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

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November 18, 2019

Abstract

Using city-level retail price data for a bundle of consumer products in the U.S., we find that changes in house price exert an important causal/leading influence on local consumer prices, but not vice versa. On average a 10% increase in house prices is associated with a 4.6% increase in consumer prices over the past three decades. Moreover, there is considerable heterogeneity in the transmission across locations and across products. The interplay between housing supply constraints and productivity gap across cities is the key to the geographical heterogeneity. Whereas housing demand shocks have a stronger impact on local consumer prices in the cities with higher concentration of college graduates, the impact of housing supply shocks is stronger in the cities with more stringent regulations on housing supply. At the product level, housing demand shocks are transmitted primarily through flexibly-priced products, while the pass-through of housing supply shock to CPs is significant in the products that are produced locally. Our results suggest that markup effect is at work in the pass-through of housing demand shock (rather than conventional channels of wealth effect or collateral effect), while local cost effect is at work in the pass-through of housing supply shock.

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

JEL Classification Numbers: C32,E20,E21

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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 of households' net wealth. In the U.S., well over 60 percent of households own their home which represents most households' largest asset and their primary source of collateral for borrowing (Bhutta and Keys, 2016). Changes in housing markets therefore would have material impacts on consumption expenditures (e.g., Abdallah and Lastrapes 2013, Kushor 2007, Mian and Sufi 2011, 2014, Rognlie 2015), which will have further implications for consumer prices (e.g., Aguiar and Hurst 2007, Kaplan and Menzio 2016). The extant literature, however, has delved into the link between house price and real economic activity, such as consumption and mortgage growth, particularly in the context of the policy transmission mechanism.[1] For instance, Iacoviello (2005) highlighted the importance of house price dynamics in the transmission of monetary policy, which mainly affect households with binding collateral constraints. More recently, the literature emphasizes features that can bring out heterogeneous and redistributive impacts of the transmission mechanism, such as incompletely insurable counter-cyclical employment risks (e.g., Gornemann et al. 2016).

This paper investigates how consumer prices (henceforth, CP) respond to changes in the housing markets and through which channels the changes transmit. Theoretical literature demonstrated that increases in house prices (hereafter, HP) could drive CP both positively and negatively. On one hand, as high HP increases net wealth and collateral values, households (particularly homeowners) will increase consumption and thus CPs (*wealth effect* or *collateral channels*, see e.g., Nakajima 2011, Mian and Sufi 2011, 2014, Mian et al. 2013). On the other hand, with higher spending on housing and rents, consumers may need to reduce their consumption on other products and hence CP decreases (*substitution effect channel*). Therefore, it remains to be an empirical exercise to understand the actual pass-through. However, it would be difficult to estimate such theoretical models and to evaluate diverse competing channels without using comprehensive data at the disaggregate level.

Here we analyze quarterly product-level CP data in 43 cities covering 25 years, departing from previous work focusing mostly on the aggregate-level analysis. This micro price dataset enables us to relate the estimated responses of CP to a variety of geographical and product characteristics, from which we can infer the underlying transmission channels of the pass-through. Another distinctive

[1] One notable exception focusing on the link between house price and consumer price is Stroebel and Vavra (2019). Using grocery price data for a relatively short time horizon, they find that retail price growth is significantly stronger in the MSAs with higher house price growth, due largely to house price-induced demand shocks.

feature of our study is to make use of the long time-series dimension of the sample. Since CP responds with time lags and differently in the short and long horizons (Ghent and Owyang 2010), a data set with long time-series is preferred in capturing its dynamic responses. Our examination of the long-run relationship between HP and CP while accounting for city- and product-level heterogeneity provides different perspectives to gauging the policy transmission mechanism.

Understanding the link between HP and CP also offers useful insights on the geographic dispersions of cost of living and ultimately consumption inequality. Recent studies identify changes in HPs as an important driver of increasing geographic price dispersions (e.g, Hsieh and Moretti 2015, Strobel and Vavra 2019). As the biggest component in CPI basket, housing alone accounts for more than a third of the index. If CP co-move strongly with local HP, however, the overall impacts of HP changes onto the cost of living and hence, consumer welfare, could be greater than what is reflected in the simple index weight. This may have a further implication on the geographic frictions impeding internal migration of workers. It also suggests that a change in HP may have a disproportionate effect on the cost of living to home owners and renters.

We first employ a factor-augmented vector autoregressive (FAVAR) model to estimate CP changes in response to aggregate housing market demand and supply shocks.[2] We find substantial heterogeneity in the response of local CP to each shock across products as well as across locations. Looking at the responses to the demand shocks, local retail prices in general increase, more so in the cities with a higher concentration of skilled workers. This is in line with the finding by Diamond (2016) that college graduates bid up HP as well as CPs by migrating to the cities with increased wages due to higher productivity. Turning to the responses to the supply shocks, local prices respond negatively overall, with stronger responses observed in the cities with tighter regulatory constraints on local housing markets. This reinforces the claim by Glaeser et al. (2008) that tightened housing-supply regulations played vital role in generating an upward trend in HPs. Focusing on the product-level heterogeneity, we also find asymmetry in the transmission channels of the demand and supply shocks. While flexibility of price adjustment is an important factor behind the differential responses of CPs to the demand shocks[3], proximity to local production is more relevant for the differential impacts of aggregate housing supply shocks.

We further our analysis by investigating the pass-through of city-level HP to CP using a Vector Error Correction Model (VECM). After controlling for local fundamentals like wage and labor market conditions, we find CPs are highly responsive to local HP changes, but not the other way around. To

[2] As detailed in Section 3, the model partially identifies the aggregate housing market demand and supply shocks only. The shocks can arise specifically from the housing market, due to the implementation of macroprudential policy measures (e.g., loan-to-value ratio and/or income-to-debt payment ratio), for instance. Or it could be due to a more broad-based shock, such as monetary policy or aggregate demand shocks. We focus on the transmission to CP without further identifying the sources of such shocks.

[3] In the absence of market frictions, frictions arising from price rigidity plays an important role.

interpret, changes in local HP exert an important leading/causal influence on local CPs, but not vice versa. The estimated average long-run effect of HP onto CPs is around 0.46, i.e., a 10% rise in HP leads to a 4.6% increase in CP, which is very close to the estimate provided in Stroebel and Vavra (2019) on the cross-sectional elasticities of local CP with respect to local HP. We also find substantial heterogeneity meaningfully associated with certain city and product characteristics. Housing supply constraints and skill differences appear to be important geographical factors behind the heterogeneity, while price flexibility seems to be crucial for the product-level heterogeneity.

The heterogeneity we find in the pass-through of HP to CP across cities and across products is informative about the underlying transmission mechanism. We probe the underlying transmission mechanism of housing market shocks to individual CPs by comparing several competing channels through which housing markets are known to influence CPs. Diverse metropolitan areas with differing economic conditions provide a potentially useful source of spatial variation to help understand the transmission mechanism taking place through various products. By looking at them, we attempt to identify how shocks in housing markets affect different CPs in different locations with different economic conditions in terms of population, income, the quality of local work forces, financial infrastructure, and housing regulations. Conventional transmission mechanism of HP to CP has been via consumers' demand side due to wealth effect or collateral effect. Because HPs affect households' borrowing decisions to consumption via housing collateral, a rise in HPs, which increases the value of collateral available to households, is likely to affect CPs. This increased demand from easier and cheaper borrowing for households against their home value, however, can offset the wealth and collateral effects of HP changes by ultimately leading to higher CPs. Moreover, it may not be necessarily transmitted to CPs if prices are not adjusted flexibly enough. Since aggregate shocks in housing market have differential regional impacts on local CPs due largely to variations in the strength of the transmission mechanism, it is essential to distinguish the source of housing market shocks between housing demand and housing supply.

