Location, Location, Location: Manufacturing and House Price Growth *

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Abstract

Exploiting data on tens of millions of housing transactions, we show that (1) house prices grew by less in manufacturing-heavy US regions, (2) that this pattern is especially present for the lowest-value homes, and (3) that price declines coincided with worse labor market outcomes, consistent with an income channel. Counterfactual accounting exercises reveal that regional differences in the growth of these lowest-value homes are an important driver of the changes in overall house price inequality. Hence, the economic decline in manufacturing-heavy areas extends far beyond income and employment flows to house prices.

Keywords: manufacturing decline, house prices, housing inequality

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1 Introduction

Over the past few decades, US manufacturing plunged from an aggregate employment share of over 21% in 1980 to just under 9% in 2010.[1] Concurrent with this aggregate decline, geographic locations where manufacturing used to account for a high share of employment, such as those in the Upper Midwest or Rust Belt, have seen lower wage and employment growth than their low-manufacturing peers.[2]

In this paper, we demonstrate that the relatively poor economic experience of manufacturing hot spots extends beyond labor market outcomes to the price of a key local asset: housing. Our analysis is based on a rich micro dataset of prices and characteristics of tens of millions of recent home transactions with broad geographical coverage. We proceed in three steps.

First, manufacturing-heavy areas saw lower house price growth on average. The right panel of Figure 1 maps the manufacturing employment share in 2000 across regions, revealing substantial heterogeneity, while the left panel plots regional house price growth from 2001-06. The negative spatial correlation between the two variables is evident. As we show below, our estimates suggest that areas with a 10 percentage point higher manufacturing share experienced an average of 4.7% lower house price growth each year. To interpret the mechanism behind this relation we present evidence consistent with the presence of an income channel: areas heavily exposed to manufacturing see worse labor market outcomes reflected in lower house price growth through depressed demand for housing.

While these differences in average growth rates are quantitatively significant, our second key finding is that they mask important distributional heterogeneity. Specifically, we leverage the strength of our micro data to show that the lowest-valued homes in manufacturing-heavy areas experienced substantially lower price growth than their peers in manufacturing-light locales. This predicted relationship between manufacturing and house price growth is significantly more muted for higher-valued homes, linking industrial structure to house price inequality both between *and* within regions.

Finally, we relate our findings to the overall evolution in cross-sectional house price inequality. To do so, we exploit our full micro distribution of U.S. house prices to document a strong positive contribution of the heterogeneity in house price growth across regions to the inequality in house values. Moreover, we show that most of this contribution is driven by the lowest-price segment.

Our paper contributes to multiple strands of work. First, it adds to the literature studying the relationship between manufacturing exposure and various labor market and social outcomes such as the polarization of the job market in the United States (Bárány and Siegel, 2018); the marriage market value of young men (Dorn et al., 2019); the recent increases in mortality and morbidity among white non-Hispanic Americans (Case and Deaton, 2017); and other phenomena (Alder et al., 2017; Feyrer et al., 2007; Kahn, 1999; Notowidigdo, 2020). Our contribution is to show that the exposure

[1] These figures are from the Bureau of Labor Statistics' Establishment Survey.

[2] See the evidence in Charles et al. (2019) and Ramey (2018) as well as in our own Online Data Appendix A.

to manufacturing is also a factor linked to rising cross-sectional inequality in house prices. As such, we add to the broader understanding of the evolution of wealth and income inequality (Kaplan et al., 2018; Ahn et al., 2018; Saez and Zucman, 2016; Song et al., 2018). Finally, our work is related to the literature that links house price movements and the broader economy (Piazzesi and Schneider, 2016; Kaplan et al., 2018; Berger et al., 2017; Guren et al., 2021; Howard and Liebersohn, 2018; Charles et al., 2016; Liebersohn, 2017; Howard and Liebersohn, 2021).

2 Data

In this section we present the data used throughout the analysis.

Housing Data Studying average and distributional shifts in house prices requires us to follow house price distributions within narrow geographic locations over time. We rely on a unique micro dataset from Zillow, the ZTRAX dataset, containing tens of millions of observations from 2001-15 with a wide geographical coverage. ZTRAX combines two sources of information: local municipalities' transaction records, including sales prices, and tax assessment data featuring detailed home characteristics. Thus, an observation in our dataset combines both the sales price *and* home characteristics for a single transaction. For this study, our focus is on single-family homes.

Geography Our geographical analysis is at the commuting zone (CZ) level, an area whose size is typically between that of a county and a state and which corresponds to a locally unified economic agglomeration. This measure ensures comparability with other recent work on industrial structure and labor market outcomes (Autor et al., 2013).

Labor Market To measure local manufacturing employment shares, as well as various other labor market outcomes and controls, we use 1% decennial Census and annual American Community Survey IPUMS micro data extracts. At the CZ level, this dataset provides universal geographic coverage within the US, and sample weights attached to the micro data allow for the formation of representative measures.

Additional Datasets To compute various ancillary statistics and provide cross checks of our main results, we also use several other additional sources: aggregated local house prices indexes from the Federal Housing Finance Agency (FHFA), local housing supply elasticities from Saiz (2010), and local industry employment from the Census County Business Patterns. See Online Data Appendix A for more details on our sample construction, exact variable definitions, and summary statistics for our datasets.

3 Average House Prices and Manufacturing

Before presenting our results, we emphasize that our primary aim in this paper is to contrast home price dynamics in manufacturing-heavy locations versus their peers in manufacturing-light areas. Our overall goal is not causal identification. However, in addition to our baseline OLS specifications, we also exploit a widely used shift-share IV strategy and present evidence consistent with an income channel causally linking manufacturing exposure to subsequent income growth and therefore to home prices via demand.

We begin by quantifying differences in the growth rate of average house prices across locations with different preexisting manufacturing exposure. Since we are not yet interested in distributional shifts, we use ZTRAX average CZ-level house price indexes. Specifically, let $p_{c,t}$ denote the log of the average house price in CZ c in year $t \in \{2001, 2006\}$. Then, we consider a regression

$$\Delta p_{c,t} = \alpha + \beta M_{c,2000} + \gamma X_{c,2000} + \delta_{div(c)} + \varepsilon_{c,t}. \tag{1}$$

where $\Delta p_{c,t}$ denotes the change in log prices between the two time periods, and $M_{c,2000}$ denotes the share of manufacturing in total employment for CZ c in the year 2000. We add standard CZ-level controls (denoted by $X_{c,2000}$) such as the (i) educational composition, (ii) share of female workers, (iii) share of foreign-born workers, and (iv) share of workers in routine cognitive occupations. We also augment the regression with controls for housing supply elasticities (Saiz, 2010). Since Figure 1 suggests that the geographical distribution of manufacturing is not random but rather concentrated in specific regions of the United States, we also include Census division indicators in our regressions. As such, our identification of the variation predicted by exposure to manufacturing comes from changes *within* Census division. Finally, because turbulence in the US housing market formed the epicenter of the financial crisis and Great Recession, we initially focus on the 2001-06 period, holding constant the various shares discussed above at their 2000 values. We later extend our analysis to the 2001-15 period.

