INTERNATIONAL REAL ESTATE REVIEW

2024 Vol. 27 No.2: pp. 203 – 247

Productivity Shocks of Dominant Companies and Local Housing Markets

Thanh Nguyen
California Department of Social Services, Sacramento, CA 95814, USA, Email: thanh.nguyen@dss.ca.gov

Arsenio Staer
Finance Department, California State University at Fullerton, Fullerton, CA 92834, USA Email: astaer@fullerton.edu

Jing Yang*
Finance Department, California State University at Fullerton, Fullerton, CA 92834, USA Email: jyang@fullerton.edu

We extend the literature on the influence of firm-level characteristics on housing markets by exploring the association between the labor productivity shocks of dominant firms and local housing prices. Using a sample of all U.S. firms from COMPUSTAT during 1980-2017, we find that the aggregate shocks of labor productivity of dominant firms at the metropolitan statistical area (MSA)-level explain for a significant portion of the local housing price changes in MSAs while controlling for other housing price determinants. About a year or more is required for the shocks to propagate through the local housing markets, which make them a viable predictor of future housing price. The productivity shock – housing price relation is stronger in areas that have more concentrated high-tech dominant firms or where dominant firms have closer links to their local non-dominant industry peers. Shocks are also more influential during economic expansion than economic contraction. Furthermore, the relation also exists at the zipcode level but the shocks propagate faster than at the MSA-level. The findings provide helpful insights for real estate practitioners and policymakers, especially in areas with a higher concentration of large companies.

Keywords

Productivity Shock, Housing Price, Local Effects, Spillover Effects

---

* Corresponding author

1. Introduction

We often observe that large firms exert significant influence on the various aspects of their local economies, including their local housing markets. For instance, for the first time in history, the top three leading U.S. automakers, General Motors, Ford, and Chrysler, experienced substantial declines in their market shares (falling below 50 percent) in 2007, which resulted in the soaring of the unemployment rate of their headquarters state, Michigan, to "a frightening 14.9 percent" (Cohn, 2017) and the subsequent crash of the local housing markets.[1] During the same year, pharmaceutical giant Pfizer closed its major lab Lipitor in Ann Arbor, a Michigan city that was relatively immune to the auto crisis, which led to the job loss of 2100 local employees and the corresponding crash in the local housing market.[2] A more recent example is related to the decision for locating the second headquarters of Amazon. According to a 2019 Curbed report: "From June 2018 to June 2019, the median asking price for a single-family home in ZIP code 22202, home to Amazon's planned Northern Virginia headquarters, skyrocketed a whopping 99.9 percent—essentially doubling over that period…"[3] Large firms really make a difference. However, the effects of firm-level shocks on the local economy are poorly understood and documented in the literature. In this study, we fill a gap in the literature by exploring how the labor productivity shocks at the firm-level of large U.S. firms are related to their local housing markets.

There are quite a few studies on the effects of economy-wide shocks on the fluctuation of fundamentals in the literature. These studies have focused on the effects of the aggregate national or local economic shocks (such as inflation, oil price, or policy shocks) while ignoring the firm-level shocks, which they argue would average out in the aggregate. In the same vein, previous real estate research uses economy-wide shocks to explain for housing price changes. For instance, Glaeser and Gyourko (2007) relate housing price dynamics to macroeconomic factors such as interest rate and local economic factors, including population and time-varying local economic shocks.

---

[1] See article titled "From rough ride to respectable: Michigan wins for most improved" by Scott Cohn for CNBC dated July 11, 2017, available at: https://www.cnbc.com/2017/07/11/michigan-automakers-from-a-rough-ride-to-a-new-manufacturing-economy.html.

[2] See article titled "A Story Of Devastation And Rebirth: The Former Pfizer Research Labs In Ann Arbor" by John LaMattina, for Forbes dated June 11, 2018, available at: https://www.forbes.com/sites/johnlamattina/2018/06/11/a-story-of-devastation-and-rebirth-the-former-pfizer-research-labs-in-ann-arbor/#281ede424425.

[3] See article titled "Amazon HQ2 ZIP code sees doubling in median list price for single-family homes: report" by Andrew Glambrone for Curbed dated July 16, 2019, available at: https://dc.curbed.com/2019/7/16/20696217/amazon-hq2-arlington-crystal-city-home-prices.

Holding a different view, several studies suggest that aggregate shocks at the firm-level affect the fundamentals of the economy. Gabaix (2011) reports that the aggregation of idiosyncratic firm-level shocks of the 100 largest U.S. firms can explain for about one-third of the variation in the national output growth. Inspired by this study, Jannati (2020) shows that the productivity shocks to the 100 largest U.S. firms can spillover through intra-sector and direct trade links, knowledge externality, and state income tax payments to other firms in their states and potentially aggregate to affect the national economy. Related to these studies, our paper explores how the aggregation of productivity shocks at the firm-level of the largest U.S. firms affects their local housing price movements. We focus on the labor productivity shocks of these firms rather than their performance shocks (which are usually related to their sales, market share, profitability and/or employee growth), because we consider productivity shocks to be relatively more influential to the local economy and local housing markets due to their more direct associations with technology and efficiency improvements, which are more likely to spillover to other firms. As far as we know, this is the first study that links productivity shocks at the firm-level to local real estate prices. Our paper is also different from real estate studies that examine the association of housing price movements with time variation on local economic factors (e.g., employment or local aggregate production output), such as Titman et al. (2014), as we propose that firm-level shocks can explain for a significant portion of local economic fluctuations.

Our study can be compared to those that explore regional or local variation to establish the causal effects of credit supply and house price shocks on real outcomes. For instance, Adelino et al. (2015) and Chaney et al. (2012) report that real estate price changes can influence the collateral value of a firm with real estate exposure, and this change in collateral value contributes to a large share of the changes in the investment and growth of this firm. Similarly, Gan (2007) demonstrates that the land market crash in Japan during the 1990s affected the credit supply of lenders with real estate exposure, eventually affecting the investment and value of a borrowing firm. The relations between mortgage credit supply and real estate prices are analyzed in detail in Favara and Imbs (2015) and Mian et al. (2017). Compared to these studies, our study does somewhat the opposite by focusing on the impacts of local businesses on house prices. We conduct a robustness test to explore the possible impacts of house prices on the productivity shocks of local dominant firms, but we find that the impacts are not substantial, as we will elaborate later.

Furthermore, our study extends the literature on the impact of local firms on housing markets. For instance, Butler et al. (2019) show that the listing decisions of local firms help to create new jobs and increase local employment, which lead to an increase in the local housing price and per capita income through economic spillover effects. Nguyen et al. (2022) show that the initial public offerings of firms increase local housing prices by affecting local economic expectations and the wealth of residents. Looking from a different perspective, this study focuses on how large firms affect the housing price movements in local areas.

We believe that the hypothesized relation between the aggregation of the labor productivity shocks of the largest firms and local housing price movements can be positive or negative. One channel that may lead to a positive relation is the "spillover" channel: the productivity shocks of the largest firms can have spillovers to other firms in the same area via intra-sector links, direct trade links, knowledge externality, state income tax payment (as explained in Jannati (2020), and local area gentrification[4]. On the other hand, the productivity shocks can negatively affect the local housing prices through the "efficiency and labor substitution" channel: the improvement in efficiency from a positive shock can reduce the need for labor, and correspondingly, the aggregation of the productivity shocks of the largest firms can reduce the overall employment level[5], thus reducing the housing demand and hence the housing prices.

Motivated by these conflicting hypotheses, we have launched this study to explore the net direction of the relation between the labor productivity shocks of large companies and their local housing price movements. Using a sample that consists of all U.S. firms in the COMPUSTAT database and data of the Federal Housing Finance Agency (FHFA) housing price indices for 403 MSAs during 1980-2017, we find that, on average, the aggregation of the labor productivity shocks of dominant firms (in terms of revenue) in an MSA explains for a significant portion of the housing price changes in that MSA, with the shock-housing price relation appearing to be positive. Moreover, this relation remains robust when we control for other housing price determinants. It takes about one year or more for the influence of the shocks to propagate through the local housing markets, which makes the aggregate shocks of the labor productivity of local dominant firms at the MSA-level a viable predictor for future housing price trends at the MSA-level.[6] We also find that this influence is greater in areas with a higher concentration of high-tech dominant firms than

---

[4] As an example of gentrification, big companies headquartered in a city are important local tax payers and investors in local education (e.g., college sponsorships), infrastructure (such as developing stadiums and other sports arenas) and social and welfare programs; therefore, their productivity shocks can generate positive externalities that make the city and its surrounding area a more appealing and expensive place.

[5] A negative relation between productivity growth and employment change is found in studies such as Gali (1999), Gali and Rabanal (2004), Basu et al. (2006), and Junankar (2013).

[6] This result is analogous to the findings in Smajlbegovic (2019), Addoum et al. (2020) and Ling et al. (2020) that news on local economic activities are relevant to the stock price of a firm, but the information is diffused slowly to the stock price as the news is not immediately available to the marginal investors in the stock, thus making the information useful in predicting the stock returns. In addition, information diffusion is found to be slower for more illiquid stocks. Real estate property markets are also illiquid (hence inefficient), which may explain for the delay in reaction to the productivity shocks of dominant firms in the local area.

those with a higher concentration of non-high-tech dominant firms, and during economic expansion as opposed to economic contraction. As expected, this shock-return relation is more robust in areas where the dominant firms have closer links to their local non-dominant industry peers, a finding that supports the spillover channel argument. Furthermore, a positive relation between the labor productivity shocks and local housing price changes also appears when the aggregation is at the zipcode level but without a time lag between the two variables. A possible explanation is that a productivity shock of a dominant firm tends to propagate rapidly over its immediate neighborhood, compared to a slower propagation over a larger geographical area.

We believe the relationship hypothesized in this paper contributes to developing a better predictive model for housing prices. The effect of dominant firms on housing markets is likely to be stronger in other countries where dominant firms constitute a larger share of the economy.

The rest of the paper proceeds as follows. The next section discusses our data sources, research hypotheses and methodology. We then provide descriptive statistics in the third section. We present our major empirical results in the fourth section. The last section concludes.

2. Data, Hypotheses and Methodology

2.1 Data

We use multiple sources to collect the data for this study: (1) company information from COMPUSTAT;[7] (2) quarterly housing price indices from the FHFA at the MSA-level; (3) economic variables from Moody's Analytics at the MSA-level; and (4) the Zillow Home Value Index (ZHVI) at the zipcode level.

We measure the housing price levels at each MSA by using the FHFA Quarterly All-Transactions House Price Index (HPI), given its comprehensive coverage of MSAs (i.e., 403 MSAs)[8]. The HPI is also one of the most popular housing price indices used in the real estate literature. The sample period for our regressions of housing returns at the MSA-level is from the first quarter of 1980 (as the starting year of the HPI data for most MSAs is 1979) to the last quarter of 2017.

---

[7] We exclude private firms from our sample of dominant firms due to the limited data availability. Some large private firms, such as Cargill and Publix, can be very influential on their local housing markets.

[8] We also use the FHFA purchase-only HPI (for 100 major MSAs) for robustness tests, which produce similar results as the FHFA all-transactions house price indexes.

We measure the housing price levels at each zipcode by using the ZHVI for single-family homes[9]. The ZHVI is a popular housing price index for zipcodes and reflects the typical value for single family residence (SFR) homes in the 35th to 65th percentile range. The sample period for our regressions for annual returns of housing at the zipcode-level is from 1998 (as the starting year of the ZHVI data is 1997) to 2017.