When the housing market shock is decomposed into demand shock versus supply shock, we find that CPs are more responsive to housing demand shock in the cities with higher concentration of skilled workers with college degree, while they are more responsive to housing supply shock in the cities with more regulations on housing supply. The impact of aggregate housing demand shock is stronger in more skilled cities with higher levels of human capital, while they are more responsive to housing supply shock in the cities with more stringent housing supply constraints. At the product level, housing demand shocks are transmitted primarily through flexibly-priced products, while the pass-through of housing supply shock to CPs is significant in the products that are produced locally. The significant positive long-run effects of HP onto CP found in all products are not well aligned with the conventional transmission mechanism due to wealth effect or collateral effect. Instead, the markup effect channel appears to be at work in the pass-through of housing demand shock to CPs, albeit less at the product level.[4] In the pass-through of housing supply shock to HPs, local cost channel is at work.

The remainder of this paper is structured as follows. The next section describes the data employed in our study and documents a descriptive analysis of the data. Section 3 provides an econometric analysis on the impact of housing markets on CPs across cities in a variety of products. In this section, we lay out our empirical results based on FAVAR and VECM analyses, with a special focus on the quantitative impacts of HP onto CPs. Section 4 explores the underlying transmission mechanism of housing market shocks to CPs by utilizing the considerable variations observed in the data across locations and across products. Section 5 concludes the paper. The Appendix contains a detailed description of the data used in the current study.

2 Data and preliminary analysis

The price data used here is the quarterly survey retail prices published by the Council for Community and Economic Research (C2ER, formerly known as the ACCRA) for selected U.S. MSAs over the period 1990.Q1 to 2015.Q4. As retail prices of individual goods and services quoted inclusive of all sales taxes levied by all jurisdictions, the price data are well suited for the purpose of our study to analyze the impacts of housing markets on the city-level retail prices for a couple of reasons. First, since the price data are absolute prices in dollars and cents collected by a single agency for specific goods and services in terms of quality (brand) and quantity (package), such as Gasoline (one gallon, regular unleaded) and Beauty Salon (woman's shampoo, trim, and blow dry), they are quite comparable across locations and thus facilitate our cross-city comparison in the relationship between HP and CP on an arguably equal footing. As described in Table A.1 in the Appendix, the products in our dataset range from basic food products such as Bread and Eggs, to manufacturing goods like Detergents and Tissues, and to services including Medical Service and Hairstyling.[5] Second, the dataset has the longest sample period currently available for many individual consumer goods and service, with a wider geographical coverage than other popular datasets for city-level prices, such as the BLS micro-data and grocery store scanner data (Nielsen or the IRI Database). The long time series is crucial for the dynamic analysis of the impacts of housing market on local CPs. Besides, the broad geographic distribution of 41 cities (see Figure 1 and Table A.3) across the nation generates a large number of time series for meaningful panel data regression analysis in identifying the underlying transmission mechanism of

[4] This finding differs from Abdallah and Lastrapes (2013). Using the state-level consumption expenditure data, they find supportive evidence of the collateral effect, as aggregate housing market shocks have larger impacts on consumption in the states where collateralizing housing equity is relatively easy.

[5] The products represented here are staples that are regularly purchased, rather than big-ticket items that one might purchase on an infrequent or once-off basis (e.g. cars, white goods, electronics). Refer to Table A.2 for the summary statistics by products.

housing market to local CPs. Tables A.2 and A.3 in the Appendix present summary statistics for 43 products and 41 cities, along with the summary statistics.

Despite its appeal to the length and width of the coverage, it has a limited coverage of products, compared to the BLS data of disaggregated price indices. Although not perfect, our price 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 locational coverage for homogeneous products. There is an extensive diversity among the selected cities in terms of the relative city size, measured by average per capita income and population as displayed in Figure 1. We focus on the metropolitan areas that account for significant share of the nation's wealth, consumption and investment because they are more vulnerable in the event of a housing market fluctuation in terms of the impact on local price level.[6]

We also draw on a number of sources for additional data on local economic environment and housing market conditions that can explain geographic variation in the response of CP to HP, as listed in Table A.4 in the Appendix. These city-level control variables are related to housing demand and supply, including per capita income, unemployment rate, population density, financial integration, the share of skilled workers, and a measure of housing supply constraints from Saiz (2010).[7] Among them, a couple of variables are certainly worthy of further discussion. Educational attainment is often used as a proxy for the worker's skill level. A large body of research links educational attainment to urban and metropolitan prosperity, generally measuring educational attainment as the proportion of adults over 25 years old with at least a bachelor's degree. Cities with higher concentrations of bachelor's degree holders are known to incubate more innovations and entrepreneurship and, relatedly, to be more resilient to economic shocks (Glaeser and Gyourko 2005, Glaeser et al. 2012). Higher levels of educational attainment in the cities are therefore predicted to exert positive effects on CPs through HP. The educational attainment data were obtained from the decennial census (for 1990 and 2010) and from American Community Survey one-year 2010 estimates. We also use city-level financial integration which is measured by the co-Herfindahl index for city-pair i and j at time t, $H_{ij,t} = \sum_{k=1}^{m} s_{i,t}^{k} \times s_{j,t}^{k}$, where $s_{h,t}^{k}$ denotes the market share of bank k in city h in terms of outstanding deposits at t. We construct the financial integration measure using the Summary of Deposits (SOD) database from the FDIC at $http://www2.fdic.gov/sod/$. Since this measure captures the sum of deposit market share of banks ($k = 1, ..., m$) operating in both cities i and j at time t, city-pairs with a higher co-Herfindahl index are likely to have more similar condition of local financial market. Intuitively, cities may have lower financial frictions (and thus less susceptible to the collateral effect) when they are more connected each other through common banks running business in both cities.

[6] Due to data insufficiency, major cities like New York, Chicago and San Francisco are not included in our dataset. The BLS provides urban CPI data for these major cities, but it does not publish information on price levels.

[7] The reader is referred to the Appendix for further discussions on the control variables employed in the current study.

Before proceeding, it is illuminating to examine the relationship between HP and CPs at the city level. To get a sense of this, we present in Figure 2 scatterplots of the annual house values (horizontal axis) against the corresponding annual CPs (vertical axis) for a couple of selected products, 'CORNFLAKE' (on the left) and 'HAIRCUT' (on the right), over the entire sample period.[8] In line with our prior intuition, there is a strong positive association between the two variables, i.e., cities with higher level of HP tend to have higher CPs. When it comes to the growth rates of prices, however, we obtain quite a different picture. As shown in the bottom panel of Figure 2, there is no clear association between the annual growth rates of HPs and CPs in both products under study, indicating that cities with faster growing HPs do not necessarily experience faster growing CPs at least contemporaneously. As discussed below, however, this does not refute their relationship at a longer run on which we focus in the current study.

3 Econometric analysis

In this section, we quantify impact of housing market shocks on local CPs. To this end, we first employ a FAVAR model where structural housing market shocks are identified with sign restrictions as in Jarocinski and Smets (2008). In particular, we investigate the dynamic response of CP to the identified exogenous aggregate housing market shocks and track the transmission of such shocks on the movement of local CPs. We consider how CPs and HPs jointly respond to appropriately identified, exogenous shocks as in Jarocinski and Smets (2008) and Abdallah and Lastrapes (2013). We then examine the pass-through of HP to CP within the framework of a VECM that is based on a long-run (co-integrating) relationship between HP and CPs. An attractive feature of the VECM analysis is that it allows us to track down the dynamic effects of HP changes on CP changes across space and products with imposing little structure. In the VECM analysis, we follow the convention in the literature (e.g., Strobel and Vavra 2019), and use exogenous local house price changes as housing market shocks. The consequent Granger-causality test is helpful in establishing the direction of causality (or predictability) between HP and CP.