Table 1 contains our first main results. In column (1), we see that home prices in areas with a higher manufacturing share in 2000 grew more slowly over the 2001-06 period than their peers, after controlling for the set of local labor market characteristics discussed above. In column (2), we verify that the negative association survives in stable fashion the inclusion of Census division fixed effects. The coefficient estimates in both columns exhibit high statistical precision. In other words, even once we control for broad geographical trends and a host of "usual suspects" in labor and housing markets, our results indicate that manufacturing-heavy areas failed to see house price growth as high as their low-manufacturing peers.

The magnitudes of the differences are large. Consider a CZ at the 75th percentile of manufacturing exposure, which has a 2000 manufacturing employment share 6.7% higher than its peer at the 25th percentile. Our estimates in column (2) predict that house price growth from 2001-06 in that same CZ will be $0.467 \times 6.7 \approx 3.1\%$ lower per year than in the manufacturing-light region. The drop of 3.1%

in house price growth each year represents a variation of 3.1 / 7.0 $\approx$ 44% relative to the interquartile range (IQR) of house price growth in the full sample.

While broad, the coverage of the ZTRAX dataset is not uniform across the United States. Hence, for robustness purposes, we run the same regressions using CZ-level house price indexes that we construct from locally aggregated data from the FHFA (see Online Appendix A for details). As evidenced in Online Appendix Table A2, we find very similar results using this alternative to the ZTRAX database, despite its wider geographical coverage.[3]

Exposure to Manufacturing and Labor Market Outcomes in the Data Our results throughout the paper are consistent with the hypothesis that the relationship between initial manufacturing exposure and house price dynamics operates through an income channel: in regions with a higher proportion of employment in manufacturing, the secular industrial decline led to disproportionate job losses and income stagnation relative to other regions. This in turn, morphed into relatively lower house price growth. We formalize this intuition in a model in Online Appendix B and note that a link between exposure to manufacturing and labor market outcomes has been studied before (Charles et al., 2019; Ramey, 2018) and is confirmed in Panel A of Online Appendix Table A3 for our level of spatial and time coverage.[4] As this table suggests, we find that CZ's heavy in manufacturing in 2000 experienced a steeper drop in manufacturing employment over the 2001-06 period, a more pronounced positive *change* in the likelihood of not working, and lower growth of average wages.

To provide additional general evidence in favor of the income channel for house prices, we rely on a standard shift-share industry employment IV approach. The underlying identifying assumption is that the past composition of industries in a CZ interacted with national employment dynamics does not impact local house price dynamics except through wage growth.[5] Specifically in our approach we implement the algorithm advocated for by Adao et al. (2019), with details of our IV construction in Online Appendix A.[6] The results are presented in column (3) of Table 1. First we note that the first-stage results confirm that the initial industry composition has reasonable explanatory power for

[3]To further validate the ZTRAX data, we note the following points. First, we note that our 179 CZ's include a disproportionate fraction of the overall population in the FHFA data. Specifically, our 179 CZ's account for 77% of the total population aged 15-65 from the 657 CZ's used for regression (1) in Online Appendix Table A2. Hence, this reinforces the view that our Zillow CZ's account for a vast majority of the U.S. data. Second, in the FHFA data restricted to the CZ's for which we have ZTRAX coverage, we estimate a manufacturing coefficient of -0.444 in column (2) of Online Appendix Table A2, which is almost identical to the -0.467 coefficient reported in column (2) of Table 1.

[4]The regressions in Appendix Table A3 rely on the 741 CZ's in the US while for the regressions in Table 1 we limit ourselves to the CZ's we cover in the Zillow data.

[5]In our view, the most relevant variable to include is labor income. One could imagine a world in which population and employment don't change, yet despite no change in employment, the fall in income would show up in house prices.

[6]See Table 6, Panel A in Adao et al. (2019). We note that a robust applied econometrics debate over the properties and potential drawbacks of shift-share approaches has arisen (Borusyak et al., 2018; Goldsmith-Pinkham et al., 2020; Adao et al., 2019; Jaeger et al., 2018).

wage growth: the estimated coefficient is 0.75, significant at the 5% level with an F-stat of 22.3. The second-stage coefficient in column (3) suggests that the instrumented variation in income is an economically and statistically significant determinant of house price dynamics. The IV coefficient indicates that a one percent change in wage income is associated with a 0.77 percent increase in house prices.

Extending the Data: 2001-15 Our analysis up to this point has focused on the 2001-06 period in order to avoid conflating the role of manufacturing exposure with that of factors specific to the 2007-09 financial crisis which was associated with a major disruption in housing markets. Yet, one may wonder whether exposure to manufacturing in 2000 may still predict house price dynamics beyond the Great Recession. Columns (4) and (5) in Table 1 show results extending our sample to 2015. As expected, the results suggest that the predictive power of past manufacturing intensity for average house price growth dissipates as structural adjustment occurs at the local level in the aftermath of the Great Recession. Column (5) reveals that manufacturing exposure in 2000 does not predict house price growth once we include region fixed effects. Yet, as we discuss next in Section 4.2, when we analyze heterogeneity across the housing price distribution, we find that low-price segments of this distribution in manufacturing-heavy areas did continue to experience lower cumulative house price growth through 2015.

4 Manufacturing Exposure and the House Price Distribution

We now turn our attention to our main question of interest: is lower house price growth in manufacturing-heavy areas distributionally neutral? Or does exposure to manufacturing predict more pronounced reductions in house price growth for low-price homes than for high-value homes? Under the income channel, we would expect heterogeneous patterns if manufacturing workers, who have taken the brunt of the detrimental labor market shifts during de-industrialization, live disproportionately in a specific portion of the house price distribution. See Online Appendix B for a simple model that formalizes this idea.

Indeed, as is evident in Figure 2, manufacturing workers are disproportionately represented in the lowest tercile of the housing distribution and much less prevalent in the highest tier.[7] Moreover, under the income channel, we would expect the income of households living in lower-priced houses to be more sensitive to the manufacturing share than that of households in high-priced houses. Panel

[7] To construct Figure 2 we exploit self-reported Census house price valuations and compute the fraction of manufacturing workers in each of three equally sized home-price terciles defined at the CZ level. We use this source as we do not have information in the ZTRAX dataset regarding the occupation of the sellers, requiring this use of IPUMS home valuation data.