The primary housing price factor that we consider in this study is the labor productivity shocks of the dominant firms. We calculate this variable by using net sales and employee data from COMPUSTAT. Following Gabaix (2011), for year y in our sample period, we categorize a firm as a dominant firm if its net sales in the prior year are among the top 100 across all firms; otherwise the firm is a non-dominant firm. Then, for each firm i, we calculate its labor productivity as [10]:

$$X_{i,y} = Ln\left(\frac{Net\ Sales_{i,y}}{Employees_{i,y}}\right) \tag{1}$$

Correspondingly, the annual labor productivity growth is

$$G_{i,y} = X_{i,y} - X_{i,y-1} \tag{2}$$

and its firm-specific component of the productivity growth is

$$\widehat{G_{i,y}} = G_{i,y} - \overline{G_y} \tag{3}$$

where $\overline{G_y}$ is the average productivity growth of all firms in the same year which represents the common shock. Then, we calculate the scaled labor productivity shock of the firm as:

$$Scaled\ Shocks_{i,y} = \left(\frac{Net\ Sales_{i,y-1}}{GDP_{y-1}}\right)\widehat{G_{i,y}} \tag{4}$$

This allows a firm to account for a larger weight if its net sales of the previous year constitute a larger share of the lagged GDP.[11] Following this, we calculate the labor productivity shocks of dominant firms at the MSA-level as the sum of scaled shocks of all dominant firms headquartered in this MSA in that year for each MSA-year combination. Similarly, for each zipcode, we calculate the labor productivity shocks of dominant firms at the zipcode-level in each year

[9] The ZHVI employed in the paper is "ZHVI All Homes (SFR, Condo/Co-op) Time Series, Raw, Mid-tier" and downloaded from https://www.zillow.com/research/data/.
[10] Gabaix (2011) mentions that in the literature, this is the primary way to measure productivity through COMPUSTAT data.
[11] Also note that we measure the productivity shocks of a firm based on the growth (rather than the level) of its productivity, therefore the productivity shock of a labor-intensive firm can be compared to that of a capital-intensive firm in our sample.

as the sum of scaled shocks of all dominant firms headquartered in this zipcode in that year.

We then explore a factor that might influence the effects of labor productivity shocks on the housing market, that is, the strength of the industry links within each area. If the dominant firms in a particular area exhibit closer industry links (i.e., business relations) with the local non-dominant firms, the productivity shocks of the dominant firms might have greater spillover effects on the non-dominant firms, thus resulting in a larger cumulative effect on the local housing markets. We use the Fama-French 48 industry portfolio to identify the industry of a firm and measure the scaled strength of industry link in an area in year y as follows:

$$Scaled\ Industry\ Link_y = \frac{\sum_j Net\ Sales_{j,y}}{\sum_i Net\ Sales_{i,y}} \tag{5}$$

where j is the firm index for a local non-dominant firm that is in the same Fama-French industry as any local dominant firm, and i is the firm index for a local firm. In other words, the scaled strength of the industry link is measured by the sum of sales of local non-dominant firms that are in the same Fama-French industry as local dominant firms, scaled by the sum of the sales of all firms in the local area. The local area can be defined as the local MSA or local zipcode. Correspondingly, we can calculate the scaled industry link at the MSA-level and zipcode-level.

In our study of the effects of productivity shocks on the housing prices, we control for the changes in several local economic variables which include: employment (calculated with raw data from the U.S. Bureau of Labor Statistics), population (calculated with raw data from the U.S. Census Bureau), gross metropolitan product (GMP, calculated with raw data from the U.S. Bureau of Economic Analysis), and so on and so forth. These data are available at the MSA-level. However, similar data are usually less available and/or less accurate at the zipcode level.[12] Correspondingly, in the regressions for housing returns at the zipcode level, the economic variable change rate at the zipcode-level is proxied by the change rate of the same variable for the MSA to which this zipcode belongs.

---

[12] For instance, the American Community Survey (ACS) provides zipcode-level population data, which are collected monthly and pooled over the entire year to produce annual estimates. This is different from the MSA population data collected by U.S. Census Bureau every 10 years, which provide population counts as of April 1 of the census year. In addition, the ACS data are based on a much smaller sample of house units and people compared to the census data, which may result in much more severe sampling errors.

2.2 Hypotheses and Methodology

This study explores whether labor productivity shocks of dominant firms are associated with the housing price changes of their headquarters cities and if so, the extent and factors that may influence the association. We use two ways to define the local area: the local MSA-level and local zipcode. Correspondingly, we develop the MSA-level and zipcode-level analyses.

We start with the MSA-level analysis. Our first model regresses the housing returns at the MSA-level on the aggregate and scaled shocks of the labor productivity of dominant firms at the MSA-level and its lagged terms, while controlling for the lagged housing returns at the MSA-level to address the serial correlation of housing returns documented in the real estate literature (for instance, Case and Shiller (1989)). We also control for local economic changes by including the growth rate of employment, GMP, or population, at the MSA-level, to ensure that the effects of productivity shocks implied by the regression results are not due to local economic changes. The sign and significance of the scaled productivity shock variables in the regression are used to test the influence of productivity shocks on the local housing markets. If j is the MSA indicator, the regression takes the following function form:

$$R_{j,q} = \varphi + \sum_{i=1}^{3} \omega_i R_{j,q-i} + \sum_{k=m}^{n} \theta_k S_{j,q-k} + \mu F_{j,q} + \varepsilon_{j,q} \,. \qquad (6)$$

where q is the quarter index. $R_{j,q}$ is the year-over-year housing return of the jth MSA at quarter q. $R_{j,q-i}$ is the $i-$year lagged annual return, with $i = 1, 2, 3$. $S_{j,q-k}$ is the $k-$year lagged aggregate and scaled labor productivity shocks of the local dominant firms, with $k = m, m+1, \dots, n$, where $n \geq m \geq 0$. Note that $S_{j,q-k}$ measures the current quarter value when $k = 0$. $F_{j,q}$ is a variable that reflects the $j-$th MSA economic change during the current quarter. φ is a constant, ω_i , θ_k and μ are coefficients, and $\varepsilon_{j,q}$ is the error term. We include three lagged annual housing returns as previous research have found that these serial correlation terms influence housing returns. For instance, Case and Shiller (1989), Campbell et al. (2009), and Titman et al. (2014) find that 1-year or 6-month lagged terms positively affect the rate of change of house prices, while the reverse usually occurs after 6 months and before the 3rd year. The coefficients of the scaled variables of the labor productivity shock, θ_k, indicate whether housing returns are affected by the local productivity shocks of the dominant firms and how soon the effects can be observed. We use a linear regression to estimate the coefficients, controlling for the time fixed effects with year and quarter dummies, and for heteroscedasticity with two-way clustered standard errors for MSAs and quarter counts (note that there are 152 quarter clusters in our 38-year sample period, from 1980 to 2017). In another robustness test, we control for variations of the economic conditions (observed and unobserved) across state and time by including the joint fixed effects of state-quarter counts (fixed effects of 7600 state-quarter counts in total for 50 states and 152 quarter clusters). The regression in Equation (6) will be used to test the following hypothesis:

Hypothesis 1: housing return increases in the current and/or previous year of the scaled productivity shocks of the local dominant firms; that is, from the regression in Equation (6), $\theta_k > 0$, for $k \in [m, m+1, \dots, n]$, where $n \geq m \geq 0$.

If our results support Hypothesis 1, this suggests that the relation between the labor productivity shocks of the dominant firms and the local housing return via positive relation channels such as spillovers, dominates their relation via negative relation channels such as efficiency and labor substitution.

Our second regression model adds the industry link measurement at the MSA-level and its interaction term with the productivity shock variables into the regression in Equation (6). Using the "spillover" channel mentioned earlier, when the dominant firms have closer ties to local non-dominant industry peers, the productivity shocks of the dominant firms would have larger industry spillover effects on local businesses, thus resulting in more prominent aggregate effects on the local housing market. We will hence test the prediction that stronger local industry links will amplify the productivity shock effects on the housing markets. We test this prediction by using:

$$\begin{aligned} R_{j,q} = \varphi' + \sum_{i=1}^{3} \omega'_i \, R_{j,q-i} + \sum_{k=m}^{n} \theta'_k \, S_{j,q-k} + \beta' G_{j,q} \\ + \textstyle\sum_{k=m}^{n} \gamma'_k \, G_{j,q} S_{j,q-k} + \mu' F_{j,q} + \varepsilon'_{j,q}, \end{aligned} \tag{7}$$

where $G_{j,q}$ is one of the $j-$th MSA's industry link measurements mentioned for quarter q. Its interaction with the productivity shocks variable $S_{j,q-k}$ is captured by $G_{j,q}S_{j,q-k}$. Other variables are similar as in the regression in Equation (6): φ' is a constant, ω'_i, θ'_k, β', γ'_k and μ' are coefficients, and $\varepsilon'_{j,q}$ is the error term. This regression will be used to test the following hypothesis:

Hypothesis 2: Hypothesis 1 has a greater effect when local industry links are closer, that is, the interaction terms $G_{j,q}S_{j,q-k}$ $(k = m \ to \ n)$ in the regression in Equation (7) are positive.

These are the major empirical tests for our MSA-level analyses. At the zipcode level, we conduct a similar analysis for Hypothesis 1, except that the housing returns are measured at the zipcode level, productivity shocks of the dominant firms are aggregated at the zipcode level, and the sample period is from 1998 to 2017. In addition, we also conduct a robustness test for Hypothesis 1 at the MSA-level by replacing dominant firms at the national level with those at the state-level. The details of these tests and their results are presented in Section 4.

3. Descriptive Statistics

Our data for labor productivity shocks at the MSA-level cover a 38-year period from 1980 to 2017. Following previous studies on productivity shocks, such as Gabaix (2011) and Jannati (2020), we exclude: (1) firms that are not located in the U.S.; (2) oil and oil-related firms (with SIC codes 2911, 5172, 1311, 4922, 4923, 4924 and 1389) and energy firms (with SIC codes between 4900 and 4940), the sales of which are most affected by worldwide commodity prices rather than productivity shocks; and (3) financial firms (with SIC codes between 6000 and 6999), the sales of which do not fit the measure in this paper. We also require firms to have positive sales and employee data for the current and previous years. There are 158,171 firm-year observations from 16,155 unique firms in COMPUSTAT in our 38-year sample period. They are located in 4,615 unique 5-digit zipcodes. There are 278 firms that have been at least once in the top 100 firms by net sales. They are located in 230 unique 5-digit zipcodes. This sample is used to calculate MSA-level aggregate productivity shocks of the dominant firms.

The MSA productivity shocks data are then merged with the FHFA housing price indices and local economic variables data. The FHFA data include the HPI indices for 403 MSAs during the 38-year sample period from 1980 to 2017. The statistical analyses of the key variables for our regression analyses at the MSA-level, including HPI return, employment growth rate, and scaled shocks, are summarized in Panel A of Table 1. There are initially 61,256 MSA-quarter observations based on available data of the scaled shocks. After excluding observations without HPI data or local economic variables, we end up with a sample of 52,957 MSA-quarter observations.

Panel B of Table 1 provides the summary statistics of the key variables for our regression analyses at the zipcode-level. In the top 100-firm sample, there are about 8,200 zipcode-year observations with available aggregate and scaled data shocks of labor productivity based on zipcode during the 20-year period from 1998 to 2017. After excluding observations without the ZHVI data or local economic variables, we end up with a sample of 5,430 zipcode-year observations. Since the majority of the zipcodes never hosted the top 100 firms in our sample period, we also conduct a robustness test for the regressions for housing returns at the zipcode level by using a top 1000 firm sample, which has approximately 82,000 zipcode-year observations with scaled data of labor productivity shocks at the zipcode-level.