3.1 FAVAR analysis

3.1.1 FAVAR model

Following Jarocinski and Smets (2008) and Abdallah and Lastrapes (2013) on which this section largely draws, we estimate the effects of aggregate housing sector shocks on CPs across cities for a variety of products, on a multivariate, dynamic common-factor model. We distinguish the exogenous sources of shocks to aggregate demand and supply of housing while allowing for heterogeneity in the

[8] The results are qualitatively similar for other products. A complete version of Figure 2 is available at the online Appendix.

response across cities and products. For this purpose, we first identify the aggregate housing market demand and supply shocks by sign restrictions, in the similar spirit with Abdallah and Lastrapes (2013). Since endogeneity exists between housing market conditions and CPs if these variables are jointly affected by a common set of underlying shocks, a series of recent papers have used sophisticated identification strategies to disentangle the impact of national aggregate shocks on HPs from that of local idiosyncratic shocks.[9] This framework allows us to examine how *aggregate* housing market shocks propagate to CPs in different locations in the short- and long-run.

We take the following FAVAR model approach originally introduced by Bernanke et al. (2005) in which the joint dynamics of the factors and macroeconomic variables are modeled as

$$\begin{aligned} \begin{bmatrix} Y_t \\ F_t \end{bmatrix} &= B_0 + B(L) \begin{bmatrix} Y_{t-1} \\ F_{t-1}, \end{bmatrix} + e_t, && (1) \\ X_t &= \lambda F_t + \gamma Y_t + \epsilon_t, && (2) \end{aligned}$$

where Y_t and F_t represent observable and unobservable factors, respectively. As is common in the literature, the factors are assumed to capture common dynamics in X_t, a vector of city-level CP changes of various goods and services. 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 (PCE). To identify the pure effect of HP on other CPs, it is reasonable to control for other effects such as labor market condition which may be ultimately related to local housing market. So, we assess the impact of national housing market shocks on local CPs, after controlling for the local labor market condition by including city-level unemployment rates. Beraja et al. (2014) show that price growth was much higher in states with lower unemployment growth relative to states with higher unemployment growth. As summarized in Table 1, our identification strategy assumes that the housing *demand* shock will drive both real HPs and the residential fixed investment upward, while the housing *supply* shock will lower real HPs and increases the residential investment. We impose the sign restrictions on those two variables to hold for three quarters after the impact. The sign restrictions are not imposed on other macro variables in Y_t nor on F_t, and we let the data determine their dynamic responses. The T-bond yield and real GDP are included in Y_t to control for the factors common to each city that may affect HPs. The lag terms of price growths capture the well-known persistence of housing price growths.

As in Bernanke et al. (2005) and Boivin et al. (2009), we estimate the FAVAR model by a two-step principal component approach: first, estimate the common unobservable factors from X_t by extracting principal components and rotate the unobservable factors so that they are orthogonal to Y_t;

[9] For instance, Abdallah and Lastrapes (2013) use a FAVAR model to study how consumer spending and housing market variables jointly respond to appropriately identified, exogenous shocks, as in Jarocinski and Smets (2008).

then, augment the common factors to Y_t for the estimation of eq.(1). Prior to estimation, all variables are standardized to be suitable for a factor model by transforming them into log first-differences to impose stationarity, except for the 5-year T-bond yield which is first-differenced only. All prices at the city level are in first-differenced logs to represent quarterly growth rates. Once the impulse responses are estimated for the variables and factors in the main VAR, we feed those back into eq.(2) to investigate how each shock at the aggregate level propagates to a number of CP changes at the city level. We normalize the impulse responses to represent a demand or a supply shock that increases private residential fixed investment by 1% 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 FAVAR results

To ensure that the aggregate housing market shocks are properly identified, we plot in Figure 3 the *median* cumulative IRFs of the housing demand shock (on the top panel) and housing supply shock (on the bottom panel) on local HP changes at each horizon upto 16 quarters.[10] The IRFs are the estimated responses of local HP growths to an unexpected, one-standard-deviation increase in the housing demand shock (top) and supply shock (bottom) and the responses are plotted as percentage deviations. The solid line represents the median response of local HPs to aggregate housing demand or supply shock among 41 cities. The dashed lines are the corresponding inter-city quartile ($25_{th}-$ and $75_{th}-$ percentile) bands. As can be seen from Figure 3, the results broadly reinforce our priors about the effects of aggregate housing market shocks: a positive effect of house demand shock and a negative effect of house supply shock. Moreover, the response of HP appears to be persistent to a demand shock, but transitory to a supply shock. Local HP rises gradually in response to a housing demand shock and continues to increase to a peak response of more than 1.5 percentage points (p.p.) at the 4-year horizon. Clearly, there is a sign of persistence in the cross-city dispersion over response horizons. As in Abdallah and Lastrapes (2013), we find the stickiness of price responses in most products under study because CPs do not respond to housing demand shocks on impact but increases only at long horizons. By contrast, the response of HP to a housing supply shock shows a U-shaped pattern. It drops immediately by about 0.2 p.p. and declines to a trough response of about 0.3 p.p. at the 1-year horizon. A similar pattern is witnessed in the 25- and 75-percentile band. The wide band of the inter-quartile indicates some cities are more responsive to the aggregate housing market shocks than others. Such a significant cross-city variation in the magnitude of these responses possibly hinges

[10] As noted by Abdallah and Lastrapes (2013), demand shocks can arise from many different sources, such as unexpected changes in mortgage markets and in the costs of borrowing induced by a monetary policy shock. Supply shocks constitute unexpected changes in the costs of producing houses and developing real estate, technological advances, changes in input prices, and regulatory changes on housing supply. Following Abdallah and Lastrapes (2013), we do not separately identify specific sources of housing shocks, such as those caused by monetary policy.

on local factors. As discussed below, variation across cities and products in the responses to aggregate housing market shocks is informative about the channels through which housing market influences local CPs.

The results of the FAVAR analysis are reported in Table 2. The left-hand side of Table 2 reports the average *peak* cumulative response of CPs to an aggregate housing *demand* shock, and on the right-hand side the average *trough* cumulative response of CPs to an aggregate housing *supply* shock over the 16-quarter horizon. A positive (negative) number in the table implies that housing market shocks lead to an increase (reduction) in CPs. The results in Table 2 illustrate several points. First, the average *peak* response of CPs to the aggregate housing demand shock is positive in most products under study, while the average *trough* response of CPs to the housing supply shock is mostly negative, in line with the graphical evidence in Figure 3 with regard to their impacts on local HPs. The housing demand shock induces on average the response of 0.241 p.p. to local CPs while the supply shock induces an average response of just -0.145 p.p. in the sample period. Second, a largely similar story holds for the intercity quartile ranges of the IRFs. The wide band of the 25- and 75-percentiles found in many products suggest that the responses in each product are highly heterogeneous across cities and might have been dominated by local shocks. It also supports the conventional wisdom that local CPs are responsive to local shocks (e.g., Moretti 2013, Diamond 2016). This is probably because local distribution costs, such as rent paid by the retail establishment, wages of the retail workers, transportation and warehousing, are a nontrivial component of the retail goods and services under study. Third, there is a substantive dispersion in the responses across products. While the price of 'WINE' increases only about 0.005 p.p. in response to the housing demand shock, 'HOUSE PRICE' rise by 1.674 p.p. at the peak. Taken together, our results from the FAVAR analysis suggest that city-level HP responds on average positively to aggregate housing demand shocks but negatively to aggregate housing supply shocks, but with a significant variation across cities and products.