B of Online Appendix Table A3 confirms this: manufacturing exposure predicts both economically and statistically larger declines in wage growth for individuals in lower-priced homes.[8] Hence, under an income channel, we would expect lower-priced homes to grow even more slowly in value in manufacturing-heavy areas than their high-priced peers, a hypothesis which we test next.

4.1 Location in the House Price Distribution

To study distributional price dynamics at the CZ level, we need to first construct a distribution of local house prices and allocate each transaction to its relevant point in this distribution. We pursue two approaches.

The first solution, our baseline, uses a hedonic approach based on projecting house prices on a list of observable house characteristics. In a nutshell, we first estimate the loading of house prices on various amenities in 2001.[9] Next, using these loadings and the amenities of houses sold in 2006, we can rank each house within the CZ-specific distribution of 2001 home prices. We therefore ensure that statements made about "high-value" or "low-value" homes reflect consistent comparisons and valuations of home characteristics across time. We then construct for each CZ and segment of the 2001 housing distribution the growth rate of mean house prices over our 2001-06 sample period, which becomes our dependent variable. See Online Appendix C for a more detailed discussion of the approach.

The second solution follows the methodology of the Standard & Poor's Case-Shiller Home Price indexes and relies only on repeated sales of individual properties. In this approach, we can directly assign a house to a part of the CZ-level price distribution in the base year (in our case 2001). We then compute the average change in house prices for these repeat sales for each segment of the initial CZ-specific house price distribution. The repeat sales approach allows us to directly study the distributional dynamics of house prices while holding permanent unobserved characteristics fixed.

The trade-offs between the two approaches are clear. The repeat sales approach does not require us to control for a pre-specified list of house characteristics. The hedonic approach, on the other hand, allows for wider data coverage across time and space. Despite the large size of our dataset, the repeat sales approach results in a significantly reduced sample size. Hence, to present a baseline relying on as broad an underlying sample as possible, we first compute local house price changes across the distribution using the hedonic method. However, in Online Appendix Table A4 we show that the main conclusions of this section hold if we instead focus on repeat sales, despite a much

[8]Moreover we note that column (1) in Panel A, which uses all 741 CZ's in the U.S. data, and column (1) in Panel B, which uses the ZTRAX geographic coverage, reveal very similar wage growth patterns after exposure to manufacturing. This similarity again reinforces the relevance and representativeness of the ZTRAX data.

[9]The amenities we include are square footage, year of construction, number of rooms, number of bathrooms, number of bedrooms, number of stories, the presence of a garage, and a set of ZIP-code level dummies. See Online Data Appendix C for further details.

smaller number of observations.

4.2 Results

We divide all transactions within each CZ in our 2001 benchmark year into three equally sized price terciles or segments: low-value, mid-value, and high-value. That is, for each CZ we split the distribution of house prices in 2001 into three equally-sized bins.[10] Using the hedonic pricing approach discussed above, we then map homes in later years into the same three segments based on a consistent valuation of their characteristics.

Our regression specification is given by

$$\Delta p_{c,s,t} = \alpha + \theta_s + \sum_s \beta_s \mathbb{1}_s \times M_{c,2000} + \gamma X_{c,2000} + \delta_{div(c)} + \varepsilon_{c,t}, \tag{2}$$

where the growth of average prices from 2001 to 2006 within each CZ $\times$ segment cell provides our main outcome measure. In the equation above, $s \in \{1, 2, 3\}$ denotes the segment or tercile of the housing distribution, and θ_s denotes the segment fixed effect. $\mathbb{1}_s$ is an indicator function which equals one when an observation belongs to the relevant housing segment and which is interacted with the manufacturing employment share. We continue to control for all the variables $X_{c,2000}$ discussed in the context of equation (1). This specification allows us to investigate whether the association between manufacturing shares and subsequent house price growth differs when moving from low-value (with $s = 1$) to mid-value (with $s = 2$) to high-value homes (with $s = 3$).

Column (1) of Table 2 reports the results. Houses in all terciles appreciated more slowly on average in high-manufacturing areas. These dynamics are however heterogeneous: while low-value homes display sharply lower growth in the face of manufacturing exposure, this difference is more muted for their high-value neighbors. In other words, manufacturing exposure predicts relatively *more* within-region house price inequality, not less.

The magnitudes at work here prove large once again. For a high-manufacturing CZ at the 75th percentile of manufacturing shares in 2000, the coefficient estimates in column (1) reveal that low-value homes experienced $0.690 \times 6.7 \approx 4.6\%$ lower yearly subsequent house price growth than the same segment in a light-manufacturing CZ at the 25th percentile of exposure. By contrast, high-value homes saw a relatively lower price growth of around $0.448 \times 6.7 \approx 3.0\%$ per year, i.e., a differential that is a third smaller in magnitude.

As discussed above, our main analysis covers 2001-06. Recall that Column (5) of Table 1 showed that the predictive power of past manufacturing intensity dissipates over the longer 2001-15 horizon during a period spanning the Great Recession. What are the dynamics across the housing distribution during this longer horizon? Column (2) in Table 2 shows tercile-level results for 2001-15. Naturally,

[10] We note that in unreported results we obtain similar findings when using a finer segmentation of the distribution, e.g., with quintiles or deciles.

exposure to manufacturing predicts more muted differences over the longer horizon. But remarkably, and in contrast to the dynamics of average prices, our estimates reveal persistent and long-lasting differences in the price growth of the lowest-value homes in manufacturing-heavy areas over one and a half decades later. By contrast, over this longer period, their high-value neighbors in manufacturing-exposed areas had not experienced any significant difference in house price growth relative to their manufacturing-light peers.

All in all, these empirical patterns are consistent with a framework in which manufacturing exposure reduces income growth, feeding into declines in the price of both homes overall and especially the price of the lowest-value homes.

5 Shifts in House Price Inequality

In light of the outsized importance of housing in overall household wealth, we next exploit the full distribution of home prices in our ZTRAX micro data to document some overall shifts in house price inequality over our sample period. To isolate the role of the lowest-value homes in the observed shifting inequality of house prices, we engage in a series of simple counterfactual accounting exercises.

The Evolution of House Price Inequality We start by documenting the evolution of house price inequality over our sample periods and across the distribution. Comparing the first two columns in the top panel of Table 3, we find that the (log) standard deviation of house prices in fact declined between 2001 and 2006, from 87.9% to 84.9%. These dynamics, however, were strikingly different across the house price distribution: while the dispersion fell for high-value (86.2% to 79.4%) and mid-value homes (85.3% to 80.6%), it instead *increased* for the lower-priced houses (92% to 93.7%). Over the longer 2001-2015 sample period, the overall dispersion rose from 87.9% to 92.8%. Again, the evolution is very different across the house price distribution: while the log standard deviation fell significantly for the high-value homes (86.2% to 72.6%), and remained practically the same for the mid-value homes, it rose from 92% to 113.2% for the bottom tercile. Next, we investigate using counterfactuals the roles of region- and segment-level heterogeneity in driving aggregate variation in house price inequality.

