67.0
17	KNOXVILLE, TN (KNX*)	25,157	741.9	27.8	163.9	0.568	68.1
18	LEXINGTON, KY (LEX)	28,076	405.3	33.4	174.2	0.522	58.7
19	LOS ANGELES, CA (LAX)	31,459	12,057.1	30.0	409.3	1.189	48.5
20	LOUISVILLE, KY (LOU*)	27,928	1,121.3	23.8	162.5	0.522	67.1
21	LUBBOCK, TX (LBB)	24,009	260.4	26.3	156.2	0.403	56.4
22	MEMPHIS, TN (MEM)	27,632	1,195.0	24.4	153.5	0.551	60.7
23	MONTGOMERY, AL (MGM)	26,111	340.4	26.2	182.9	0.515	64.8
24	ODESSA, TX (ODS*)	23,000	126.9	13.0	167.4	0.585	65.4
25	OKLAHOMA CITY, OK (OKC)	27,121	1,101.9	27.0	159.2	0.669	64.1
26	OMAHA, NE (OMA)	30,860	766.7	31.3	163.7	0.628	65.6
27	PHILADELPHIA, PA (PHL)	33,571	5,678.2	31.8	270.2	0.905	67.2
28	PHOENIX, AZ (PHX)	27,280	3,163.3	27.3	189.5	0.946	61.9
29	PORTLAND, OR (POR*)	29,594	1,869.5	32.9	244.5	0.613	61.2
30	RALEIGH, NC (RDU)	30,653	799.9	41.3	186.3	0.415	65.7
31	RENO-SPARKS, NV (RNO)	33,645	336.6	26.3	214.2	1.153	57.5
32	SALT LAKE CITY, UT (SLC)	26,507	918.9	29.8	190.6	0.314	67.1
33	SAN ANTONIO, TX (SAT)	25,538	1,729.8	24.5	163.8	0.670	62.2
34	SOUTH BEND, IN (SBN)	25,736	309.8	24.1	169.8	0.743	70.3
35	SPRINGFIELD, IL (SPI)	29,162	200.8	29.6	172.3	0.530	69.9
36	ST. CLOUD, MN (STC)	24,374	166.8	22.4	169.2	1.071	69.8
37	ST. LOUIS, MO (STL)	30,428	2,667.5	28.5	161.9	0.921	69.3
38	TACOMA, WA (SEA)	35,396	2,966.6	36.7	206.5	0.676	59.8
39	TUCSON, AZ (TUS)	24,845	819.9	29.0	179.7	0.752	61.9
40	WACO, TX (WAC*)	22,662	228.9	20.4	155.6	0.566	59.4
41	YORK, PA (YRK*)	27,903	381.8	21.0	196.4	0.521	74.6
	Average	27,820	1,542.6	28.0	184.4	0.642	64.2

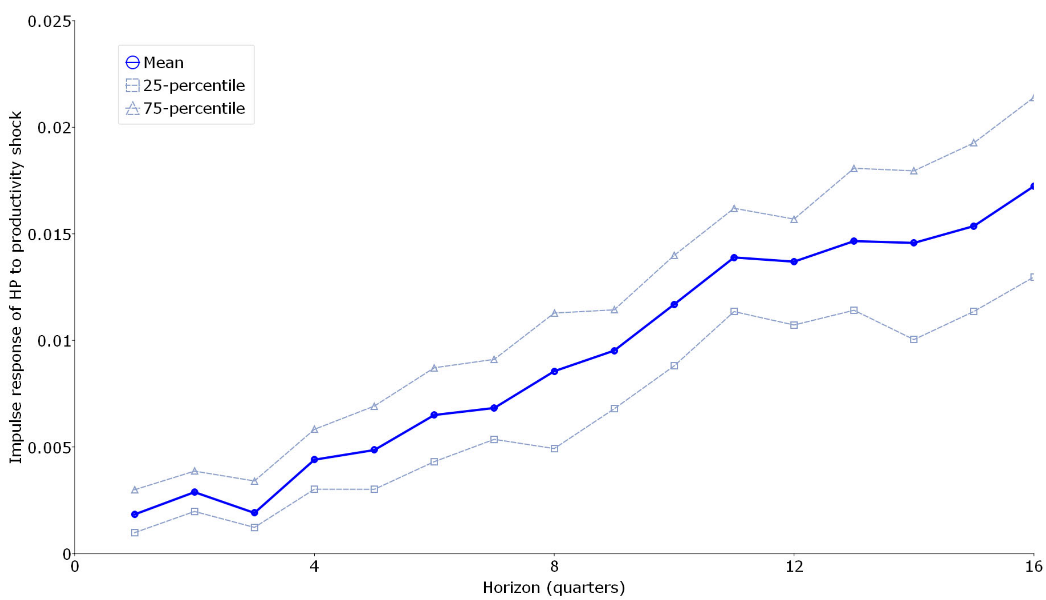
Note: The 'share of skilled' refers to the proportion of the adult population that has obtained a bachelor's degree or higher. The city codes used in the study are the airport codes for the corresponding cities, with the exception of those that are marked with an asterisk.

Table A.5: Description of city-level and product-level characteristics

Variable	Description	Source
Income	Per capita personal income of the U.S. Metropolitan area during 1990-2016	BEA website
Population	Average population density of the U.S. Metropolitan area during 1990-2016	Census Bureau website
Homeownership rate	Average fraction of the owner-occupied houses out of the entire occupied housing units during 2000-2018	Census Bureau website
Unemployment rate	Average city-level unemployment rate (s.a.) over 1990-2016	BLS website
Share of skilled worker	Share of adults over 25 years old with at least a bachelor's degree (1990-2016)	Census Bureau website
Remoteness	City-level remoteness measure by Wolf (2000) over 1990-2016	Authors' computation
Financial Integration	Annual total deposits by the all branches of all insured banks during 1994-2017	Summary of Deposits at the FDIC website
Housing supply elasticity	City-level housing supply elasticities based on the systematic historical sensitivity of local house prices to regional housing cycles	Guren's website
Price flexibility	The frequency of price changed and expenditure weights for 43 products for the period 1998-2005	Nakamura and Steinsson (2008), Table 17
Production proximity	The proximity of production to the market place	O'Connell and Wei (2002)



(a) Credit supply shock



(b) Productivity shock

Figure A.1: IRFs of credit supply shock (top) and productivity shock (bottom) to local CP