3.2 VECM analysis

3.2.1 VECM model

While the FAVAR approach in the preceding section allows us to identify structural shocks and examine the impacts of the identified aggregate shocks on the movement of local CPs, it does not permit us to track the impact of local housing market shocks. In this section, we complement our analysis within the framework of a VECM model in which we investigate how local HP shocks transmit to local CPs at the city level. Implicit in this analysis is the assumption that local HP changes are exogenous without identifying the shocks that drive the price changes (e.g., Strobel and Vavra 2019). Since quantities adjust sluggishly in the housing market in the short run, HP can be viewed as an informative indicator of the changes in housing demand.

The VECM analysis permits us to examine short-run and long-run relationships among variables involved, while imposing little structural restrictions. To be specific, VECM allows for possible interactions between HP and CP with less restriction than the traditional structural model of the housing market in which HP is typically assumed to be exogenous.[11] This approach seems desirable in a study like ours that employs MSA data because the distinction between purely endogenous and exogenous variables is often difficult to make. Moreover, the VECM approach has the advantage of enabling us to empirically determine the direction of causality from HP to CP or from CP to HP. As shown in Figure 2, higher HPs are often associated with higher CPs, but empirically establishing the causality from HP to CP is challenging because causal relationships can run from both sides. Within the framework of VECM, we make formal inference about the causal relationship while controlling for other factors. The VECM analysis also enables us to estimate the short-run and long-run responses of both CP and HP to a one standard deviation change in one of the two variables, referred to as impulse response function (IRF). It takes into account the likely interactions between CP and HP not captured by a traditional reduced form equation. Given that housing market shocks can affect CPs over time as we have seen from the FAVAR analysis, it is important to measure the extent to which the changes in HPs can explain the changes in CPs over time. Despite its appealing feature in determining the direction of causality, VECM was not much popularly used in the study of housing market mainly due to the lack of appropriate HP data. Since most housing prices are in index form, it has been challenging for researchers to look into the long-run cointegration relationship formulated in the error-correction terms in the VECM.[12]

We estimate the following bivariate VECM in which HP and CP are simultaneously determined as well as determining,

$$\begin{bmatrix} \Delta HP_{i,t} \\ \Delta CP_{i,t} \end{bmatrix} = \begin{bmatrix} a_i^{HP} \\ a_i^{CP} \end{bmatrix} + \begin{bmatrix} \rho_{HP} \\ \rho_{CP} \end{bmatrix} \hat{\epsilon}_t + \sum_{j=1}^{k} \begin{bmatrix} \gamma_{11,j} & \gamma_{12,j} \\ \gamma_{21,j} & \gamma_{22,j} \end{bmatrix} \begin{bmatrix} \Delta HP_{i,t-j} \\ \Delta CP_{i,t-j} \end{bmatrix} + \sum_{h=0}^{k} \delta_h \Delta X_{t-h} + \begin{bmatrix} e_t^{HP} \\ e_t^{CP} \end{bmatrix}, \tag{3}$$

where a_i^{HP} and a_i^{CP} denote fixed effects and $\hat{\epsilon}_t = (CP_{t-1} - \hat{\beta} HP_{t-1})$ is the error correction term which measures the deviation from the long-run equilibrium relationship. The cointegrating vector $(1, -\beta)$ between the two variables yields a consistent estimate of the long-run relationship. If there is a deviation from the long-run relationship between HP and CP (as captured by $\hat{\epsilon}_t$), then either HP or CP should adjust to correct for the deviation. The parameter ρ_{CP} therefore captures the speed at which CP adjusts to their long-run equilibrium after a shock to HP. If the parameter estimate of $\hat{\rho}_{CP}$ is significant, then CP in the current period moves to correct the deviation from the last period.

[11] Consisting of an endogenous system of equations with lagged endogenous variables, the basic idea of VECM is akin to vector autoregression (VAR) model except that it includes an error correction term to capture deviation from the long-run relationship between variables.

[12] A notable exception is the work by Gallin (2008) who studied the long-run relationship between HPs and rents using a VECM model. The author finds little evidence of the long-run relationship between the two in the U.S.

Unlike the conventional univariate equation, the VECM allows not only the endogeneity but also the asymmetry of the convergence speed, i.e., $\rho_{CP} \neq \rho_{HP}$. Regressing naively HP changes onto CP changes, without also considering changes in local fundamentals and labor market conditions, may miss the fact that labor is quite mobile across places within the U.S. So, as in Gallin (2008), we augment the current and lagged changes in city-level wages and the unemployment rate as control variables ($X_t = [W_t, U_t]$) in eq.(3) to control for the "cyclical sensitivity" in the relationship between HP and CP.[13] The lagged terms of HP and CP contain information on short-run dynamics, such as transactions costs or HP cyclicality. City fixed effects are included in both the cointegrating equation and the VECM to control for many other factors than wage and labor market conditions that influence CPs at the local level.

Since the VECM approach requires establishing a cointegrating relationship between variables involved, we first implement a popular unit-root test, the DF-GLS test under the null hypothesis of unit-root nonstationarity, to the price series as a prerequisite for a formal cointegration test. As presented in Table 3, the DF-GLS test fails to reject the unit-root null for the HP series of the entire cities and in the vast majority of CP series, indicating strong evidence of unit-root for city-level price series. In turn, we apply the Hausman-type cointegration test developed by Choi et al. (2008) to examine whether city-level HPs have a long-run cointegration relationship with CPs. As presented in the last column of Table 3, the Hausman-type cointegration test fails to reject the null hypothesis of cointegration at the 5% significance level in the vast majority of the 1,763 HP-CP combinations. The low rejection rate of the null hypothesis of cointegration indicates a long-run steady state relationship between HP and CP, vindicating our use of the VECM approach.

3.2.2 VECM results

Table 4 presents the results of the city-level VECM analysis. We note strong evidence that local CPs are influenced by local HPs, but not vice versa. As reported in the left panel of Table 4, $\hat{\rho}_{CP}$ is significant and positive in all products but one, while $\hat{\rho}_{HP}$ is mostly negative and insignificant. To interpret, CPs correct for the disequilibrium, or deviation from the long-run relationship between HP and CP, is corrected primarily by CP movements, not by HP movements. The cross-product average of $\hat{\rho}_{CP}$ is around 0.194, suggesting that on average about 20 percent of the gap between HP and CP is reduced each quarter. Again, there is a substantial variation in the response of CP to HP across products, ranging from 0.012 ('AUTO MAINTENANCE') to 0.548 ('LETTUCE'). Interestingly, the adjustment speed of CPs is faster in the perishable products.

[13] Using U.S. city data for the period 1965-2004, Van Nieuwerburgh and Weill (2010) find that wages account for about 30% of the variation in HPs across regions, and that the dispersion in MSA-level wages, which can be thought of as reflecting local labor productivity, has been large enough to account for the spatial distribution in HPs. Beraja et al. (2014) also emphasize the importance of local factors such as local labor market condition in the distribution of prices.

Within the VECM in eq.(3), we can also implement the Granger (non-)causality test by looking at whether or not changes in HP can help predict changes in CP. This is equivalent to testing the null hypothesis that HP does not Granger cause CP ($H_0 : HP \nRightarrow CP$) with a standard F-test,

$$H_0 : \rho_{HP} = \gamma_{12,j} = 0 \quad \text{for } j = 1, ..., k.$$

Likewise, the null hypothesis that CP does not Granger cause HP ($H_0 : CP \nRightarrow HP$) can be represented as $H_0 : \rho_{CP} = \gamma_{21,j} = 0$ for $j = 1, ..., k$. Rejecting the null hypothesis of noncausality of HP to CP ($H_0 : HP \nRightarrow CP$) simply implies that changes in HP is helpful in predicting change in CPs without providing any further assessment on the strength of the improvement in the forecast. The left panel of Table 4 presents the rejection rates of the Granger non-causality null hypothesis for each product. The rejection rates of $H_0 : CP \nRightarrow HP$ are in general quite high in most products under study, while that of $H_0 : HP \nRightarrow CP$ is relatively low. This indicates a one-way Granger causality (or predicatability) running from HP to CP, but not the other way around.