A Simple Accounting Framework To account in more detail for these shifts in inequality, we introduce some additional notation and an accounting framework which can be mapped directly to our data. We write the log price $p_{h,c,s,t}$ of house h in CZ c in home value segment s in year t as

$$p_{h,c,s,t} = \mu_{c,s,t} + \sigma_{c,s,t}\varepsilon_{h,c,s,t}.$$

Above, $\mu_{c,s,t}$ is the average price in the CZ $\times$ segment $\times$ year cell, and $\sigma_{c,s,t}$ is the standard deviation of the same cell. The value $\varepsilon_{h,c,s,t}$ represents the normalized home price, featuring zero mean and unit standard deviation within a cell. We can directly and easily compute estimates of each of the values in the decomposition above from our micro data. This simple accounting framework reveals that an increase in the variance or inequality of overall house prices can in principle stem from one or a combination of three channels: (i) an increase over time in within-cell dispersion $\sigma_{c,s,t}$ which is common across all $c \times s$ cells, (ii) heterogeneous shifts over time in the within-cell dispersions $\sigma_{c,s,t}$, or (iii) heterogeneity in the growth over time of average prices $\mu_{c,s,t}$ across cells.

Our empirical results so far, which document distinct growth rates for average prices $\mu_{c,s,t}$ in $CZ \times$ segment cells, map directly to the third channel. Next, we seek to quantify the importance of this growth rate heterogeneity through a series of simple counterfactual exercises.

The Role of Heterogeneity Across Regions and House Price Segments In our first scenario, we shut down all heterogeneity in the growth of mean house prices $\mu_{c,s,t}$ across CZ (c) or house-price tercile (s) and recompute the dispersion of house prices in both 2006 and 2015. The second row of the bottom panel of Table 3 reveals that this counterfactual generates a much stronger decrease in inequality between 2001 and 2006, from 87.9% to 78.4% instead of 84.9%. Over the 2001-2015 period, which saw an increase from 87.9% to 92.8% in the log standard deviation, the counterfactual instead generates a *drop* to 85.4%. In other words, the changes in house price inequality are overwhelmingly driven by heterogeneity in house price growth *across* regions and price segments, instead of variations *within* region-segment cells.

The Role of Low-Value Houses In our second counterfactual, we focus on the role of low-value homes by shutting down heterogeneity across regions in the growth rate of this segment alone, allowing for inter-regional differences in the mid- and high-price segments. The third row in the bottom panel of Table 3 reveals that the 2006 standard deviation of log prices under this counterfactual scenario equals 81.9% (starting from 87.9% in 2001): hence, without the contribution from the lower-price segment, inequality in house values would have been significantly lower than in reality (84.9%). The crucial role played by the cross-regional divergence of the lowest-priced homes is also evident from the 2015 counterfactual: between 2001 and 2015, ignoring this margin generates a *decline* in overall inequality, from 87.9% to 87.3%, while the observed dispersion in 2015 is 92.8%. We can therefore conclude that differences in the average growth rates of *only* the lowest-valued homes across regions have been a significant positive contributor to the inequality in house prices over our sample period.

For our third exercise, we narrow the analysis even further: we aim to identify the portion of the change in the overall inequality in house prices that is predicted *solely by the manufacturing exposure of the lowest-value homes*. This effectively shuts down only the heterogeneity in the growth rates of the lowest-value segment of homes that is predicted by our regressions in Table 2. The last row of Table 3 shows that for 2001-2006, without the contribution of this very narrow source of heterogeneity, inequality in house values would have been only slightly lower than in reality, accounting for 6% of the observed change. If we instead consider the 2001-2015 period, the resulting increase in standard deviation would have been 16% smaller than the observed increase.[11] In other words, heterogeneity in average growth rates for the lowest-value homes predicted only by their exposure to manufacturing accounts for around one sixth of the increase in total house price inequality over the 2001-2015 period.

All in all, we conclude that our counterfactual exercises lead to the striking conclusion that regional differences, and in particular those for the very lowest-value homes, prove critical for understanding increased cross-sectional house price inequality.

6 Conclusions

Our analysis leverages a rich dataset of tens of millions of house price transactions tracked by Zillow. We show that areas with higher exposure to the US manufacturing sector experienced lower growth in home prices on average in recent years. Furthermore, the lowest-value homes in these regions experienced an even heavier decline in price growth relative to their higher-value neighbors. In other words, manufacturing exposure predicts shifts in both cross-region and within-region inequality in house prices.

In an exercise leveraging our full distribution of house prices at the micro level, we show that a recent increase in house price inequality is fully accounted for by heterogeneity across regions in the growth of prices of the lowest-value homes, exactly those dwellings disproportionately predicted to grow more slowly in the face of manufacturing exposure.

Thus, we conclude that the relative decline of manufacturing-heavy areas extends far beyond income and employment flows to include shifts in important local asset prices.

[11] For 2001-2006, the contribution of this channel is about 6% of the observed change, i.e. $\frac{0.847-0.879}{0.849-0.879}$. For 2001-2015 it would have been $0.920 - 0.879 = 0.041$, which is 16% smaller than the observed increase to 0.928.