Panel C lists the 19 MSAs that most frequently hosted the top 100 dominant firms from 1980 to 2017. Each of these MSAs hosted more than 1% share of the dominant firms, which span almost all major cities or districts across the U.S., including New York, Chicago, Dallas, Atlanta, Minneapolis, San Francisco, Washington DC, Detroit, Boston, Cincinnati, San Jose, St. Louis, Seattle, Memphis, Philadelphia, Los Angeles, Houston, and so on and so forth, which yield a total of 3,004 dominant firm-years, or about 79% of the total dominant firm-years in our sample. The top 2 MSAs, New York and Chicago, yield almost 30% of the dominant firm-year counts. However, the time trends show that both cities hosted dominant firms less frequently over time, as did St. Louis. On the other hand, San Jose and Boston have been hosting more and more dominant firms. Washington DC, Seattle, and Los Angeles have also become more popular as host district/cities.

Table 1 Summary Statistics

Panel A: MSA-Level Data

Variable	N	Mean	Min	Max	Std. Dev.
Return	52957	.0360	-.5281	.7117	.0610
MSA_scaled_shock	61256	1.38e-06	-.0046	.0055	.0002
GMP growth rate	61256	.0548	-.3408	.5144	.0466
Employment growth rate	61256	.0147	-.2841	.2207	.0296
Population growth rate	61256	.0107	-.3552	.3080	.0136

Notes: Panel A presents the summary statistics for the main dependent and independent variables for the MSA-level analysis for the sample period of 1980-2017. Return is an HPI quarterly return at the MSA-level. GMP growth rate, employment growth rate and population growth rate are the year-on-year rates of change at the MSA-level measured quarterly. MSA_scaled_shock is the labor productivity shock at the firm-level aggregated over all firms at time t domiciled in an MSA.

Panel B: Zipcode-Level Data

Variable	N	Mean	Min	Max	Std. Dev.
zip_1m_ret	7225	0.0391	-0.369	0.335	0.0739
zip_5m_ret	8069	0.0392	-0.291	0.276	0.0704
zip_10m_ret	8233	0.0381	-0.294	0.267	0.0694
zip_20m_ret	8236	0.0359	-0.284	0.259	0.0688
zip_30m_ret	8240	0.0349	-0.283	0.245	0.0677
zip_scaled_shock	8248	0.00001	-0.00389	0.00829	0.00048
MSA population growth rate	7696	0.00929	-0.01120	0.04980	0.00876

Notes: Panel B presents the summary statistics for the main dependent and independent variables for the zipcode-level analysis for the sample period of 1998-2017. Zip_#m_ret is constructed as follows: circle with radius of # miles (#=1, 5,10, 20 or 30) is plotted around the firm headquarters zipcode centroid. Then for this circle, the annual zipcode housing returns within the circle are averaged to build a housing price return index at the zipcode-level following Hartman-Glaser et al. (2022). Annual housing returns at the zipcode level are calculated from the ZHVI. Zip_scaled_shock is the labor productivity shock of the top 100 firms aggregated over all firms at time t domiciled in a zipcode. MSA population growth rate is the year-on-year rate of change in the MSA population calculated by using the 4th quarter.

Panel C: Top 19 MSAs Ranked by Frequency of Hosting Dominant Firms

Rank	MSA	1980-1989	1990-1999	2000-2009	2010-2017	All Years	Share
1	New York-Jersey City-White Plains, NY-NJ (MSAD)	175	165	152	109	601	15.82%
2	Chicago-Naperville-Arlington Heights, IL (MSAD)	130	149	124	85	488	12.84%
3	Dallas-Plano-Irving, TX (MSAD)	74	74	55	46	249	6.55%
4	Atlanta-Sandy Springs-Roswell, GA	56	72	50	32	210	5.53%
5	Minneapolis-St. Paul-Bloomington, MN-WI	51	37	42	35	165	4.34%
6	San Francisco-Redwood City-South San Francisco, CA (MSAD)	39	32	33	24	128	3.37%
7	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSAD)	25	29	37	33	124	3.26%
8	Detroit-Dearborn-Livonia, MI (MSAD)	33	28	35	22	118	3.11%
9	Boston, MA (MSAD)	25	28	29	35	117	3.08%
9	Cincinnati, OH-KY-IN	38	25	30	24	117	3.08%
11	San José Sunnyvale-Santa Clara, CA	7	19	40	42	108	2.84%
12	St. Louis, MO-IL	41	34	18	11	104	2.74%
13	Seattle-Bellevue-Everett, WA (MSAD)	10	17	32	29	88	2.32%
14	Memphis, TN-MS-AR	7	22	30	21	80	2.11%
15	Philadelphia, PA (MSAD)	17	15	24	23	79	2.08%
16	Los Angeles-Long Beach-Glendale, CA (MSAD)	12	20	23	20	75	1.97%
17	Houston-The Woodlands-Sugar Land, TX	11	19	16	19	65	1.71%
18	Fayetteville-Springdale-Rogers, AR-MO	6	10	17	16	49	1.29%
19	Providence-Warwick, RI-MA	5	15	11	8	39	1.03%
	Total of top 19 MSAs					3004	79.1%
	Total of entire sample					3800	100.0%

Notes: Panel C lists 19 MSAs that are the most frequent hosting cities among the top 100 dominant firms during 1980-2017. The numbers show firm-year counts. There is a 3800 total firm-year count for our 38-year sample period. Each of these MSAs hosts more than 1% share of the top 100 dominant firm-year count.

Panel D: Top 19 Industries Ranked by Frequency of Dominant Firms

Rank	Industry Name	1981-1990	1991-2000	2001-2010	2011-2017	All Years	Share
1	Telephone Communications (No Radiotelephone)	93	127	48	2	270	7.1%
2	Retail-Grocery Stores	67	61	50	23	201	5.3%
3	Pharmaceutical Preparations	21	47	63	42	173	4.6%
4	Air Transportation, Scheduled	28	48	37	39	152	4.0%
5	Retail-Department Stores	48	36	29	15	128	3.4%
6	Retail-Variety Stores	19	41	31	22	113	3.0%
7	Motor Vehicles & Passenger Car Bodies	34	28	21	21	104	2.7%
8	Retail-Drug Stores and Proprietary Stores	1	10	38	30	79	2.1%
9	Food And Kindred Products	28	20	22	8	78	2.1%
10	Aircraft	33	20	10	12	75	2.0%
11	Wholesale-Drugs, Proprietaries & Druggist's Sundries	8	15	27	24	74	1.9%
12	Computer & Office Equipment	23	31	10	8	72	1.9%
13	Search, Detection, Navigation, Guidance, Aeronautical Sys	15	19	18	16	68	1.8%
14	Beverages	12	20	15	10	57	1.5%
15	Trucking & Courier Services (No Air)	9	12	19	16	56	1.5%
16	Services-Computer Programming, Data Processing, Etc.	8	8	22	17	55	1.4%
17	Papers & Allied Products	16	20	14	1	51	1.3%
18	Railroads, Line-Haul Operating	25	9	2	14	50	1.3%
19	Conglomerates	16	0	17	17	50	1.3%
	Total of top 19 industries					1906	50.2%
	Total of the entire sample					3800	100.0%

Note: Panel D lists 19 business sectors that have most frequently hosted (at least a count of 50) the top 100 dominant firms during 1980-2017.

Panel E: Top 17 Firms Ranked by Frequency of being Dominant Firms

Frequency Rank (tie)	Firm Name	Frequency	Share	State	MSA	1980 Revenue Rank	2017 Revenue Rank
1	Ford Motor Co	38	1.00%	MI	Detroit-Dearborn-Livonia, MI (MSAD)	3	8
1	General Motors Co	38	1.00%	MI	Detroit-Dearborn-Livonia, MI (MSAD)	1	10
1	Kroger Co	38	1.00%	OH	Cincinnati, OH-KY-IN	18	14
1	General Electric Co	38	1.00%	MA	Boston, MA (MSAD)	6	15
1	Boeing Co	38	1.00%	IL	Chicago-Naperville-Arlington Heights, IL (MSAD)	22	20
1	Intl Business Machines Corp	38	1.00%	NY	New York-Jersey City-White Plains, NY-NJ (MSAD)	4	23
1	Johnson & Johnson	38	1.00%	NJ	New York-Jersey City-White Plains, NY-NJ (MSAD)	79	25
1	Procter & Gamble Co	38	1.00%	OH	Cincinnati, OH-KY-IN	16	31
1	PepsiCo Inc.	38	1.00%	NY	New York-Jersey City-White Plains, NY-NJ (MSAD)	50	32
1	DowDuPont Inc.	38	1.00%	MI	Saginaw, MI	17	34
1	United Technologies Corp	38	1.00%	CT	Hartford-West Hartford-East Hartford, CT	13	36
1	Caterpillar Inc.	38	1.00%	IL	Chicago-Naperville-Arlington Heights, IL (MSAD)	26	44
1	Honeywell International Inc.	38	1.00%	NJ	New York-Jersey City-White Plains, NY-NJ (MSAD)	55	53
1	Coca-Cola Co	38	1.00%	GA	Atlanta-Sandy Springs-Roswell, GA	51	61
1	3M Co	38	1.00%	MN	Minneapolis-St. Paul-Bloomington, MN-WI	49	66
1	Raytheon Co	38	1.00%	MA	Boston, MA (MSAD)	72	81
1	Sears Holdings Corp	38	1.00%	IL	Chicago-Naperville-Arlington Heights, IL (MSAD)	9	100
	Total of top 17 firms	646	17.00%				
	Total of the entire sample	3800	100.00%				

Note: Panel E lists 17 firms that have been on the list of top 100 firms for all 38 years during 1980-2017.

Panel D lists the 19 business sectors that most frequently produced the top 100 dominant firms (with at least a count of 50 each) in our sample period. These sectors are quite diversified, and their capacity to produce dominant firms varies over time. Finally, Panel E lists the 17 firms that have been in the top 100 for all 38 years of our sample period. These firms are mostly located in the East and the Midwest, but many were ranked lower in 2017 than in 1980. For instance, in 1980, 4 of these 17 firms were ranked within the top 6, including GM, Ford, IBM and GE; while in 2017, none of these were ranked within the top 7, with the top 7 firms (Walmart, Berkshire Hathaway, Apple, McKesson, CVS, Amazon and AT&T) starting to rise in the rankings mostly after 1980.

4. Effects of Productivity Shocks of Dominant Firms on Local Housing Price Changes

We now report the results from the panel data regressions of housing returns following the regression in Equation (6), which is to test Hypothesis 1 – the housing return increases in the current and/or previous year of the scaled productivity shocks of the local dominant firms, with local defined as the local MSA or local zipcode where a dominant firm is headquartered. The results are reported in Tables 2 to 6.

4.1 Effects on Local Housing Price at the MSA-Level

4.1.1 Main Results

Table 2 shows the results from the regression of the housing price changes at the MSA-level (which we designate as housing returns).[13] Panel A reports the regression results for all MSAs with year and quarter fixed effects. In the regression specification in Equation (1), we include 1-year, 2-year, and 3-year lagged returns, as well as the scaled shocks at the MSA-level and their 1-year and 2-year lagged terms. In the other regression specifications, we also include an economic variable at the MSA-level to control for local economic conditions, which is the annual rate of change in employment in the specification of Equation (2), annual rate of change in the GMP in the specification of Equation (3), and annual rate of change in population in the specification of Equation (4). Standard errors are adjusted for the clustering by MSA and the quarter count. Consistent with previous research, the housing returns in all of the regression specifications exhibit a short-term momentum (with the 1-year lagged return significantly positive) and a long-term reversal (with the 3-year lagged return significantly negative). Additionally, as expected and consistent with the findings in the literature, the rate of change in employment, GMP, and population all positively affect the housing return.