Albeit intriguing, the city-level VECM may provide fragile inference if variables involved are cross-sectionally dependent. This is particularly pertinent to our case because local prices are likely to be strongly correlated across cities possibly through common national factors. This renders us to utilize a panel VECM (PVECM) to check the robustness of our findings from the city-level VECM analysis, following Holly et al. (2010) who suggest to deal with the cross-sectional dependence (CSD) by using the Common Correlated Effects (CCE) estimates. In PVECM, we estimate the sensitivity of CP to HP after controlling for other explanatory variables of CP such as wage and local labor market conditions. As reported in the right panel of Table 4, the PVECM results generally confirm our results from the bivariate VECM that CPs are adjusted to HP rather than the other way around. Although somewhat weaker than before, we still find supportive evidence of the causality running from HP to CP.[14] The coefficient of $\hat{\rho}_{CP}$ is statistically significant in many products under study, while the coefficient of $\hat{\rho}_{HP}$ is insignificant in all products. The long-run causal relationship running from HP to CPs is found in food and rent related products that are highly influenced by local factors. Not surprisingly, prices of some products adjust to HP much faster than those in other products. The fastest adjustment speed is found in 'GROUND BEEF' (almost 39% per quarter), while the adjustment speed is quite slow for 'MEN'S SHIRT' (less than 1% per quarter). In general, the adjustment speed appears to be faster for non-durable products which are typically produced locally in a more competitive envionment, compared to manufacturing goods that are produced nationally. As presented in the last column of Table 4, a significant variation exists in the long-run effect (LRE) of HP onto CP, ranging from 0.024 (MAN'S SHIRT) to 0.994 (GASOLINE). That being said, it is interesting to note that the average

[14] The weaker evidence of causality running from HP to CP might have come from the fact that some products, which are nationally produced, are likely driven by common national factors that are effectively removed in the PVECM.

LRE across products is around 0.46, i.e., 10% increase in HPs is associated with a 4.6% increase in CPs, which is very close to the elasticity of CP to HP reported by Stroebel and Vavra (2019).

4 Transmission mechanisms from housing markets to CPs

Our analysis so far suggests that the impacts of housing market shocks on local CPs are nontrivial and persist over time. On average urban CPs respond positively to aggregate housing demand shock and negatively to aggregate housing supply shock. The key observation here is the heterogeneity observed along two dimensions across cities and products. This heterogeneity, however, has important implications for the underlying transmission mechanism stemming from differences in housing market structure and/or housing finance (e.g., Abdallah and Lastrapes 2013). The literature has featured a range of the transmission channels, some of which are simultaneously at work to result in the heterogeneous transmission we observe. To disentangle the channels and identify which one is dominant, we implement a regression analysis here by relating the estimated pass-through of aggregate housing market shocks to a set of city and product characteristics that are potentially relevant for the transmission mechanism.

4.1 Diverse transmission channels

The literature has focused on the transmission mechanism of HP to consumption expenditures, but much less so on to CPs. A review of the consumption literature reveals that changes in HP affect consumption spending mainly through two channels: (i) *wealth effect*, and (ii) *collateral effect*. According to the wealth effect channel, increases in HPs might lead to increased consumption spending as homeowners' wealth increases.[15] In the collateral effect channel, rising home values increase consumers spending, in particular for credit-constrained households by relaxing their financial constraints through increased value of collateral (e.g., Iacoviello 2005). The collateral channel therefore hinges on the friction of local financial market condition. Since consumption spending bears a strong positive relationship to CPs, it may be reasonable to posit that these demand-side channels have similar effects on CPs. Recent study by Stroebel and Vavra (2019) suggests another channel related to pricing practice exercised by firms or local retailers ((iii) *markup effect*). The authors maintain that a higher retail price growth in the cities with higher HP growth is attributable to firms' responses to HP-induced demand shocks. Local retail price changes may also reflect the pass-through of HPs to local production costs such as rents ((iv) *local cost effect*). Given that urban HPs are known to respond differently to the differences in the housing supply constraints (e.g., Gyourko et al. 2008), supply-side frictions in

[15] Abdallah and Lastrapes (2013) and Iocoviello (2011), however, argue that this channel of a pure 'wealth effect' of house prices on aggregate spending might not be that strong because the asset value of home is in general offset by the implicit (or explicit) rental cost of using the home.

local housing market may have an important influence on this channel.

We then probe how these diverse channels are at work in our data. To this end, we regress the estimated IRFs of CPs to each aggregate housing shock obtained from the FAVAR analysis onto a set of city and product characteristics. The city characteristics considered here include per capita income, population density, fraction of college graduates, unemployment rate, remoteness, financial integration, and housing supply constraint measure constructed by Saiz (2010).[16] Table 5 links each characteristics variable to the corresponding transmission channels. For example, we expect a stronger wealth effect in cities with a lower income level and with a smaller share of skilled workers (college graduates) because consumers with lower income or less skills are more inclined to materialize HP changes as collateral to finance consumption expenditures.

In a similar context, collateral effect is likely weaker in cities with a larger share of skill workers who are likely less responsive to HP changes because skill workers are less constrained by the financial frictions. Moreover, one would expect a stronger collateral effect in cities with tighter financial integration where local mortgage markets are more closely connected to others through nationally operating financial institutions which make it easier for homeowners to access home equity (e.g., Abdallah and Lastrapes 2013).[17] Population density can capture markup effect channel in the sense that cities with a larger urban density are likely to have lower markups due to a more competitive market environment (e.g., Handbury and Weinstein 2015, Melitz and Ottaviano 2008).[18] The markup effect is also likely stronger in cities that are geographically and economically isolated as it is relatively easy for firms to exercise a pricing-to-market practice. The share of skill workers is relevant for the markup effect as well, along the same lines as in Stroebel and Vavra (2019) regarding the impact of HP-induced demand shocks on retail prices. Given the well-established cyclical behavior of markup rates (e.g., Nekarda and Ramey 2013), one could view that local unemployment rates is associated with the markup effect. Finally, local cost effect is stronger in cities with more stringent housing supply constraints because HP changes can induce retail price changes through the impact on local costs (e.g., rent). We use the Saiz's (2010) measure of housing supply elasticity for housing supply constraint.

For the product characteristics, we consider degree of price flexibility and proximity of production to markets, which have been identified as important factors in the literature (e.g., Parsley and Wei 1996, O'Connell and Wei 2002). We divide 43 products into three groups depending on how fast

[16] Details regarding the definitions and sources of the variables are provided in the appendix.

[17] According to Abdallah and Lastrapes (2013), the collateral effect dominates the wealth effect because spending in states with well-developed institutions for housing finance is more sensitive to housing demand shocks than spending in states with less developed mortgage markets.

[18] Melitz and Ottaviano (2008), for instance, document that competitive pressures tend to rise with population size such that larger markets facing tougher competition have lower average markups. Handbury and Weinstein (2015) also illustrate that the retailer Herfindahl index in selected U.S. cities are negatively correlated with city size, and positively with markups.

their prices are adjusted[19]: (i) most flexibly priced; (ii) less flexibly priced; and (iii) least flexibly priced, as presented in Table A.1. It is well established in the literature that a varying speed of price adjustment across products has significan explanatary power on the product-level differences in the transmission mechanism of shocks. Price flexibility is also related to the markup effect channel because the firm's markup rate tends to vary with the stickiness of price adjustments (e.g., Stroebel and Vavra 2019).[20] Price flexibility is known to be a decent surrogate for market competition as well, with a fiercer competition in more flexibly priced products. Since local cost shocks are transmitted faster to local CPs in a more competitive market environment, it is also related to the local cost effect channel.