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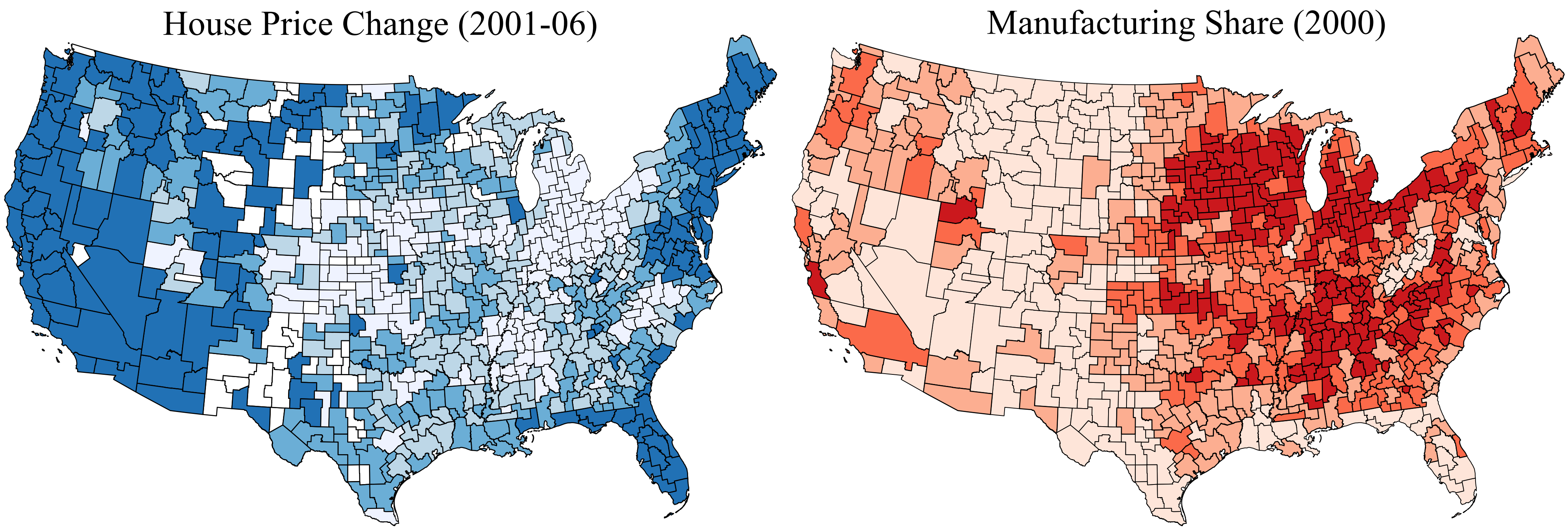
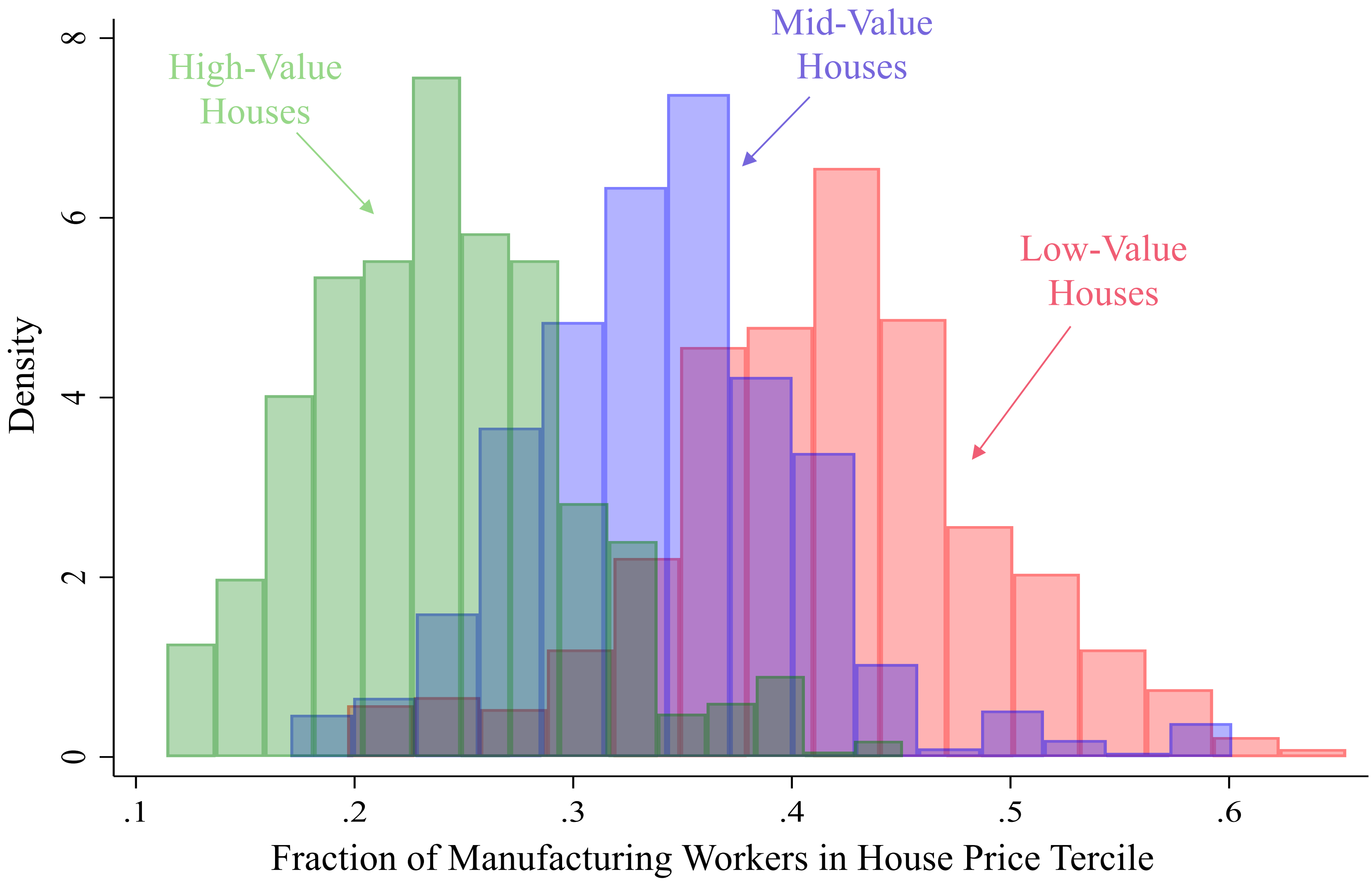
Figure 1: House Prices and Manufacturing



Note: Both maps plot the contiguous US in commuting zones. The left map in blues indicates average percentage house price appreciation from 2001-06, based on local Federal Housing Finance Agency indexes. The right map in reds indicates the manufacturing share of employment in 2000 based on US Census IPUMS microdata. Darker shades indicate larger values.

Figure 2: Manufacturing Workers by House Price Tercile



Note: For a given house price tercile, the figure plots the distribution across commuting zones of the share of manufacturing workers living in that house price category. The underlying data is the US Census IPUMS microdata in the year 2000.

Table 1: House Prices and Manufacturing

Percent Change in House Prices	(1) OLS	(2) OLS	(3) IV	(4) OLS	(5) OLS
Manufacturing Share	-0.488***	-0.467***		-0.118**	0.005
	(0.142)	(0.137)		(0.048)	(0.042)
Percent Change in Wage Income			0.771**		
			[0.0325]		
Controls	Yes	Yes	No	Yes	Yes
Fixed Effects	No	Census Division	Census Division	No	Census Division
Underlying House Transactions	19,670,168	19,670,168	19,670,168	43,686,431	43,686,431
Commuting Zone Observations	179	179	179	179	179
Years	2001-06	2001-06	2001-06	2001-15	2001-15
Adjusted R^2	0.226	0.249		0.128	0.285

Note: Regressions run at the commuting zone level with the average percentage house price growth over 2001-06 or 2001-15 on the manufacturing employment share in 2000 or wage income growth 2001-06. Controls include the Saiz (2010) housing supply elasticity, the percentage of routine cognitive jobs, the college educated working share, the female working share, and the foreign working share. Standard errors in parentheses are clustered at the state level. *, **, *** denote significance at the 10%, 5%, and 1% levels. In column (3), we follow Adao, et al. (2019) and instrument for CZ-level wage growth with a shift-share IV based on 3-digit 1998 NAICS employment shares. The brackets under the coefficient report the p-value associated with the second-stage estimate computed using the Adao, et al. (2019) procedure, and the main text reports first-stage results.