[13] We exclude 8 observations from our regression analyses due to their outlier values for the scaled shock at the MSA-level.

Table 2 Effects of Labor Productivity Shocks on MSA-level Housing Price Returns

Panel A: All MSAs (With Year and Quarter Fixed Effects)

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lagged return	0.510***	0.456***	0.478***	0.482***
	(0.000)	(0.000)	(0.000)	(0.000)
2-year lagged return	0.073**	0.072**	0.069**	0.068**
	(0.024)	(0.019)	(0.025)	(0.029)
3-year lagged return	-0.149***	-0.121***	-0.138***	-0.147***
	(0.000)	(0.000)	(0.000)	(0.000)
MSA_scaled_shock	1.580	1.066	0.570	2.587*
	(0.289)	(0.402)	(0.646)	(0.065)
1-year lagged_MSA_scaled_shock	4.247**	3.592**	3.775**	4.931***
	(0.029)	(0.041)	(0.026)	(0.009)
2-year lagged_MSA_scaled_shock	2.259	2.797**	2.665**	3.101**
	(0.111)	(0.030)	(0.047)	(0.014)
Employment growth rate		0.516***		
		(0.000)		
GMP growth rate			0.248***	
			(0.000)	
Population growth rate				0.624***
				(0.000)
Constant	0.020***	0.014***	0.009***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	48,846	48,846	48,846	48,846
Adjusted R-squared	0.5265	0.5574	0.5468	0.5412
YEAR FE	YES	YES	YES	YES
QTR FE	YES	YES	YES	YES
Clustering by MSA and quarter_count	YES	YES	YES	YES

Panel B: All MSAs (With State – Quarter_count Joint Fixed Effect)

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lagged return	0.273***	0.249***	0.258***	0.254***
	(0.000)	(0.000)	(0.000)	(0.000)
2-year lagged return	0.085***	0.084***	0.082***	0.081***
	(0.000)	(0.000)	(0.000)	(0.000)
3-year lagged return	-0.067***	-0.056***	-0.062***	-0.064***
	(0.000)	(0.002)	(0.001)	(0.001)
MSA_scaled_shock	-0.094	-0.394	-0.374	0.256
	(0.908)	(0.612)	(0.622)	(0.749)
1-year lagged_MSA_scaled_shock	3.058*	2.526*	2.494*	3.276**
	(0.051)	(0.067)	(0.082)	(0.029)
2-year lagged_MSA_scaled_shock	0.938	0.952	0.929	1.265
	(0.513)	(0.468)	(0.494)	(0.336)
Employment growth rate		0.324***		
		(0.000)		
GMP growth rate			0.167***	
			(0.000)	
Population growth rate				0.487***
				(0.000)
Constant	0.025***	0.021***	0.017***	0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	47,954	47,954	47,954	47,954
Adjusted R-squared	0.7761	0.7846	0.7818	0.7823
State-quarter_count FE	YES	YES	YES	YES
Clustering by MSA and quarter_count	YES	YES	YES	YES

Panel C: All MSAs (Including Only One Shock Variable, with Population Growth Rate Controlled)

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lagged return	0.482***	0.254***	0.493***	0.257***
	(0.000)	(0.000)	(0.000)	(0.000)
2-year lagged return	0.068**	0.081***	0.065**	0.077***
	(0.029)	(0.000)	(0.038)	(0.000)
3-year lagged return	-0.147***	-0.064***	-0.151***	-0.068***
	(0.000)	(0.001)	(0.000)	(0.000)
1-year lagged_MSA_scaled_shock	4.763***	3.212**	4.640**	3.173**
	(0.007)	(0.028)	(0.011)	(0.035)
Population growth rate	0.622***	0.487***		
	(0.000)	(0.000)		
1-year lagged population growth rate			0.365***	0.301***
			(0.000)	(0.000)
Constant	0.015***	0.020***	0.017***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	48,846	47,954	48,846	47,954
Adjusted R-squared	0.5410	0.7823	0.5316	0.7785
Year FE and quarter FE	YES		YES	
State-quarter_count FE		YES		YES
Clustering by MSA and quarter_count	YES	YES	YES	YES

Panel D: 65 MSAs That Have Top 100 Dominant Firms

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lagged return	0.561***	0.360***	0.567***	0.364***
	(0.000)	(0.000)	(0.000)	(0.000)
2-year lagged return	0.014	0.038	0.010	0.029
	(0.688)	(0.278)	(0.784)	(0.419)
3-year lagged return	-0.117***	-0.037	-0.119***	-0.040
	(0.000)	(0.206)	(0.000)	(0.163)
1-year lagged_MSA_scaled_shock	4.202**	3.226*	4.082**	3.353*
	(0.011)	(0.069)	(0.014)	(0.074)
Population growth rate	0.651***	1.024***		
	(0.000)	(0.000)		
1-year lagged population growth rate			0.405***	0.643***
			(0.001)	(0.000)
Constant	0.014***	0.015***	0.017***	0.018***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	9,266	6,077	9,266	6,077
Adjusted R-squared	0.5756	0.8124	0.5680	0.8048
Year FE and quarter FE	YES		YES	
State-quarter_count FE		YES		YES
Clustering by MSA and quarter_count	YES	YES	YES	YES

Panel E: 65 MSAs That Have Top 100 Dominant Firms, Excluding 6 MSAs with Dominant Real Estate/Construction-Related Firms

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lagged return	0.559***	0.358***	0.564***	0.350***
	(0.000)	(0.000)	(0.000)	(0.000)
2-year lagged return	0.014	0.054	0.010	0.046
	(0.687)	(0.174)	(0.772)	(0.255)
3-year lagged return	-0.117***	-0.042*	-0.119***	-0.042*
	(0.000)	(0.071)	(0.000)	(0.071)
1-year lagged_MSA_scaled_shock	3.374**	2.732	3.136*	2.845
	(0.050)	(0.154)	(0.068)	(0.150)
population growth rate	0.728***	0.957***		
	(0.000)	(0.000)		
1-year lagged population growth rate			0.479***	0.700***
			(0.000)	(0.000)
Constant	0.014***	0.016***	0.017***	0.019***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8,358	5,060	8,358	5,060
Adjusted R-squared	0.5769	0.8293	0.5688	0.8246
Year FE and quarter FE	YES		YES	
State-quarter_count FE		YES		YES
Clustering by MSA and quarter_count	YES	YES	YES	YES

Panel F: All MSAs Excluding MSAs That Are Across Multiple States

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lagged return	0.480***	0.252***	0.490***	0.255***
	(0.000)	(0.000)	(0.000)	(0.000)
2-year lagged return	0.063**	0.078***	0.060*	0.074***
	(0.046)	(0.000)	(0.060)	(0.000)
3-year lagged return	-0.147***	-0.063***	-0.151***	-0.067***
	(0.000)	(0.001)	(0.000)	(0.000)
1-year lagged_MSA_scaled_shock	5.603**	3.977**	5.412**	3.899*
	(0.017)	(0.047)	(0.023)	(0.055)
Population growth rate	0.641***	0.488***		
	(0.000)	(0.000)		
1-year lagged population growth rate			0.375***	0.300***
			(0.000)	(0.000)
Constant	0.014***	0.020***	0.017***	0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	43,063	42,162	43,063	42,162
Adjusted R-squared	0.5392	0.7836	0.5291	0.7798
Year FE and quarter FE	YES		YES	
State-quarter_count FE		YES		YES
Clustering by MSA and quarter_count	YES	YES	YES	YES

Notes: Table 2 presents the results of the regression in Equation (6) to test the effects of labor productivity shocks on housing price changes at the MSA-level for the sample period of 1980-2017, in the six panels. Return is an HPI quarterly return at the MSA-level, and 1-year lagged return, 2-year lagged return and 3-year lagged return are its 1-year, 2-year and 3-year lagged terms, respectively. GMP growth rate, employment growth rate, population growth rate and 1-year lagged population growth rate are the year-on-year change rates at the MSA-level measured quarterly. MSA_scaled_shock is the labor productivity shock at the firm-level aggregated over all firms domiciled in an MSA, and 1-year lagged_MSA_scaled_shock and 2-year lagged_MSA_scaled_shock are its 1-year and 2-year lagged terms, respectively. Year FEs are the year fixed effects. Quarter FEs are the fixed effects of 1st, 2nd, 3rd, and 4th quarters in a year. State-quarter_count FEs are the state and quarter_count joint fixed effects, where quarter_count includes 152 quarters for 38 years of the data (1980-2017). P-values are in the parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

The results in Panel A show that the scaled shock variables at the MSA-level have positive coefficients in all of the specifications, and additionally, the 1-year and/or the 2-year lagged term is mostly significant at the 1-5% levels. In the specification of Equation (4), when the population growth rate is used to control for local economic conditions, all three shock variables are significantly positive, but the 1-year lagged term appears to be the most influential shock variable based on the coefficient magnitude and the significance level. Furthermore, the overall effect of the three shock variables is higher than that in the other regression specifications. This is probably because the local employment and local GMP growth rates might be related to the local productivity shocks of the dominant firms, so their presence in the regressions might reduce the effects of the productivity shocks. In general, our results are in line with the prediction of **Hypothesis 1** that the housing return increases in the current and/or previous year of the scaled productivity shocks of the local dominant firms. Specifically, the results indicate that generally, it takes about one year or more for the productivity shocks of the dominant firms in an area to influence the local housing price changes; additionally, the population growth rate may be a better control variable for local economic changes than employment and GMP growth rates, either of which might be related to the local productivity shocks of the dominant firms.

We then conduct several robustness tests, with their results reported in other panels of Table 2. Panel B is similar to Panel A except that the fixed effect is the joint fixed effect of the state-quarter count (instead of the year and quarter fixed effects). As mentioned earlier, this joint fixed effect controls for variations in the economic conditions (observed and unobserved) across states and time. We find that the 1-year lagged MSA scaled shock is significantly positive in all four specifications at a significance level of 5-10%, and the effect is the highest when the local population growth rate is used to control for the local economy (based on the coefficient size and significance level). The current and 2-year lagged shock coefficients are not significant in this panel.

The previous panels (especially Panel B) indicate the dominance of the 1-year lagged shock term among all three shock variables in affecting the local housing returns at the MSA-level. In addition, the population growth rate is a better control variable for local economic changes than the other local factors, such as the employment and GMP growth rates, as the latter might be related to the productivity shocks. Correspondingly, we conduct another robustness test by re-estimating the regression in Equation (6) to include this 1-year lagged term as the only shock variable, controlling for the population growth rate. The results are reported in the regression specifications of Equations (1) and (2) of Panel C, with the two regression specifications corresponding to the different sets of fixed effects. We find that the 1-year lagged scaled shock is positive at a 1-5% significant level in both specifications.