Proximity of production to the marketplace is another useful product category as it is related to product-level markup rates and market frictions. The products are therefore divided into three groups: generally not locally-produced products (Category A); maybe locally-produced products (Category B); and always locally-produced products (Category C). This classification is to help understand how general market frictions and markup rates affect the pass-through of housing markets to CPs. Many of the Category A (non-locally produced) products are branded and hence are differentiated from potential substitutes. Since they tend to be nationally-distributed and nationally-priced, the markup set by producers will play a pivotal role in shock transmission. For the Categories B and C products that are locally-produced, consumers have less allegiance to specific producers and thus the ability of producers to set the prices is limited. So, the markup effect is likely to have little bearing on them. Since they are generally provided by competing local-producers, however, competition is more important for them. Also, because they are harder to transport, they are more likely affected by local factors like housing markets and local production costs (e.g., rent). To sum, local cost channel serves a main transmission mechanism for locally- produced products, while markup effect is likely more relevant for the pass-through in nationally produced products. In this sense, the significance of pass-through in less flexibly-priced product group can be viewed as supportive evidence of the markup effect channel, while the significance of pass-through in more flexibly-priced products points toward the relevance of the local cost channel.

4.2 Regression analysis

To determine which channels are at work in transmitting shocks from housing markets to local CPs, we run the following regression model where the IRF estimates from the FAVAR models in eqs.(1)-(2)

[19] We obtain the data of price flexibility for our consumer products by utilizing the extensive dataset constructed by Nakamura and Steinsson (2008, Table 17) who document the duration of unchanged prices for non-shelter consumer prices for some 270 entry-level items (ELIs) for the period 1998-2005.

[20] Markups, however, could vary for reasons besides sticky prices as noted by Stroebel and Vavra (2019) and the empirical evidence on the importance of price stickiness in explaining markup variation in the literature is rather mixed.

are regressed onto a set of the aforementioned city and product characteristics variables.

$$IRF_{ih}^{m} = \alpha_m + \sum_{s=1}^{2} \gamma_s D_s + X_i^{'}\beta + \varepsilon_{ht}^{m}, \tag{4}$$

where $m = 1, ..., 43$, $i = 1, ..., 41$, and $h = 0, ..., 4$ years. IRF_{ih}^{m} represents the h-year cumulative effect of housing market shock on the price of the m_{th} product in city i. D_s denotes a product group dummy variable based on the price flexibility or the production proximity as outlined above. It takes on the value of one if product belongs to a specific product group and zero otherwise. ε_{ih}^{m} is the error term that could be cross-sectionally correlated and possibly heteroskedastic.[21] X_i embraces the set of city-level characteristics variables discussed earlier.

We conduct two sets of regression analyses with the IRFs from housing demand and supply shocks separately. Our regression results reported in Table 6 illustrate several points. First, the significance of explanatory variables differs across the sources of housing market shocks. In the case of housing demand shock as presented in the top panel of Table 6, we find that the share of college graduate has significant explanatory power on the cross-city differences in the pass-through of housing market shock to CPs. It has a significant positive coefficient over all the response horizons, i.e., the pass-through of housing demand shock is stronger in the cities with a higher concentration of college graduates (with higher skills). This is not only consistent with a large body of recent evidence pointing to the importance of skills and ideas in determining urban success, but also echoes the finding by Moretti (2013) on a systematic positive relationship between changes in HPs and changes in the number of college graduates in a city. The positive significance of skill difference across cities, however, is aligned neither with wealth effect nor with collateral effect channels in which stronger pass-through is expected in cities with a lower share of skill workers. Since skill workers with college degree are typically less constrained by the financial frictions, for instance, they are less subject to the collateral effect channel compared to their unskilled counterparts. The insignificance of 'Financial integration' further weakens the relevance of the collateral effect channel because housing demand shocks are likely to have a greater pass-through to CPs in cities with a tighter financial integration where it is easier to use home equity as collateral (e.g., Abdallah and Lastrapes 2013). Our hypothesis here is that the relaxation of credit constraints with higher HPs is more effective in the cities that were financially more integrated with others. The insignificance of 'Per capita income' also runs counter to the wealth effect channel argument. For the markup effect channel, however, we find mixed evidence. While there is supportive evidence of markup effects at the city level, we fail to find any compelling evidence at the product level. The significance of both 'Share of skill workers' and 'Remoteness' indicates that the markup

[21] We use robust 'clustered standard errors' here because standard heteroscedastic robust standard errors may overstate the true standard errors in the presence of a high degree of clustering among the city and product combinations. Since the impacts of housing market shocks are more likely correlated across cities for a given product rather than across products for a given location, standard errors are clustered by observations by cities rather than by products.

effect channel can explain the cross-city heterogeneity observed in the pass-through of housing demand to CPs. When it comes to the impact of housing supply shock, constraints in housing supply appear to be significant for the cross-city differences in the pass-through, confirming our prior intuition that housing market frictions can amplify and propagate shocks to local CPs. CPs are far more responsive to housing supply shocks in cities with more stringent housing supply constraints.

At the product level, price flexibility has some explanatory power on the pass-through of housing demand shock across products, whereas production proximity can explain the pass-through of housing supply shock. Housing demand shocks transmit to CPs primarily in the products whose prices are adjusted more frequently, perhaps because the shocks are absorbed by a quicker adjustment of prices. By contrast, the pass-through of housing demand shock is not much significant in the less flexibly priced products where firms' markup rate is relatively large.[22] Moreover, the pass-through of housing supply shock is significant in the locally-produced products, but not in the nationally-produced products, lending support to the local cost channel. In this sense, the 15%-20% elasticities of local retail price to changes in house prices reported in Stroebel and Vavra (2019) can be viewed as an upper bound of housing market pass-through because they focus on grocery products that are produced locally and sold in a more competitive environment.

We further delve into whether and why price flexibility is a meaningful feature to explain the cross product differences noted in the pass-through of HP to CPs. Given that the transmission of shocks to CPs by nature depends on the market frictions that impede price adjustments, a reasonable candidate for the cross-product heterogeneity in the transmission mechanism is the frictions. On the theoretical front, it is well established in the macroeconomics literature that differing responses exist betweens ticky and flexible price sectors to national and local shocks, especially in the transmission mechanism of shocks. To investigate the product characteristics that can explain the cross-product heterogeneity found in $\hat{\rho}_{CP}$, we relate $\hat{\rho}_{CP}$ to the degree of price flexibility at the product level. This is because how fast prices can adjust to a shock is conceptually related to how quickly CPs can correct for the deviation from the long-run equilibrium. The top panel of Figure 4 reveals that the speed of adjustment from CP to HP ($\hat{\rho}_{CP}$) is positively associated with the degree of price flexibility, i.e., local CPs respond faster to HP changes in the products whose prices are adjusted more frequently. In the bottom panel of Figure 4, we plot the relationship between the degree of price flexibility across products against the LRE of pass-through of HP to CP estimated in the PVECM. A clear positive association shown in Figure 4 suggests that the LRE of HP on CPs is greater in the products whose prices are adjusted more frequently, probably because shocks pass through faster in those products. This reinforces our

[22] This result seems to be at odds with the finding by Beraja et al. (2014) that cross-state patterns of CPs are not well explained by the flexibility of prices. Examining the nature of household shopping behavior in response to changes in local economic activity, Beraja et al. (2014) find that nominal wage rigidities played a more important role than price stickiness in the transmission of local economic shocks during the Great Recession. They argue that prices respond very quickly to changes in local economic conditions, but not to housing market shocks.

prior intuition that price flexibility is an important transmission mechanism through which shocks in housing markets pass through CPs.