Table 2: House Prices and Manufacturing across the Distribution

Percent Change in House Prices	(1)	(2)
Years	2001-06	2001-15
Manufacturing Share * Low-Value Houses	-0.690*** (0.151)	-0.088* (0.047)
Manufacturing Share * Mid-Value Houses	-0.583*** (0.142)	-0.029 (0.041)
Manufacturing Share * High-Value Houses	-0.448*** (0.123)	0.071 (0.045)
Controls	Yes	Yes
Fixed Effects	Census Division	Census Division
Underlying House Transactions	19,670,168	43,686,431
Commuting Zone x Tercile Obs.	535	535
Adjusted R^2	0.286	0.366

Note: Regressions run at the commuting zone x house price tercile level with the percent change in average house prices for the relevant cell on the manufacturing employment share in 2000. The terciles reflect 2001 home values. Controls include the Saiz (2010) housing supply elasticity, the percentage of routine cognitive jobs, the college educated working share, the female working share, and the foreign working share. Standard errors in parentheses are clustered at the state level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Table 3: House Price Inequality

Panel A: Observed Data

Log Standard Deviation in Year:	2001	2006	2015
All Houses	0.879	0.849	0.928
Low-Value Houses	0.920	0.937	1.132
Mid-Value Houses	0.853	0.806	0.876
High-Value Houses	0.862	0.794	0.726

Panel B: Counterfactuals

Log Standard Deviation for All Houses in Year:	2001	2006	2015
Observed	0.879	0.849	0.928
Removing All Regional and Segment House Price Growth Differences	0.879	0.784	0.854
Removing Low-Value House Price Growth Differences	0.879	0.819	0.873
Removing Mfg.-Predicted Low-Value House Price Growth Differences	0.879	0.847	0.920
Underlying House Transactions	2,664,242	2,255,561	3,196,915

Note: The top panel reports observed inequality in house prices in various categories in the indicated year. The bottom panel reports the inequality for all homes in each year under various counterfactuals described in the text.

Appendix for Online Publication Only

A Data

We use five distinct sources of data in the paper. Table A1 in this appendix provides descriptive statistics on the relevant outcomes used in the paper.

Zillow ZTRAX Our baseline house price data is drawn from the Zillow ZTRAX micro dataset, used under agreement with Zillow. This dataset contains two main files: a set of transaction records with property identifiers and sale prices and a set of property-level tax assessments with various house characteristics recorded including the property ZIP code. The combined data features broad geographic coverage and around 80 million home transactions. We focus on single-family homes in commuting zones with more than a minimum number of observations. We take two approaches to computing CZ-level or CZ $\times$ housing segment-level growth rates in average prices.

Our baseline approach relies on hedonic regressions run only on the year-2001 portion of our sample. We detail this approach in Appendix C.

Our second, alternative approach relies on a repeat sales method. For each CZ or each CZ $\times$ housing segment cell, we select the sample of properties in that cell which sold more than once in our period of interest. We then compute the annualized growth rate of the price based on the earliest and latest transactions over this period. The median house price growth rate in a particular cell forms our outcome of interest for Table A4 in this appendix.

For all homes in our ZTRAX analysis, we map properties to commuting zones by ZIP code.

FHFA Home Price Indexes The Federal Housing Finance Agency publishes county-level home prices indexes, which we map to CZ's using the geographical correspondences on David Dorn's website. Taking averages of growth rates in each period across counties in a CZ provides a CZ-level measure of house price growth according to this data source. Table A2 in this appendix reports house price regressions based on these FHFA house price growth measures.

US Census IPUMS The US Census provides IPUMS micro data extracts based on anonymized samples of the decennial Census as well as the annual American Community Survey (ACS). Sampling weights are provided for each individual person-level record. For our calculations of pre-existing manufacturing employment shares as well as the other labor market controls including the local routine share, the share of college educated workers, the share of female workers, and the share of immigrants in the year 2000, we rely on the year-2000 decennial Census extract. To map employment to routine vs non-routine categories, we rely on the mapping in Jaimovich et al. (2020). For the growth of wages, employment, the likelihood of not working, the likelihood of working in manufacturing, the likelihood of working in construction, and the likelihood of working in all other sectors, we rely on the annual ACS extracts. For housing values in the IPUMS data, we use self-reported home values conditional upon homeownership.

To compute CZ-level aggregates for any outcome of interest, we map the US Census' Public Use Microdata Areas or PUMAs to CZ's using the mappings provided by David Dorn.

Saiz (2010) Housing Supply Elasticities As a control at the local level, we use the Saiz (2010) measure of local housing supply elasticities. For regions in which this housing supply elasticity is not available, we use the predicted housing supply elasticity based on the associated Wharton Residential Land Use Regulatory Index (WRLURI) value and projections of the local housing supply elasticity on the WRLURI for an overlapping sample.

Shift-Share Instrument To construct the shift-share IV for wage income growth used in the text, we use data from the US Census County Business Patterns or CBP database. CBP reports employment $L_{j,r,t}$ in 6-digit NAICS industry j in county r in year t. We first aggregate across counties to obtain a measure of employment $L_{j,c,t}$ for CZ c in the same industry and year. Our shift-share instrument $Z_{c,t}$ for wage changes in CZ c through year t is given by

$$Z_{c,t} = \sum_j \frac{L_{j,c,1998}}{L_{c,1998}} \Delta L_{j,t}.$$

Above, we use the notation $L_{c,1998} = \sum_j L_{j,c,1998}$ for the total employment in CZ c in 1998, and $L_{j,t} = \sum_d L_{j,d,t}$ is total national employment in industry j. The operator Δ converts to growth rates. Stated more plainly, our instrument construction follows conventional approaches to shift-share empirical design and is simply equal to the weighted average of national employment growth within narrowly defined industries, weighting these shifts by the share of each industry in the CZ's pre-existing employment distribution.

B Model

Our empirical results established that exposure to manufacturing is negatively associated with future house price growth across locations and that this relationship is especially pronounced for low-value homes. In what follows we present a simple model in which these findings arise naturally if (1) regions are heterogeneous in their exposure to the manufacturing sector as depicted in Figure 1 and (2) manufacturing workers who have experienced worse labor market outcomes than non-manufacturing workers live disproportionately in lower-priced houses as depicted in Figure 2. We then document and discuss empirical evidence consistent with these assumptions, providing a framework that rationalizes our results through an income channel.