Note that in the regressions so far, the population growth rate is included to control for the local economic changes that may affect the concurrent local house price movements, and it is the only explanatory variable without time lags in the regressions. The natural question is, could it also have a delayed influence on the local housing markets? To answer this question, we develop regression specifications of Equations (3) and (4) in Panel C by replacing the population growth rate with its 1-year lagged term. We find that the coefficient of this lagged term is still positive but with a noticeably smaller magnitude than in the specifications of Equations (1) and (2) (0.365 vs. 0.622 when year and quarter fixed effects are included, and 0.301 vs. 0.487 when the joint state and quarter count fixed effects are included). Nevertheless, the coefficients of the lagged population growth rate are still 1% significant. More importantly, the effect of the 1-year lagged shock variable remains positive at the 5% significance level. The results of the specifications of Equations (3) and (4) are interesting because they indicate the possibility of forecasting housing price movements based on recent local housing price changes, the productivity shocks of large firms and economic growth.

Given that only 65 MSAs in our sample have ever had at least one top 100 dominant firm in at least one year in our sample period, we re-estimate the regressions in Panel C by using only these 65 MSAs. The results are shown in Panel D, and generally similar to those in Panel C, with the 1-year lagged scaled shock term significant at the 5-10% levels.

Furthermore, in the list of firms that have been one of the top 100 dominant firms, there are seven firms that are in the real estate and/or construction related sector, including Home Depot, Lowe's, Caterpillar, Fluor, Halliburton, Lennar, and PulteGroup. They are headquartered in 6 MSAs, including Atlanta, Charlotte, Chicago, Dallas, Houston and Miami. To reduce the possible influence of these real estate dominant firms on the relation between productivity shocks of the dominant firms and local real estate housing market changes, we re-estimate the regressions in Panel D for the panel data of the 65 MSAs that ever had top 100 firms, but excluding these 6 MSAs that have real estate/construction related dominant firms. As reported in Panel E, the coefficient of the 1-year lagged scaled shock term is smaller in magnitude and less significant compared to the results in Panel D, but still significant at the 5-10% level for two of the four regression specifications. These results indicate that including real estate/construction-related firms does enhance the relation between productivity shock and real estate, but is not the only driver of this relation.

Finally, an MSA could span some parts of adjacent states, such as New York-Jersey City-White Plains, NY-NJ (MSAD), and Washington DC-Arlington-Alexandria, Washington DC-VA-MD-WV (MSAD). For this kind of MSA, we define its state (when determining the fixed effect of its state-quarter count) as the headquarters state of the largest dominant firm in this MSA. To reduce the possible bias in the results due to the cross-state nature of these MSAs, other than the fixed effect of the state-quarter count, we also control for the MSA-level economic factors (such as population growth rate at the MSA-level) in the regressions. In addition, we conduct a robustness test to further determine the validity by re-estimating the regressions in Panel C for the data of all the MSAs except those across multiple states. As reported in each regression specification of Panel F, the coefficient of the 1-year lagged scaled shock term remains positive and significant at the 5-10% level while the sample size is reduced by about 10%.

4.1.2 Alternative Econometric Methods

Two-Stage Regressions

As mentioned earlier, there is evidence in the literature that local housing markets may affect business performance, thus indicating a potential reverse causality from house prices to local businesses. To address this issue, the independent variables in our main tests include a 1-year lag of the productivity shock variable at the MSA-level which precedes the dependent variable, that is, the contemporaneous housing return. To further address the causality concern, we also develop a two-stage robustness test. In the first stage, we estimate the regression of 1-year lagged MSA scaled shocks on 1-year, 2-year and 3-year lagged housing returns - the explanatory variables included in the housing return regression in Equation (6). In the second stage, we estimate the housing return regression in Equation (6) but with only two explanatory variables: the residual from the first stage shock regressions, which reflects the aggregated labor productivity shocks of the dominant firms at the MSA-level that cannot be explained by historical local housing returns, and a control variable for local economic changes. In both stages, we control for the year/quarter dummies or the state-quarter count dummies, and heteroscedasticity with two-way (MSA and quarter count) clustered standard errors. The results are listed in Table 3.

The results of the first stage regression do not suggest any significant impact of the historical local housing returns on the aggregate level of productivity shock of the local dominant firms, with the adjusted R-square of each regression specification close to zero. In the second stage, the coefficients of the residual shock variable are similar to those of the shock variable in the one-stage regressions reported in Panel C. The coefficient of the residual of the 1-year lagged MSA scaled shock is positive, with a magnitude of 3.2 to 5.3, and significant at 5% in each regression specification.

In other words, after removing a small amount of a local productivity shock that could be associated with contemporaneous and lagged housing returns, the remainder of the shock variable is still significantly linked with the housing returns, which agrees with our main findings. This further supports our argument that the causality most likely flows from the productivity shocks of the dominant firms to the local housing returns.

Table 3 Robustness Test with Two-Stage Regressions for All MSAs

[First Stage Regression] Dependent Variable – 1-year lagged_MSA_Scaled_Shock

VARIABLES	(1) & (3)	(2) & (4)
1-year lagged return	0.001	-0.001
	(0.927)	(0.471)
2-year lagged return	-0.001	-0.001
	(0.414)	(0.307)
3-year lagged return	0.001*	0.001
	(0.051)	(0.649)
Constant	0.001	0.001
	(0.889)	(0.232)
Observations	48,861	47,975
Adjusted R-squared	0.0023	-0.0143
Year FE and quarter FE	YES	
State-quarter_count FE		YES
Clustering by MSA and quarter_count	YES	YES

[Second Stage Regression] Dependent Variable – Housing Return

VARIABLE	(1)	(2)	(3)	(4)
1-year lagged_MSA_scaled shock: first stage regression residual	5.187**	3.254**	5.322**	3.262**
	(0.018)	(0.025)	(0.017)	(0.028)
Population growth rate	1.029***	0.600***		
	(0.000)	(0.000)		
1-year lagged population growth rate			0.842***	0.472***
			(0.000)	(0.000)
Constant	0.024***	0.029***	0.026***	0.030***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	48,846	47,954	48,846	47,954
Adjusted R-squared	0.3766	0.7615	0.3639	0.7580
Year FE and quarter FE	YES		YES	
State-quarter_count FE		YES		YES
Clustering by MSA and quarter_count	YES	YES	YES	YES

Notes: Table 3 presents the results of the two-stage regressions to explore the causality in the relationship between shock and housing return for the sample period of 1980-2017. The first-stage is a regression of the 1-year lagged scaled shocks at the MSA-level. The second-stage is a regression of housing return. Return is the HPI quarterly return at the MSA-level, and 1-year lagged return, 2-year lagged return and 3-year lagged return are its 1-year, 2-year and 3-year lagged terms, respectively. Population growth rate and 1-year lagged population growth rate are the year-on-year rate of change at the MSA-level in the population measured quarterly and its 1-year lagged term. 1-year lagged_ MSA_scaled_shock is the 1-

year lagged labor productivity shock at the firm-level aggregated over all firms domiciled in an MSA. Year FEs are the year fixed effects. Quarter FEs are the fixed effects of 1st, 2nd, 3rd, and 4th quarters in a year. State-quarter_count FEs are the joint fixed effect of state and quarter_count, where quarter_count includes 152 quarters for 38 years of the data (1980-2017). P-values are in parentheses. * significant at 10%; ** significant at 5%; and *** significant at 1%.

Matching Sample Method

To address the concern that productivity shock variables might be correlated with other housing market determinants, thus resulting in the productivity shock being coincidental with or influenced by the variation in housing markets, we use a matching sample method as another robustness test. As discussed earlier, in all of the main tests, we incorporate very restrictive joint fixed effects for the state-quarter count to control for the variations of the economic conditions (observed and unobserved) across different combinations of state-quarter counts. These fixed effects, however, might not control for the omitted variables that vary across MSAs within each state-quarter count. To mitigate this concern, we implement a coarsened exact matching procedure (Blackwell et al., 2009) to create a subsample with more homogenous treated and control observations. We match an MSA with productivity shock (a treated observation) with MSAs without productivity shock (control observations) that have similar economic characteristics. Specifically, for each quarter, we divide MSAs in each of the U.S. Census Bureau-designated divisions into 25 bins based on their annual population growth rate of the previous year (quintiles from low to high) and annual GMP growth rate (quintiles from low to high)[14]. Then, we match each MSA with productivity shock to MSAs without productivity shock if they are from the same state and in the same bin[15]. MSAs with productivity shock that have no match are dropped from the sample. The results are presented in Table 4.

Panel A shows that the matching procedure results in a reasonably well-balanced matched sample. The matched sample includes 3,013 treated and 4,645 control observations. Their means and medians are not significantly different. Panel B reports the results of the regression in Equation (6) with the matched sample. Given that we have used the population and GMP growth rates to match the MSAs, the control variable for local economic changes in the regression of Panel B is the employment growth rate or its 1-year lagged term. In general, the effects of the 1-year lagged scaled shock at the MSA-level are positive and significant in all of the regression specifications.

---

[14] https://en.wikipedia.org/wiki/List_of_regions_of_the_United_States. The U.S. Census Bureau defines four statistical regions. Each region consists of two or three divisions which result in a total of 9 divisions.

[15] The small number of MSAs in most states prevent us from dividing MSAs within each state into bins.

Table 4 Robustness Test with Matching Sample Approach for All MSAs

Panel A: Comparison Between MSA with Shock and Matched MSA without Shock

	Mean			Median		
	Treated (N=3013)	Untreated (N=4645)	p-value for difference	Treated (N=3013)	Untreated (N=4645)	p-value for difference
GMP growth rate (%)	5.64	5.73	0.38	5.48	5.56	0.65
Population growth rate (%)	1.04	1.08	0.20	0.84	0.86	0.75

Panel B: Regression of Housing Return Using Matched Sample

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lagged return	0.5107***	0.2530***	0.5253***	0.2399***
	(0.000)	(0.000)	(0.000)	(0.000)
2-year lagged return	0.0277	0.0456	0.0225	0.0365
	(0.484)	(0.126)	(0.585)	(0.203)
3-year lagged return	-0.1070***	-0.0282	-0.1330***	-0.0323
	(0.000)	(0.335)	(0.000)	(0.269)
1-year lagged_MSA_scaled_shock	3.0503*	1.6772*	3.3713**	2.2958**
	(0.064)	(0.083)	(0.034)	(0.029)
Employment growth rate	0.6490***	0.4433***		
	(0.000)	(0.000)		

(Continued…)

(Panel B Continued)

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lag employment growth rate			0.3326***	0.3684***
			(0.000)	(0.000)
Constant	0.0142***	0.0235***	0.0189***	0.0254***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6825	6,654	6825	6,654
Adjusted R-squared	0.6481	0.8520	0.6255	0.8492
Year FE and quarter FE	YES		YES	
State-quarter_count FE		YES		YES
Clustering by MSA and quarter_count	YES		YES	YES

Notes: Table 4 reports the results of matching sample regressions. Matched sample is created via the coarsened exact matching procedure (Blackwell et al., 2009). For every quarter, the MSAs in each of the U.S. census bureau-designated divisions are divided into 25 bins based on the annual population growth rate (quintiles from low to high) and annual GMP growth rate (quintiles from low to high) of the previous year. Then, an MSA with productivity shock is matched to MSAs without productivity shock if they are from the same state and are in the same bin. Panel A compares MSAs with productivity shock (treated observations) and their matched MSAs without productivity shock (untreated observations). T-test (Wilcoxon ranksum test) is used to test the difference in mean (median). Panel B reports the results of regressions following Equation (6), but using the matched sample. Return is the HPI quarterly return, at the MSA-level and 1-year lagged return, 2-year lagged return and 3-year lagged return are its 1-year, 2-year and 3-year lagged terms, respectively. GMP growth rate, population growth rate and employment growth rate are the rate of change year-on-year at the MSA-level measured quarterly. 1-year lag employment growth rate is the 1-year lagged term of the employment growth rate. 1-year lagged_MSA_scaled_shock is the 1-year lagged term of the labor productivity shock at the firm-level aggregated over all firms domiciled in an MSA. Year FEs are the year fixed effects. Quarter FEs are the fixed effects of 1st, 2nd, 3rd, and 4th quarters in a year. State-quarter_count FEs are the joint fixed effect of the state and quarter_count, where quarter_count includes 152 quarters for 38 years of the data (1980-2017). P-values are in the parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

4.1.3 Economic Significance

Are these effects of productivity shocks of the dominant firms economically significant? To answer this question, we use the results in Panel D of Table 2 as an example. The regression sample includes 65 MSAs that have hosted at least one top 100 dominant firm during at least one year in our sample period. For this sample, the standard deviation of the key independent variable, the 1-year lagged scaled shock at the MSA-level, is 0.000385. We assume that the median house value of these 65 MSAs in the 4th quarter of 2017 is $250,000 (or more)[16]. The result of the regression specification in Equation (1) of Panel D indicates that one standard deviation increase in the 1-year lagged scaled shock at the MSA-level is associated with an average of at least a $380 current-year value appreciation for a representative house with a value equal to this median house value. In addition, this impact on the current housing return will also extend to the housing return of the following year which is correlated with that of the current year, which means that a one standard deviation increase is associated with at least a $213 value appreciation for this house in the following year. The productivity shocks may also generate indirect effects on local housing prices by influencing other local economic factors such as employment, GMP and population. The combination of direct and indirect effects of one standard deviation of the scaled shock at the MSA-level may lead to an accumulated house appreciation of close to $1000 per year, which is not a trivial number. This also means that the productivity shocks of the dominant firms can potentially bring a significant amount of aggregate property tax income increase to the local government.