The importance of price flexibility in explaining the cross-product heterogeneity in the pass-through of HP onto CP is well aligned with the transmission mechanism based on the firms' price-setting behavior highlighted by Stroebel and Vavra (2019). According to the authors, retail price changes reflect not the pass-through of local retail rents or land prices, but the markup changes influenced by local HP changes. They assert that changes in HP transmit to CP mainly through firms' pricing-to-market practice as firms charge higher prices in locations with higher HPs.[23] Our finding on the significance of pass-through in more flexibly priced products, however, runs counter to the role of firms' pricing-to-market power because markup rates tend to be smaller in those products. At least, there is no compelling reason to believe that the wealth or collateral effect of HP changes is stronger in the products whose prices are adjusted frequently.

Combined together, our results suggest that the markup effect channel is at work at the city level, but not at the product level. For the transmission of housing supply shock, the local cost channel seems to be dominant.

5 Concluding remarks

Using survey price data collected in the selected U.S. cities over the past 25 years, this paper examined the short-run and long-run effects of housing markets onto local CPs for a variety of products. After investigating the responsiveness of city-level CPs to aggregate housing market shocks within the framework of FAVAR model, we estimated the pass-through of HP to CP within the framework of VECM model by looking at how HP changes affect the changes in local CPs. Our empirical results reveal that CPs in general are highly responsive to HP, but not the other way around. The short-run and long-run effects of HP, however, varies widely across products. The estimated HP elasticity of CPs is about 0.46, controlling for city-level income and local labor market conditions. On average, a 10% rise in housing price tends to increase CPs by around 4.6%. Given products, the sensitivity of CPs to HP also varies considerably across cities.

The impact of HP onto CP is closely associated with the factors identified in the literatures on skill-biased technical change and job polarization. When the housing market shock is decomposed into demand shock versus supply shock, we find that CPs are more responsive to housing demand shock in the cities with higher concentration of skilled workers with college degree and in the cities that are

[23] Using weekly store-level retail price data from IRI Worldwide for chain grocery and drug stores from 2001 to 2011 for products in 31 categories (about 15% of household spending in the Consumer Expenditure Survey), Stroebel and Vavra (2019) attribute the effect of HP to CP to markup changes. They also contend that local productivity shocks that reduce HPs and housing wealth cause retail prices to fall. Their retail price data, however, include only tradable goods in grocery and drug stores which are typically not produced locally and hence are not much susceptible to local shocks.

distant from others economically and geographically. Given that consumers with lower income or less skills, who typically face a tighter borrowing constraint, are more likely to materialize HP changes, our results are not much aligned with the conventional channels of wealth effect or collateral effect. Instead, our finding is pointing toward markup effect channel related to pricing practice exercised by firms or local retailers (e.g., Stroebel and Vavra 2019). For the pass-through of housing supply shock to CPs, we find it is stronger in cities with more regulations on housing supply or with inelastic house supply, consistent with local cost channel. Our results also suggest that the effect of HP on CPs hinges on certain product characteristics, such as how fast prices are adjusted to shocks and where are they are produced. While housing demand shocks transmit to CPs primarily in the products whose prices are adjusted more frequently, the pass-through of housing supply shocks is taking place mainly in the products that are locally produced. Since markup effect should be smaller in the flexibly priced products as they are produced in a more competitive environment, the markup effect channel seems at work in the pass-through of HP to CP at the city level but not at the product level. Significant pass-through of housing supply shock to the prices of products that aer locally produced appears to lend credence to the local cost channel.

Combined together, we view that the interplay between markup effect and local cost effect might have played an important role in the transmission of housing market shocks on local CPs. The growing dispersion of intercity HPs might also have led to the geographic cost-of-living differences primarily through the products with more flexible price adjustments. In this vein, our findings complement the literature on the geographic income inequality because stronger effect of HP onto CP may alleviate the geographic dispersion of the purchasing power of uneven distribution of local income. However, the pass-through of HP to CP that alleviates the geographic dispersion of the purchasing power might take place in some cities through some products, but not in all.

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Appendix: Data Description

Table A.1: 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	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	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.2: Summary statistics

Product	Price level						% deviation from city average price [min,max]
	mean	min	max	ratio(%)	Dispersion (CV)	Moran's I	
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 CPs 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 (e.g., Stock and Watson 2010).

Table A.3: Summary statistics at the city level

city code	city name (code)	per capita income ($)	weekly wage ($)	population (1,000 people)	% of bachelor higher degree	home price ($1,000)
1	AMARILLO (AMA)	24,933 (L)	551.85	225.7 (L)	21.9 (L)	166.9
2	ATLANTA (ATL)	29,895 (H)	725.99	4,124.2 (H)	34.0 (H)	189.0
3	CEDAR RAPIDS (CID)	28,688 (H)	627.70	234.0 (L)	26.6 (L)	174.4
4	CHARLOTTE (CLT)	28,281 (H)	689.81	1,720.9 (H)	31.7 (H)	175.2
5	CHATTANOOGA (CHA)	25,707 (L)	568.90	476.7 (L)	22.4 (L)	170.6
6	CLEVELAND (CLE)	30,168 (H)	669.55	2,116.9 (H)	26.3 (L)	186.4
7	COLORADO SPRINGS (COS)	28,253 (H)	606.75	525.7 (L)	34.8 (H)	190.3
8	COLUMBIA, MO (COU)	26,777 (L)	522.88	135.4 (L)	43.3 (H)	173.0
9	COLUMBIA, SC (CAE)	25,843 (L)	559.08	646.1 (L)	29.9 (H)	164.9
10	DALLAS (DAL)	30,870 (H)	746.67	5,122.2 (H)	30.1 (H)	157.7
11	DENVER (DEN)	34,063 (H)	755.54	2,099.7 (H)	37.1 (H)	231.4
12	DOVER (DOV)	24,721 (L)	540.38	131.6 (L)	19.4 (L)	184.2
13	HOUSTON (HOU)	31,677 (H)	791.38	4,724.4 (H)	28.1 (H)	155.6
14	HUNTSVILLE (HSV)	27,952 (H)	712.31	346.3 (L)	34.1 (H)	164.3
15	JONESBORO (JBR)	21,746 (L)	478.09	106.2 (L)	19.6 (L)	156.7
16	JOPLIN (JLN)	22,405 (L)	488.40	154.4 (L)	18.1 (L)	156.8
17	KNOXVILLE (KNX*)	25,157 (L)	590.00	741.9 (L)	27.8 (L)	163.9
18	LEXINGTON (LEX)	28,076 (H)	596.10	405.3 (L)	33.4 (H)	174.2
19	LOS ANGELES (LAX)	31,459 (H)	768.22	12,057.1 (H)	30.0 (H)	409.3
20	LOUISVILLE (LOU*)	27,928 (H)	609.10	1,121.3 (H)	23.8 (L)	162.5
21	LUBBOCK (LBB)	24,009 (L)	513.25	260.4 (L)	26.3 (L)	156.2
22	MEMPHIS (MEM)	27,632 (H)	639.77	1,195.0 (H)	24.4 (L)	153.5
23	MONTGOMERY (MGM)	26,111 (L)	556.48	340.4 (L)	26.2 (L)	182.9
24	ODESSA (ODS*)	23,000 (L)	620.24	126.9 (L)	13.0 (L)	167.4
25	OKLAHOMA CITY (OKC)	27,121 (H)	579.05	1,101.9 (H)	27.0 (L)	159.2
26	OMAHA (OMA)	30,860 (H)	593.40	766.7 (L)	31.3 (H)	163.7
27	PHILADELPHIA (PHL)	33,571 (H)	758.68	5,678.2 (H)	31.8 (H)	270.2
28	PHOENIX (PHX)	27,280 (H)	653.52	3,163.3 (H)	27.3 (L)	189.5
29	PORTLAND (POR*)	29,594 (H)	680.71	1,869.5 (H)	32.9 (H)	244.5
30	RALEIGH (RDU)	30,653 (H)	645.46	799.9 (L)	41.3 (H)	186.3
31	RENO-SPARKS (RNO)	33,645 (H)	621.32	336.6 (L)	26.3 (L)	214.2
32	SALT LAKE CITY (SLC)	26,507 (L)	616.31	918.9 (L)	29.8 (H)	190.6
33	SAN ANTONIO (SAT)	25,538 (L)	575.58	1,729.8 (H)	24.5 (L)	163.8
34	SOUTH BEND (SBN)	25,736 (L)	568.57	309.8 (L)	24.1 (L)	169.8
35	SPRINGFIELD (SPI)	29,162 (H)	661.14	200.8 (L)	29.6 (H)	172.3
36	ST. CLOUD (STC)	24,374 (H)	527.69	166.8 (L)	22.4 (L)	169.2
37	ST. LOUIS (STL)	30,428 (H)	664.89	2,667.5 (H)	28.5 (H)	161.9
38	TACOMA (SEA)	35,396 (H)	773.51	2,966.6 (H)	36.7 (H)	206.5
39	TUCSON (TUS)	24,845 (L)	572.94	819.9 (L)	29.0 (H)	179.7
40	WACO (WAC*)	22,662 (L)	535.64	228.9 (L)	20.4 (L)	155.6
41	YORK (YRK*)	27,903 (H)	598.73	381.8 (L)	21.0 (L)	196.4
	Average	27,820	623.31	1,542.6	28.0	184.4