Consider an environment with two regions A and B of equal working population size normalized to 1. In each region there are two equal sized housing segments, low (L) and high (H). Half the population lives in L-type houses, the rest in H-type houses. The only regional difference is the share working in manufacturing with $Pop_A^{MFG} > Pop_B^{MFG}$. All manufacturing workers, irrespective of region, earn the same income Y^{MFG}. All non-manufacturing workers earn Y^{Other}.

Let the fraction of manufacturing workers who live in the L segment be $\frac{\alpha}{2}Pop_A^{MFG}$. The three possible cases for α are

$$\begin{cases} \alpha = 1, & \text{manufacturing workers are equally distributed} \\ \alpha > 1, & \text{manufacturing workers are disproportionately housed in the L segment} \\ \alpha < 1, & \text{manufacturing workers are disproportionately housed in the H segment} \end{cases}$$

Then, total income of workers in segment L in region A is

$$Y_{A,L} = \frac{\alpha}{2}Pop_A^{MFG} \times Y^{MFG} + \left(\frac{1}{2} - \frac{\alpha}{2}Pop_A^{MFG}\right) \times Y^{Other},$$

while income in the H segment is

$$Y_{A,H} = \left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG} \times Y^{MFG} + \left(\frac{1}{2} - \left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG}\right) \times Y^{Other}.$$

The same two equations hold in Region B with modified subscripts.

Assume that there is a log-linear mapping between the change in income of workers in a given segment and the segment's equilibrium housing price. It then suffices to analyze the variation in incomes of the two segments (L and H) in the two locations (A and B), i.e. $Y_{A,L}$, $Y_{A,H}$, $Y_{B,L}$, $Y_{B,H}$. Let hatted variables denote percentage deviations and assume that $\widehat{Y^{MFG}} < \widehat{Y^{Other}} = 0$. Log-linearizing the income of each of the four categories yields

$$\widehat{Y}_{Region,Segment} = X_{Region,Segment} \times \widehat{Y^{MFG}}$$

where $Region \in \{A, B\}$ and $Segment \in \{L, H\}$. The values $X_{Region,Segment}$, which are coefficients governing the impact of manufacturing income changes in the log-linearization, are functions of the model's underlying parameters.[12]

[12] Specifically,

$$X_{A,L} = \frac{\frac{\alpha}{2}Pop_A^{MFG} \times Y^{MFG}}{\frac{\alpha}{2}Pop_A^{MFG} \times Y^{MFG} + \left(\frac{1}{2} - \frac{\alpha}{2}Pop_A^{MFG}\right) \times Y^{Other}},$$

$$X_{A,H} = \frac{\left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG} \times Y^{MFG}}{\left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG} \times Y^{MFG} + \left(\frac{1}{2} - \left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG}\right) \times Y^{Other}},$$

$$X_{B,L} = \frac{\frac{\alpha}{2}Pop_B^{MFG} \times Y^{MFG}}{\frac{\alpha}{2}Pop_B^{MFG} \times Y^{MFG} + \left(\frac{1}{2} - \frac{\alpha}{2}Pop_B^{MFG}\right) \times Y^{Other}}, \text{ and}$$

$$X_{B,H} = \frac{\left(1 - \frac{\alpha}{2}\right) Pop_B^{MFG} \times Y^{MFG}}{\left(1 - \frac{\alpha}{2}\right) Pop_B^{MFG} \times Y^{MFG} + \left(\frac{1}{2} - \left(1 - \frac{\alpha}{2}\right) Pop_B^{MFG}\right) \times Y^{Other}}.$$

Our empirical facts map to the following three relations between the coefficients. First, a sufficient condition for larger movements in absolute terms in regions with more manufacturing is that $X_{A,L} > X_{B,L}$ and $X_{A,H} > X_{B,H}$, in which case region A sees a bigger fall in labor income. These conditions are satisfied given that $Pop_A^{MFG} > Pop_B^{MFG}$. Online Appendix Table A3 reveals that areas with higher pre-exposure to manufacturing did in fact exhibit lower wage and employment growth empirically.

Second, the relative size of cross-sectional differences for the lower part of the house price distribution maps into $(X_{A,L} - X_{B,L}) > (X_{A,H} - X_{B,H})$. This condition holds if $\alpha > 1$, i.e., if manufacturing workers are *not* equally distributed across the two segments but instead cluster in the L segment. In this case, the lower quality housing segment exhibits a higher cross-sectional variance. In Figure 2 in the paper, we showed that manufacturing workers are indeed disproportionately represented in the lowest tercile of the housing distribution.

All in all, the empirical patterns we documented in the paper are consistent with our theoretical model in which manufacturing exposure causes reduced income and employment growth, feeding into declines in the price of both homes overall and especially the price of the lowest-value homes.

C Hedonic Approach

Our baseline hedonic approach to tercile calculations involves estimating the equation

$$p_{h,2001} = \beta' X_h + \delta_{ZIP(h)} + \varepsilon_{h,2001}$$

based on data in the year 2001. Above, p_h is the log price of property h and X_h is a vector of home characteristics including the log square footage, the property age, the total number of rooms, bedrooms, and bathrooms, the number of stories, and an indicator for the presence of a garage. $\delta_{ZIP(h)}$ is a full set of ZIP code-level fixed effects. Then, for any property h sold in a later year t, the hedonically adjusted price of property h on a year-2001 basis is the predicted value from the specification above. For each CZ or each CZ $\times$ housing segment cell, we then compute the mean value of the hedonically adjusted prices of homes sold in that cell. Our main house price specifications in Tables 1-2 use the annualized growth rate of these average prices as the main outcome.

More precisely, our hedonic approach involves the following four steps, taking as an example the construction of house price changes between 2001 and 2006:

(A) We run the regression directly above based on the year-2001 sales transactions. This allows us to obtain the loadings of house prices on the different covariates included in our regression (square footage, year of construction, number of rooms, number of bathrooms, number of bedrooms, number of stories, the presence of a garage, and a set of ZIP-code level dummies). These loadings are then held constant for the rest of the analysis.

(B) Next, we estimate the 2001-price of a house that is sold in 2006 (but not 2001), based on these constant loadings and the specific observed amenities of the house. In other words, we compute (or rather impute) the “2001 price” for each house based on its characteristics and the constant loadings. This allows us to make sure that we are comparing a similar house (in terms of the “pricing of amenities”) over time.

(C) Armed with the results from step (B) we can rank each house that is sold in 2006 within the distribution of 2001 home prices at the CZ level.

(D) The results from step (C) allow us now to compute the average growth rate of house prices for each tercile (or for that matter any part of the distribution) of the 2001 home prices in a given CZ. This allows us to make statements about “high-value” or “low-value” homes reflecting consistent comparisons (constant loadings) across time.