In summary, our regression results at the MSA-level in Tables 2, 3 and 4 generally confirm the prediction in Hypothesis 1 that, overall, housing return increases in the scaled productivity shocks of the current year and/or previous years of local dominant firms. They also suggest that it generally takes about one year or more for the shocks to reach the local MSA housing markets.

4.2 Effects on Local Zipcode Housing Price

Table 5 shows the results of the tests for the effects of labor productivity shocks at the firm-level on neighboring zipcode housing returns. We include the current scaled productivity shock of dominant firms at the zipcode-level and its

---

[16] See article titled "Average Home Seller Profits at 10-Year High of $54,000 in Q4 2017" by ATTOM Team, at ATTOM on January 30, 2018, available at: Home Sales Report 2017 (attomdata.com), which states that the "U.S. median home price in 2017 was $235,000". Since the 65 MSAs used to host top 100 dominant firms, their housing markets are likely to be more expensive than in other places of the U.S., so it is reasonable for us to assume that their median home value in 2017 is at least $250,000, which is a little bit higher than the U.S. average.

1-year and 2-year lagged terms. The control variable for the local economic situation is the annual growth rate of the local population, which is proxied by the population growth rate of the MSA where the zipcode is located, due to the lack of sufficient data for the population at the zipcode-level.

Panel A lists the results when dominant firms are defined as the top 100 firms by revenue headquartered in approximately 205 zipcodes[17]. Five regression specifications are presented, with the dependent variables being the ZHVI returns, which are the annual rate of change of the ZHVI for homes within a 1-mile[18], 5-mile, 10-mile, 20-mile and 30-mile radius from the center of the zipcode. We find that the ZHVI returns exhibit a short-term momentum and a long-term reversal, as they are positively related to their 1-year lagged terms and negatively related to their 2-year and/or 3-year lagged terms, all at the 1% significance level. The local population growth rate is also positively related to the ZHVI returns at the 1% significance level. Interestingly, the current shock variable is positive at the 1% to 5% significance levels, while the 1-year and 2-year lagged shock variables are insignificant. This is different from our earlier finding that only the 1-year lagged shock variable is significantly positive in the regressions at the MSA-level. A possible explanation is that the influence of a large firm propagates more rapidly over its immediate neighborhood than over a larger geographical area. We also find that the magnitude of the current shock variable coefficient persistently declines when the radius from the center increases. Intuitively, the influence of the productivity shocks at the zipcode-level may decay with the housing markets more distant from the epicenter of the shocks.

To resolve the problem that there might be too few zipcodes in the sample of top 100 firms, we conduct a robustness test by defining dominant firms as the top 1000 firms by revenue headquartered in 1,426 zipcodes. The corresponding results are listed in Panel B, which are in general, similar to those in Panel A. Our findings suggest that the productivity shocks of the dominant firms can affect their immediate neighborhoods quickly, and after one year or more, the influence will be diffused to the local MSA housing prices, thus indicating that the geographic range of the influence of dominant firms is substantial.

[17] Differences in the MSA sample are due to a shorter sampling period and different zipcode coverage by the ZHVI database.

[18] We thank a discussant for suggesting the use of a 1-mile radius specification. The 1-mile radii mostly contain zipcodes themselves, hence these regressions essentially use the zipcode returns of the firm headquarters.

Table 5 Effects of Labor Productivity Shocks on Neighboring Zipcode Housing Returns

Panel A: Dominant Firms Are Top 100 Firms

	(1) zip_1m_ret	(2) zip_5m_ret	(3) zip_10m_ret	(4) zip_20m_ret	(5) zip_30m_ret
1-year lag zip_1m_ret	1.192*** (0.000)				
2-year lag zip_1m_ret	-0.263*** (0.000)				
3-year lag zip_1m_ret	-0.110*** (0.000)				
1-year lag zip_5m_ret		1.252*** (0.000)			
2-year lag zip_5m_ret		-0.251*** (0.000)			
3-year lag zip_5m_ret		-0.129*** (0.000)			
1-year lag zip_10m_ret			1.327*** (0.000)		
2-year lag zip_10m_ret			-0.326*** (0.000)		
3-year lag zip_10m_ret			-0.111*** (0.000)		
1-year lag zip_20m_ret				1.403*** (0.000)	
2-year lag zip_20m_ret				-0.417*** (0.000)	
3-year lag zip_20m_ret				-0.084*** (0.010)	
1-year lag zip_30m_ret					1.490*** (0.000)
2-year lag zip_30m_ret					-0.532*** (0.000)
3-year lag zip_30m_ret					-0.045 (0.205)
MSA population growth rate	0.486*** (0.000)	0.339*** (0.000)	0.281*** (0.000)	0.219*** (0.000)	0.182*** (0.001)
zip_scaled_shock	1.139** (0.021)	1.050*** (0.002)	1.031*** (0.002)	0.944*** (0.001)	0.773*** (0.002)
1-year lagged_zip_scaled_shock	-0.788 (0.213)	-0.080 (0.739)	-0.175 (0.294)	-0.047 (0.760)	-0.006 (0.961)

(Continued…)

(Panel A Continued)

	(1) zip_1m_ret	(2) zip_5m_ret	(3) zip_10m_ret	(4) zip_20m_ret	(5) zip_30m_ret
2-year lagged_zip_scaled_shock	0.783 (0.229)	0.713 (0.123)	0.624 (0.157)	0.379 (0.284)	0.267 (0.331)
State-quarter_count FE	Yes	Yes	Yes	Yes	Yes
Clustering by MSA and quarter_count	Yes	Yes	Yes	Yes	Yes
N	5,232	5,890	6,047	6,053	6,053
Adjusted R^2	0.918	0.962	0.972	0.979	0.983

Panel B: Dominant Firms Are Top 1000 Firms

	(1) zip_1m_ret	(2) zip_5m_ret	(3) zip_10m_ret	(4) zip_20m_ret	(5) zip_30m_ret
1-year lag zip_1m_ret	1.229^{***} (0.000)				
2-year lag zip_1m_ret	-0.251^{***} (0.000)				
3-year lag zip_1m_ret	-0.125^{***} (0.000)				
1-year lag zip_5m_ret		1.313^{***} (0.000)			
2-year lag zip_5m_ret		-0.288^{***} (0.000)			
3-year lag zip_5m_ret		-0.135^{***} (0.000)			
1-year lag zip_10m_ret			1.366^{***} (0.000)		
2-year lag zip_10m_ret			-0.344^{***} (0.000)		
3-year lag zip_10m_ret			-0.122^{***} (0.000)		
1-year lag zip_20m_ret				1.450^{***} (0.000)	
2-year lag zip_20m_ret				-0.438^{***} (0.000)	
3-year lag zip_20m_ret				-0.101^{***} (0.001)	

(Continued…)

(Panel B Continued)

	(1) zip_1m_ret	(2) zip_5m_ret	(3) zip_10m_ret	(4) zip_20m_ret	(5) zip_30m_ret
1-year lag zip_30m_ret					1.536*** (0.000)
2-year lag zip_30m_ret					-0.561*** (0.000)
3-year lag zip_30m_ret					-0.056* (0.092)
MSA population growth rate	0.110** (0.039)	0.080* (0.061)	0.071* (0.068)	0.055* (0.081)	0.046* (0.085)
zip_scaled_shock	0.852*** (0.007)	0.700** (0.024)	0.696** (0.046)	0.652** (0.026)	0.528** (0.046)
1-year lagged_zip_scaled_shock	-0.503 (0.407)	-0.041 (0.861)	-0.118 (0.418)	-0.083 (0.544)	-0.074 (0.512)
2-year lagged_zip_scaled_shock	0.379 (0.584)	0.361 (0.390)	0.333 (0.369)	0.204 (0.472)	0.140 (0.510)
State-quarter_count FE	Yes	Yes	Yes	Yes	Yes
Clustering by MSA and quarter_count	Yes	Yes	Yes	Yes	Yes
N	42,308	45,668	46,225	46,518	46,554
Adjusted R^2	0.931	0.961	0.970	0.978	0.982

Notes: Table 5 reports the coefficient estimates for a regression of the average zipcode-level housing returns around the dominant firm zipcode for data during 1998-2017. Dominant firms are defined as top 100 firms by revenue in Panel A, and top 1000 firms by revenue in Panel B. Dependent variable zip_#m_ret is constructed as follows: circle with radius of # miles (#=1, 5, 10, 20 or 30) is plotted around the dominant firm headquarters zipcode centroid, then for this circle the year-over-year zipcode housing returns within the circle are averaged to build a housing price return index at the zipcode level following Hartman-Glaser et al. (2022). Year-over-year housing returns on the zipcode level are calculated quarterly from the monthly ZHVI. The independent variables include the 1-year, 2-year and 3-year lagged values of the zipcode-level returns for the appropriate circles; the current value and 1-year, 2-year and 3-year lagged values of Zip_scaled_shock (which is the labor productivity shock at the firm-level aggregated over all firms domiciled in a zipcode); and MSA population growth rate (which is the year-on-year population change rate at the MSA-level calculated in the 4th quarter). The regressions employ state and quarter_count (a year-quarter) fixed effects along with double clustering on the MSA and quarter_count following Petersen (2009). P-values are in parentheses. * significant at 10%; ** significant at 5%; and *** significant at 1%.

4.3 Effects of Locally Dominant Firms

In this section, we investigate the impact of the productivity shocks to locally (instead of nationally) dominant firms on housing returns[19]. Jannati et al. (2020) highlight the link between productivity shocks to large local firms and a significant portion of aggregate U.S. macroeconomic fluctuations. It is possible that productivity shocks to locally dominant firms could also be associated with local housing returns. To test this hypothesis, we replicate our main test by using the definition of a locally dominant firm in Jannati et al. (2020). We follow the sample selection criteria in Section 2 and remove firms located outside of the U.S. as well as oil, energy and financial firms. We also impose a requirement of positive sales and employee data for the years in the sample. Next, in each state and year, we categorize a firm as a locally dominant firm if it is in the top 10 firms headquartered in that state ranked by the sales in the previous year[20]. Then, we calculate its labor productivity, annual labor productivity growth, firm-specific component and scaled labor productivity shock as in Equations 1, 2, 3 and 4. In line with Section 2.1, we aggregate scaled productivity shocks for each MSA-year combination in the next step, to obtain the productivity shock of locally dominant firms at the MSA-level. As a final step, we run several regression specifications analogous to those in Panel C of Table 2.