Note: 'H' and 'L' respectively denote 'high' and 'low' groups. City codes are the airport codes of the corresponding cities except for those asterisked.

Table A.4: Description of city-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
Unemployment rate	City-level unemployment rate (s.a.) 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 Wolff (??) 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 market constraints	The Saiz's house supply elasticities and	Saiz websites

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 measure is 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 current 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.

Table 1: 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 2: 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	0.1027	[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 3: Rejection rates of unit-root and cointegration tests

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

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 4: Bivariate VECM and the Granger-causality test results

Product	Bivariate VECM				Panel VECM		
	Average adjustment speed		Rejection rates of		Average adjustment speed		Long-run
	$\hat{\rho}_{CP}$	$\hat{\rho}_{HP}$	$HP \nRightarrow CP$	$CP \nRightarrow HP$	$\hat{\rho}_{CP}$	$\hat{\rho}_{HP}$	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 following bivariate vector error correction model (VECM),

$$\begin{bmatrix} \Delta HP_{i,t} \\ \Delta CP_{i,t} \end{bmatrix} = \begin{bmatrix} a_i^{HP} \\ a_i^{CP} \end{bmatrix} + \begin{bmatrix} \rho_{HP} \\ \rho_{CP} \end{bmatrix} \hat{\epsilon}_{i,t-1} + \sum_{j=1}^{k} \begin{bmatrix} \gamma_{11,j} & \gamma_{12,j} \\ \gamma_{21,j} & \gamma_{22,j} \end{bmatrix} \begin{bmatrix} \Delta HP_{i,t-j} \\ \Delta CP_{i,t-j} \end{bmatrix} + \sum_{h=0}^{k} \Delta X_{i,t-h}\beta_h + \begin{bmatrix} e_t^{HP} \\ e_t^{CP} \end{bmatrix},$$

where $\hat{\epsilon}_{i,t-1} = HP_{i,t-1} - \hat{\beta}_i CP_{i,t-1}$ and $X_{i,t} \in$ {wage, unemployment rate}. 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.

Table 5: Transmission mechanisms and the related variables

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

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

Table 6: The cumulative IRFs of housing demand and supply shocks

Explanatory Var.	contemporaneous	After 1 year	After 2 years	After 3 years	After 4 years
	Housing demand shock				
Constant	-0.081* [0.046]	-0.166 [0.111]	-0.084 [0.160]	-0.043 [0.210]	0.003 [0.241]
Dummy for FLEX group	0.024†[0.012]	0.077* [0.042]	0.120* [0.061]	0.151†[0.074]	0.165†[0.080]
Dummy for Med FLEX gp	0.011 [0.015]	0.030 [0.044]	0.048 [0.059]	0.070 [0.072]	0.081 [0.080]
Income	0.000 [0.001]	-0.001 [0.003]	-0.006 [0.004]	-0.008 [0.006]	-0.009 [0.006]
Pop. Density	0.001 [0.001]	0.001 [0.003]	0.003 [0.005]	0.006 [0.007]	0.008 [0.007]
Share of college grad	0.001‡[0.000]	0.004‡[0.001]	0.005‡[0.002]	0.006‡[0.002]	0.006‡[0.002]
Remoteness	0.011 [0.012]	0.049* [0.030]	0.101‡[0.046]	0.137‡[0.058]	0.160‡[0.065]
Unemployment rate	0.005 [0.004]	0.012 [0.011]	0.005 [0.014]	-0.001 [0.017]	-0.006 [0.019]
Financial integration	-0.002 [0.011]	-0.014 [0.030]	0.007 [0.041]	0.012 [0.052]	0.017 [0.059]
Saiz	-0.005‡[0.002]	-0.013‡[0.006]	-0.011 [0.008]	-0.008 [0.010]	-0.005 [0.011]
	Housing supply shock				
Constant	0.291‡[0.124]	0.157 [0.158]	0.185 [0.179]	0.179 [0.175]	0.191 [0.170]
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]
Income	-0.007* [0.004]	-0.004 [0.005]	-0.005 [0.006]	-0.005 [0.006]	-0.006 [0.006]
Pop. Density	-0.003 [0.004]	0.000 [0.006]	0.000 [0.007]	0.001 [0.007]	0.002 [0.007]
Share of college grad	-0.001 [0.002]	0.000 [0.002]	0.001 [0.003]	0.002 [0.003]	0.002 [0.003]
Remoteness	-0.012 [0.040]	-0.059 [0.055]	-0.064 [0.065]	-0.053 [0.065]	-0.043 [0.064]
Unemployment rate	-0.010 [0.011]	0.001 [0.015]	0.000 [0.018]	-0.001 [0.018]	-0.002 [0.017]
Financial integration	-0.007 [0.042]	-0.073 [0.055]	-0.075 [0.064]	-0.074 [0.064]	-0.073 [0.063]
Saiz	-0.005* [0.003]	-0.020‡[0.009]	-0.024‡[0.010]	-0.024‡[0.010]	-0.024‡[0.010]

Note: The regression equation is

$$IRF_{it}^{m} = \alpha_m + \gamma_1 D_{1i} + \gamma_2 D_{2i} + X_i'\beta + \varepsilon_{it}^{m},$$

where $m = 1, ..., 44$, $i = 1, ..., 41$, and $t = 0, ..., 4$ years. $IRF_{i,t}^{m}$ represents the t-year *median* cumulative effect of housing market shocks for m_t that increase private residential fixed investment by 1% at the impact. For the house demand shock, D_{1i} and D_{2i} respectively represent dummy variables for the most flexible price group (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 denote a set of city-level characteristics including income, population density, unemployment rate, share of college graduates, remoteness, financial integration, and Saiz's housing supply constraint. Clustered standard errors are used by clustering observations by cities rather than by products.