Table A1: Descriptive Statistics

Panel A: Zillow Microdata on Home Characteristics in 2001					
Variable	Mean	Median	IQR	Year	N
Sales Price ($)	272638	149000	144200	2001	2,676,821
Square Feet	1854	1644	962	2001	2,676,821
Age	27.2	20.0	43.0	2001	2,676,821
Total Rooms	4.0	1.0	6.0	2001	2,676,821
Bathrooms	4.5	5.0	3.0	2001	2,676,821
Bedrooms	3.5	4.0	1.0	2001	2,676,821
Garage?	0.5	0.0	1.0	2001	2,676,821
Panel B: Commuting Zone Outcomes, House Price Sample					
	Mean	Median	IQR	Years	N
House Price Growth	0.081	0.078	0.070	2001-06	179
Low-Value House Price Growth	0.078	0.084	0.087	2001-06	179
Mid-Value House Price Growth	0.080	0.074	0.085	2001-06	178
High-Value House Price Growth	0.080	0.075	0.073	2001-06	178
Low-Value House Price Growth	0.010	0.016	0.033	2001-15	179
Mid-Value House Price Growth	0.021	0.025	0.027	2001-15	178
High-Value House Price Growth	0.032	0.033	0.023	2001-15	178
Manufacturing Share of Employment	0.097	0.090	0.067	2000	179
Routine Share of Employment	0.149	0.147	0.028	2000	179
College Educated Working Share	0.503	0.516	0.122	2000	179
Female Working Share	0.512	0.514	0.021	2000	179
Foreign Working Share	0.086	0.057	0.072	2000	179
Housing Supply Elasticity	2.300	2.281	0.969	-	179
Panel C: Commuting Zone Outcomes, Labor Market Sample					
	Mean	Median	IQR	Years	N
Wage Growth	0.172	0.164	0.108	2001-06	741
Change in Not Working Share	-0.089	-0.087	0.037	2001-06	741
Change in Manufacturing Work Share	0.003	0.003	0.019	2001-06	741
Change in Construction Work Share	0.026	0.024	0.015	2001-06	741
Change in Other Work Share	0.010	0.016	0.033	2001-06	741
Manufacturing Share of Employment	0.085	0.078	0.071	2000	741
Routine Share of Employment	0.152	0.150	0.028	2000	741
College Educated Working Share	0.465	0.463	0.121	2000	741
Female Working Share	0.507	0.510	0.024	2000	741
Foreign Working Share	0.057	0.037	0.047	2000	741

Note: The top panel reports various descriptive statistics from the Zillow house price transaction sample in 2001. The middle panel reflects the aggregate commuting zone house price sample. The bottom panel reflects the aggregate commuting zone labor market sample. This data is based on aggregated values from the Zillow house price data as well as US Census IPUMS microdata. The housing supply elasticity is drawn from Saiz (2010).

Table A2: FHFA House Prices and Manufacturing

Percent Change in House Prices	(1)	(2)
Sample	FHFA	Zillow
Manufacturing Share	-0.210***	-0.444***
	(0.060)	(0.080)
Controls	Yes	Yes
Fixed Effects	Census Division	Census Division
Commuting Zone Observations	657	179
Years	2001-06	2001-06
Adjusted R^2	0.534	0.714

Note: Regressions run at the commuting zone level with the average percentage house price growth from the FHFA over 2001-06 on the manufacturing employment share in 2000. The first column is estimated on the FHFA sample, while the second column restricts to the sample covered by the Zillow ZTRAX dataset. Controls include the Saiz (2010) housing supply elasticity, the percentage of routine cognitive jobs, the college educated working share, the female working share, and the foreign working share. Standard errors in parentheses are clustered at the state level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Table A3: Manufacturing Shares and the Labor Market

Panel A : CZ level	(1)	(2)	(3)	(4)	(5)
Percent Change in	Wage Income	Not Working	Manufacturing Work	Construction Work	Other Work
Manufacturing Share	-0.495***	0.295***	-0.141***	0.003	-0.157***
	(0.174)	(0.046)	(0.031)	(0.022)	(0.053)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Census Division	Census Division	Census Division	Census Division	Census Division
Underlying Census Records	8,908,337	8,908,337	8,908,337	8,908,337	8,908,337
Commuting Zone Observations	741	741	741	741	741
Years	2001-06	2001-06	2001-06	2001-06	2001-06
Adjusted R^2	0.267	0.414	0.291	0.204	0.277

Note: Regressions run at the commuting zone level with the indicated dependent variable over 2001-06 on the manufacturing employment share in 2000. Controls include the percentage of routine cognitive jobs, the college educated working share, the female working share, and the foreign working share. Standard errors in parentheses are clustered at the state level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Panel B : CZ/tercile level	(1)	(2)	(3)	(4)
Percent Change in	Wage Income			
	Aggregate	Tercile 1	Tercile 2	Tercile 3
Manufacturing Share	-0.479**	-0.646***	-0.439***	-0.336*
	(0.218)	(0.178)	(0.126)	(0.181)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Census Division	Census Division	Census Division	Census Division
Commuting Zone Observations	179	179	179	179
Years	2001-06	2001-06	2001-06	2001-06
Adjusted R^2	0.255	0.225	0.184	0.115

Note: Regressions of the percent change in wages on the manufacturing employment share in 2000 for each tercile of the 2001 house price distribution defined at the commuting zone level, for areas that are covered by the Zillow dataset. Controls include the percentage of routine cognitive jobs, the college educated working share, the female working share, and the foreign working share. Standard errors in parentheses are clustered at the state level. *, **, *** denote significance at the 10%, 5%, and 1% levels.

Table A4: Repeat Sale House Prices and Manufacturing across the Distribution

Percent Change in House Prices	(1)	(2)
Years	2001-06	2001-15
Manufacturing Share * Low-Value Houses	-1.146*** (0.357)	-0.800** (0.303)
Manufacturing Share * Mid-Value Houses	-0.159 (0.274)	-0.171 (0.191)
Manufacturing Share * High-Value Houses	0.076 (0.276)	0.037 (0.151)
Controls	Yes	Yes
Fixed Effects	Census Division	Census Division
Underlying House Transactions	909,816	519,294
Commuting Zone x Tercile Obs.	132	129
Adjusted R^2	0.446	0.513

Note: Regressions run at the commuting zone x house price tercile level with the percent change in average house prices for the relevant cell on the manufacturing employment share in 2000. Price changes are based on houses with repeat transactions between 1999-2002 and 2005-2008 (for "2001-2006 sample") or 2013-2015 (for "2001-2015 sample"). The terciles reflect 2001 home values. Controls include the Saiz (2010) housing supply elasticity, the percentage of routine cognitive jobs, the college educated working share, the female working share, and the foreign working share. Only commuting zones with at least 200 observations and terciles with at least 50 are used. Standard errors in parentheses are clustered at the state level. *, **, *** denote significance at the 10%, 5%, and 1% levels.