Table 6 shows the results from the regression of productivity shocks to locally dominant firms at the MSA-level on housing price changes. Following the regression design in Panel C of Table 2, we implement year and quarter fixed effects in Columns (1) and (3) and fixed effects of state-quarter counts in Columns (2) and (4). Furthermore, in Columns (1) and (2), we control for the contemporaneous population growth and in Columns (3) and (4), for the lagged population growth. The results are broadly similar to our main test results in Section 4.1.1, with the 1-year lagged productivity shock being highly significant with p-values ranging from 0.033 to 0.097 in the different specifications. In comparing Table 6 with Panel C of Table 2, we observe that the magnitude of the shock coefficient of locally dominant firms is slightly smaller and p-values are somewhat larger but still significant, most likely reflecting wider variation in firm-level shocks as more smaller firms are included in the sample of locally dominant firms. In conclusion, the regression results of locally dominant firms provide additional evidence that support the link between firm productivity shocks and local housing returns, as elucidated in Section 4.1.1.

---

[19] We thank one of the anonymous referees for suggesting that we explore this issue.
[20] We use top 10 firms per state for the test to be broadly comparable to the main tests that use top 100 firms across all states. We also replicate our tests with locally dominant firms at the MSA-level and obtain similar results.

Table 6 Effects of Labor Productivity Shocks of Locally Dominant Firms on MSA-Level Housing Returns

VARIABLE	(1) return	(2) return	(3) return	(4) return
1-year lagged return	0.4980***	0.2542***	0.5090***	0.2567***
	(0.000)	(0.000)	(0.000)	(0.000)
2-year lagged return	0.0633**	0.0814***	0.0600*	0.0773***
	(0.047)	(0.000)	(0.061)	(0.000)
3-year lagged return	-0.1462***	-0.0639***	-0.1505***	-0.0676***
	(0.000)	(0.000)	(0.000)	(0.000)
1-year lagged_MSA_scaled_shock	3.2687**	2.0379*	3.1709**	2.0337*
	(0.033)	(0.088)	(0.041)	(0.097)
Population growth rate	0.6129***	0.4864***		
	(0.000)	(0.000)		
1-year lagged population growth rate			0.3519***	0.3003***
			(0.000)	(0.000)
Observations	48,854	48,854	48,854	48,854
Adjusted R-squared	0.5643	0.7848	0.5548	0.7809
Year FE and Quarter FE	YES		YES	
State-quarter_count FE		YES		YES

Notes: Table 6 presents the results of the regression in Equation (6) to test the effects of labor productivity shocks of the top 10 locally dominant companies on housing price changes at the MSA-level for the sample period of 1980-2017. We define locally dominant companies as the top 10 companies ranked by lagged sales every year in each state. *Return* is the HPI quarterly return at MSA-level, and *1-year lagged return*, *2-year lagged return* and *3-year lagged return* are its 1-year, 2-year and 3-year lagged terms, respectively. *Population growth rate* and *1-year lagged population growth rate* are the rate of change year-on-year of the population measured quarterly and its 1-year lag respectively. *1-year lagged_MSA_scaled_shock* is the 1-year lagged the labor productivity shock at the firm-level aggregated over all locally dominant firms domiciled in an MSA. *Year FE*s are the year fixed effects. *Quarter FE*s are the fixed effects of 1st, 2nd, 3rd, and 4th quarters in a year. *State-quarter_count FEs* are the joint fixed effect of state and quarter_count, where quarter_count includes 152 quarters for 38 years of the data (1980-2017). *P*-values are in parentheses. * significant at 10%; ** significant at 5%; and *** significant at 1%.

4.4 Subsample Comparisons

In this section, we will show if there is any cross-area heterogeneity or time variation in the influence of productivity shocks of dominant firms on their local housing markets, by comparing the regression results for the various subsamples of our main sample.

4.4.1 High-Tech Versus Non-High-Tech Dominated MSAs

We first explore the possible cross-area heterogeneity in the productivity shock – housing return relationship, especially for high-tech and non-high-tech dominated MSAs. This is interesting because it will help us to compare the effects of different labor productivity shocks; that is, those driven by technology changes and those by other factors (such as layoffs, etc.). Our data does not provide any direct clue on the types of labor productivity changes of a dominant firm, so we design an indirect analysis to explore this issue. First, we categorize each dominant firm as a high-tech firm if its SIC belongs to the "Office of Technology" (i.e., SIC codes 3510 to 3590, 4812 to 4899, and 7370 to 7374) or has one of the other high-tech SIC codes (i.e., 3600 to 3695, 5045, 5731 to 5734, 7377, and 7385), or as a non-high-tech firm otherwise. Subsequently, we define each MSA of the 65-MSA sample (which includes MSAs that have dominant firms during the sample period) as a high-tech dominated MSA if the high-tech firm count in its top 100 dominant firm count during the sample period of 1980-2017 is at least 50%, and as a non-high-tech dominated MSA otherwise. We then run the regression in Equation (6) for each of these two subsamples and report the results in Table 7. The difference between the results of the two subsamples is quite substantial. The 1-year lagged shock variable has a much larger coefficient in the high-tech dominated MSA subsample than in the non-high-tech dominated MSA subsample, which is 20.094 and 2.722, respectively, and both being 5% significant. For a robustness test, in an unreported regression similar to the ones in Table 7 but including the interaction of the high-tech MSA dummy with the 1-year lagged shock variable, the interaction term is 13.297 with a 5% significance. When we change the cutoff of the proportion of high-tech dominant firm count for the high-tech dominated MSAs from 50% to 100%, the interaction term is 16.235 with a 1% significance. These imply that the labor productivity shocks related to high-tech firms might be much more influential than those unrelated to high-tech firms. In other words, technology-driven productivity changes may result in more powerful spillovers than those driven by other factors.

Table 7 High-Tech Versus Non-High-Tech Dominated MSAs – for 65 MSAs That Have Top 100 Dominant Firms

VARIABLE	(1) return in high-tech dominated MSAs	(2) return in non high-tech dominated MSAs
1-year lagged return	0.247	0.355***
	(0.119)	(0.000)
2-year lagged return	0.025	0.048
	(0.715)	(0.234)
3-year lagged return	0.048	-0.024
	(0.515)	(0.435)
1-year lagged_MSA_scaled_shock	20.094**	2.722**
	(0.025)	(0.044)
Population growth rate	1.506**	0.911***
	(0.012)	(0.000)
Constant	0.006	0.014***
	(0.673)	(0.000)
Observations	582	4,503
Adjusted R-squared	0.8321	0.8193
State-quarter_count FE	YES	YES
Clustering by MSA and quarter_count	YES	YES

Notes: Table 7 presents the results of the regression in Equation (6) to compare the effects of labor productivity shocks on housing price changes at the MSA-level for high-tech dominated and non-high-tech dominated MSAs during the sample period of 1980-2017. First, a dominant firm is categorized as a high-tech firm if its SIC belongs to the "Office of Technology" (i.e., SIC codes 3510 to 3590, 4812 to 4899, and 7370 to 7374) or has one of the other high-tech SIC codes (i.e., 3600 to 3695, 5045, 5731 to 5734, 7377, and 7385), and categorized as a non-high-tech firm otherwise. Subsequently, an MSA is defined as a high-tech dominated MSA if the proportion of high-tech firm count in its top 100 dominant firm count during the sample period of 1980-2017 is at least 50%, and as a non-high-tech dominated MSA otherwise. Return is the HPI quarterly return at the MSA-level, and 1-year lagged return, 2-year lagged return and 3-year lagged return are its 1-year, 2-year and 3-year lagged terms, respectively. Population growth rate is the rate of change year-on-year at the MSA-level in population measured quarterly. 1-year lagged_MSA_scaled_shock is the 1-year lagged the labor productivity shock at the firm-level aggregated over all firms domiciled in an MSA. State-quarter_count FEs are the joint fixed effect of state and quarter_count, where quarter_count includes 152 quarters for 38 years of the data (1980-2017). P-values are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

4.4.2 Expansion Versus Contraction Periods

We now want to know if there is any time variation in the influence of productivity shocks of the dominant firms on their local housing markets, especially during economic expansions as compared to economic contractions. Correspondingly, we divide our sample of 65 MSAs that have hosted top 100 dominant firms into two subsamples: the "expansion" and the "contraction" subsamples. Each quarter in our sample period 1980-2017 is categorized into the "expansion" or "contraction" period based on the definitions of "expansion" and "contraction" by the National Bureau of Economic Research (NBER)[21]. We then run the regression in Equation (6) for both subsamples and report the results in Table 8. We find that there are many more quarters in the "expansion" rather than the "contraction" subperiods, with subsample sizes of 5,292 and 785 observations, respectively. The 1-year lagged shock variable has a 10% significant coefficient of 3.444 for the expansion subsample while appearing insignificant for the contraction subsample. In other words, the productivity shocks of dominant firms are more influential on the local housing markets during economic booms than downturns. This difference may be due to the short-sell constraints and disposition effects in the housing markets, which make housing market investors less active in selling houses when facing negative economic shocks as compared to buying houses when facing positive economic shocks. It could be further intensified by the traditional commission contract used in the U.S. with the house seller taking the obligation to pay the commission fees to both the seller and buyer agents in a house transaction, which makes a house sale particularly costly to the house owner.

4.5 Possible Channel – Spillover

In this section, we will elaborate on a test that explores a possible channel through which the labor productivity shocks of dominant firms affect their local housing markets, that is, the "spillover channel" mentioned earlier. More specifically, we will provide a possible determinant of the magnitude of the productivity shock-housing return relationship - the closeness of local industry links, which is a reflection of the strength of the spillovers from the dominant firms to their related local firms. When dominant firms have closer links to their local non-dominant industry peers, intuitively, the productivity shocks of the dominant firms will have larger industry spillover effects on their non-dominant industry peers, thus yielding more prominent cumulative effects on the local housing market. We, hence, implement the regression in Equation (7) to test Hypothesis 2 that the effects in Hypothesis 1, that is, the effects of the productivity shocks of dominant firms on the local housing price changes, are amplified by a closer local industry link.

---

[21] NBER expansion and contraction classification can be found at https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions

We regress the housing returns at the MSA-level on the explanatory variables in Table 2, as well as the local industry link and its interaction with the productivity shocks variables. Given that Table 2 reports that the productivity shocks of dominant firms exhibit the most noticeable impact on the local housing price changes with a one-year lag, our regressions include the interaction term between the industry link and the 1-year lagged scaled productivity shock. In our full sample, out of over 40,000 MSA-quarter observations, only 1,790 have non-zero industry links, and they also appear in the sample of 65 MSAs that ever hosted top 100 dominant firms. These observations are included in this regression. Table 9 exhibits the results of two regression specifications that differ in the included local economic variable, population growth rate or its 1-year lagged term. The regressions incorporate the state and quarter-count joint fixed effect. The standard errors are adjusted for MSA and quarter-count clustering.

We find that in both regression specifications, the interaction term has a large, positive coefficient with a magnitude above 33 at the 10% significance level. This finding generally confirms a positive interaction between the closeness of the local industry link and the productivity shock–housing return relationship predicted in Hypothesis 2. On the other hand, the 1-year lagged scaled productivity shock itself no longer has any independent role in determining the housing price changes. These results suggest that the productivity shocks of the dominant firms affect the local housing markets mainly through their spillover effects to other related firms in the local areas. In practice, many dominant firms may have a business sphere of influence beyond their immediate MSAs where their headquarters are located, as, for instance, most of their employees may work and live in other MSAs, or their products are primarily sold to other MSAs. As a result, their productivity shocks might not necessarily be highly associated with the local housing markets. However, if these firms have close business relations with other firms near their headquarters, their shocks may spillover to these related firms, whose business may be more concentrated in the local areas, eventually resulting in a robust indirect response from the local housing markets.

Table 8 Expansion Versus Contraction Periods – For 65 MSAs That Have Top 100 Dominant Firms

VARIABLE	(1) return in expansion	(2) return in contraction
1-year lagged return	0.379***	0.247*
	(0.000)	(0.068)
2-year lagged return	0.074*	-0.167*
	(0.039)	(0.097)
3-year lagged return	-0.030	-0.085
	(0.326)	(0.251)
1-year lagged_MSA_scaled_shock	3.444*	-0.506
	(0.084)	(0.938)
Population growth rate	1.018***	1.062***
	(0.000)	(0.001)
Constant	0.016***	0.012*
	(0.000)	(0.092)
Observations	5,292	785
Adjusted R-squared	0.8081	0.8236
State-quarter_count FE	YES	YES
Clustering by MSA and quarter_count	YES	YES

Notes: Table 8 presents the results of the regression in Equation (6) to compare the effects of labor productivity shocks on housing price changes at the MSA-level in expansion and contraction periods during the sample period of 1980-2017. A year-quarter in the sample period belongs to an "expansion" period or a "contraction" period based on the definitions of "expansion" or "contraction" of the national economy by the National Bureau of Economic Research (NBER) at https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions. Return is the HPI quarterly return at the MSA-level, and 1-year lagged return, 2-year lagged return and 3-year lagged return are its 1-year, 2-year and 3-year lagged terms, respectively. Population growth rate is the rate of change year-on-year at the MSA-level in the population measured quarterly. 1-year lagged_MSA_scaled_shock is the 1-year lagged the labor productivity shock at the firm-level aggregated over all firms domiciled in an MSA. State-quarter_count FEs are the joint fixed effect of state and quarter_count, where quarter_count includes 152 quarters for 38 years of the data (1980-2017). P-values are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9 Effect of Industry Link – For All MSAs (With Same Results for 65 MSAs That Have Top 100 Dominant Firms)

VARIABLE	(1) return	(2) return
1-year lagged return	0.397***	0.401***
	(0.000)	(0.000)
2-year lagged return	-0.074	-0.083
	(0.168)	(0.119)
3-year lagged return	0.023	0.025
	(0.610)	(0.579)
1-year lagged_MSA_scaled_shock	-0.855	-1.039
	(0.764)	(0.763)
1-year lagged_industry_link	0.013	0.020
	(0.395)	(0.189)
Shock and link interaction	33.136*	34.708*
	(0.061)	(0.081)
Population growth rate	1.164***	
	(0.000)	
1-year lagged population growth rate		0.519*
		(0.091)
Constant	0.015***	0.022***
	(0.002)	(0.000)
Observations	1,790	1,790
Adjusted R-squared	0.8296	0.8199
State-quarter_count FE	YES	YES
Clustering by MSA and quarter_count	YES	YES

Notes: Table 9 presents the results of regressions following the regression in Equation (7) to test the effect of industry link on the relation between labor productivity shocks and housing price changes at the MSA-level for the sample period of 1980-2017. 1-year lagged_industry_link is the 1-year lagged term of industry link, where industry link is calculated as the sum of sales of non-dominant firms in an MSA that are in the same Fama-French industry as the dominant firms, divided by the sum of sales of all firms in the MSA, and the corresponding regression uses observations with firms having nonzero values of 1-year lagged_industry_link. Return is the HPI quarterly return at the MSA-level, and 1-year lagged return, 2-year lagged return and 3-year lagged return are its 1-year, 2-year and 3-year lagged terms, respectively. Population growth rate is the rate of change year-on-year at the MSA-level measured quarterly, and its 1-year lagged term is 1-year lagged population growth rate. 1-year lagged_MSA_scaled_shock is the 1-year lagged term of the labor productivity shock at the firm-level aggregated over all firms at time t domiciled in an MSA. State-quarter_count FEs are the joint fixed effect of state and quarter_count where quarter_count includes 152 quarters for 38 years of the data (1980-2017). P-values are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

5. Conclusions

In this study, we extend the sparse literature on the influence of firm-level characteristics on the housing markets by exploring the relationship between the labor productivity shocks of the leading companies and local housing price movements, which can be positive or negative based on different relationship channels.

Using a sample that consists of all U.S. firms from the COMPUSTAT database during the period of 1980 to 2017, we find that the labor productivity shocks of dominant firms (in terms of revenue) explain for a significant share of the local housing price changes at the MSA-level, with the latter increasing at the level of the former after we control for other housing price determinants. We also find that it takes about one year or more for the influence of the shocks to propagate through the local housing markets of an MSA, which makes shocks a viable predictor for future housing price changes at the aggregate level of productivity of local dominant firms.

Our analysis with the aggregation at the zipcode level provides evidence for a similar but immediate relation between the productivity shocks and local housing price movements, thus indicating that the influence of dominant firms may gradually diffuse from the nearby neighborhood to a wider geographical area. Furthermore, we find that this influence is stronger in MSAs with a higher concentration of high-tech dominant firms than in other MSAs, and during economic expansions than during economic contractions. The influence is also more prominent when the dominant firms have closer links to the local non-dominant industry peers, which suggests stronger spillovers from the former to the latter.

We expect that our findings can provide valuable insights to real estate market participants, including regulators, developers, financiers, brokers, investors, and consumers, as well as decision-makers, particularly in areas with a high concentration of large companies and significant industry productivity volatility.

Acknowledgments

We acknowledge the helpful comments from two anonymous reviewers of the International Real Estate Review, Editor Sing Tien Foo, as well as Adrian Lee, Jonathan Lee, Desen Lin, Atanas Mihov, Daxuan Zhao, Tingyu Zhou and the participants of the 2019 GCREC Conference in Shanghai, China, 2020 Financial Management Association Annual Meeting, 2020 Southern Finance Association Annual Meeting, 2022 AsRES-AREUEA Joint Conference and 2022 European Financial Management Association Annual Conference.

References

Addoum, J. M., Kumar, A., and Law, K. (2020). Geographic Diffusion of Accounting Information, Analyst Behavior, and State-Level Return Predictability. *Cornell University Working Paper*.

Adelino, M., Schoar, A., and Severino, F. (2015). House Prices, Collateral, and Self-Employment. *Journal of Financial Economics, 117*(2), 288–306.

Basu, S., Fernald, J. G., and Kimball, M. S. (2006). Are Technology Improvements Contractionary? *American Economic Review, 96*(5), 1418-1448.

Blackwell, M., Iacus, S., King, G., and Porro, G. (2009). CEM: Coarsened Exact Matching in Stata. *The Stata Journal, 9*, 524–546.

Butler, A. W., Fauver, L., and Spyridopoulos, I. (2019). Local Economic Spillover Effects of Stock Market Listings. *Journal of Financial and Quantitative Analysis, forthcoming*.

Campbell, S., Davis, M., Gallin, J., and Martin, R. (2009). What Moves Housing Markets: A Variance Decomposition of the Rent–Price Ratio, *Journal of Urban Economics,* 66(2), 90–102.

Case, K., and Shiller, R. J. (1989). The Efficiency of the Market for Single-Family Homes. *American Economic Review, 79*, 125–137.

Chaney, T., Sraer, D., and Thesmar, D. (2012). The Collateral Channel: How Real Estate Shocks Affect Corporate Investment. *American Economic Review, 102*(6), 2381–2409.

Chang, Y., Hornstein, A., and Sarte, P. D. (2006). Understanding How Employment Responds to Productivity Shocks in a Model with Inventories. *Federal Reserve Bank of Richmond Working Paper 2006-06*.

Chen, P., and Semmler, W. (2018). Short and Long Effects of Productivity on Unemployment. *Open Economies Review, 29*, 853-878.

Cochrane, J. H. (1994). Shocks. *NBER Working Paper Series No. 4698*. Available at https://www.nber.org/papers/w4698.

Favara, G., and Imbs, J. (2015). Credit Supply and the Price of Housing. *American Economic Review, 105*(3), 958–992.

Francis, N., and Ramey, V. A. (2004). The Source of Historical Economic Fluctuations: An Analysis Using Long-Run Restrictions. *NBER International Seminar on Macroeconomics*, 17-73.

Gabaix, X. (2011). The Granular Origins of Aggregate Fluctuations. *Econometrica, 79*(3), 733-772.

Gali, J. (1999). Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations? *American Economic Review, 89*, 249-271.

Gali, J., and Rabanal, P. (2004). Technology Shocks and Aggregate Fluctuations: How Well Does the RBC Model Fit Postwar U.S. Data? *IMF Working Papers No. 04/234*.

Gan, J. (2007). The Real Effects of Asset Market Bubbles Loan-and Firm-Level Evidence of a Lending Channel. *Review of Financial Studies, 20*(6), 1941–1973.

Hartman-Glaser, B., Thibodeau, M., and Yoshida, J. (2022). Cash to Spend: IPO Wealth and House Prices. *Real Estate Economics, 51*(2).

Glaeser, E. L., and Gyourko, J. (2017, May). Housing Dynamics. *Harvard Institute of Economic Research, Discussion Paper Number 2137*.

Jannati, S. (2020). Geographic Spillovers of Dominant Firms' Shocks. *Journal of Banking and Finance, 118*, 105844.

Jannati, S., Korniotis, G., and Kumar, A. (2020). Big Fish in a Small Pond: Locally Dominant Firms and the Business Cycle. *Journal of Economic Behavior & Organization, 180*, 219–240.

Junankar, R. N. (2013). Is There a Trade-off between Employment and Productivity? *IZA Discussion Paper No. 7717*.

Ling, D. C., Wang, C., and Zhou, T. (2020). Asset Productivity, Local Information Diffusion, and Commercial Real Estate Returns. *University of Florida Working Paper*.

Mayer, C., and Sinai, T. (2007). U.S. House Price Dynamics and Behavioral Economics. *Policymaking Insights on Behavioral Economics, September*, 261-295.

Mian, A., Sufi, A., and Verner, E. (2017). How Do Credit Supply Shocks Affect the Real Economy? Evidence From the United States In the 1980s. *NBER Working Paper No. 23802*.

Nguyen, T., Staer, A., and Yang, J. (2022). Initial Public Offerings and Local Housing Markets. *Journal of Real Estate Research, 44*(2), 184-218.

Nordhaus, W. (2005). The Sources of the Productivity Rebound and the Manufacturing Employment Puzzle. *NBER Working Paper Series No. 11354*.

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies, 22*, 435–480.

Saiz, A. (2010). The Geographic Determinants of Housing Supply. *Quarterly Journal of Economics, 125*, 1253–1296.

Smajlbegovic, E. (2019). Regional Economic Activity and Stock Returns. *Journal of Financial and Quantitative Analysis, 54*(3), 1051–1082.

Titman, S., Wang, K., and Yang, J. (2014). The Dynamics of Housing Prices. *Journal of Real Estate Research, 36*, 283–317.