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LOCATION, LOCATION, LOCATION: MANUFACTURING AND HOUSE PRICE GROWTH

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Abstract

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Keywords: Manufacturing decline, House Prices, housing inequality

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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 and (2) that this pattern is especially present for the lowest-value homes. Counterfactual accounting exercises reveal that regional differences in the growth of these lowest-value homes more than fully account for an observed increase in overall house price inequality. We conclude that the relative economic decline of manufacturing-heavy areas extends far beyond income and employment flows to include shifts in important local asset prices, a pattern which matters for total house price 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. A more careful analysis below suggests that exposure to manufacturing accounts for 44% of the variation in house price growth across regions.

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. We rationalize these findings with a model featuring regional differences in manufacturing exposure and segmentation in the housing market.

We find that exposure to manufacturing quantitatively matters in accounting for the evolution of house price inequality. Less wealthy residents – in terms of house valuation – of areas that were more exposed to manufacturing endured less favorable house price dynamics relative to areas that were less exposed to manufacturing. Therefore, in our third contribution, we relate our findings to the overall evolution in house price inequality. To do so, we exploit our full micro distribution of U.S. house prices and demonstrate that inequality in house price growth recently increased by over 11%; that the increase is mostly regional in nature; and that the weak house price growth of the lowest-value homes in manufacturing-heavy areas directly accounts for around one-sixth of the increase in total house price inequality over our period.

Our paper contributes to three strands of work. First, it adds to the literature studying the relationship between manufacturing exposure and various labor market and social outcomes (Autor et al., 2018; Alder et al., 2017; Feyrer et al., 2007; Kahn, 1999; Notowidigdo, 2020), expanding the scope

[1] These figures are from 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 wealth inequality as embodied in house prices. Second, our work contributes to an understanding of the evolution and consequences of wealth and income inequality (Kaplan et al., 2018; Ahn et al., 2018; Saez and Zucman, 2016; Song et al., 2018). Third, we add to a broader literature linking house price movements and the macroeconomy (Piazzesi and Schneider, 2016; Kaplan et al., 2018; Berger et al., 2017; Guren et al., 2020; Howard and Liebersohn, 2018; Charles et al., 2016).

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) and local housing supply elasticities from Saiz (2010). See Online Data Appendix A for more details on our sample construction, exact variable definitions, and summary statistics for each of the datasets used in this paper.

3 Average House Prices and Manufacturing

Before presenting our results, we emphasize that our aim in this paper is to contrast home price dynamics in manufacturing-heavy locations versus their peers in manufacturing-light areas. While we are careful to control for various commonly used confounding factors such as region-specific trends, local labor market composition, and housing supply elasticities, our overall goal is not causal identification: our empirical strategy of course does not rule out the possibility of remaining omitted factors or reverse causality potentially at work.

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 prices in CZ c in year $t \in \{2001, 2006\}$. Then, we consider a regression

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

where $M_{c,2000}$ denotes the share of manufacturing in total employment for CZ c in the year 2000. We add standard CZ-level controls 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 epicentre of the financial crisis and Great Recession, we initially focus on the 2001-2006 period, holding constant the various shares discussed above at their 2000 values. We later extend our analysis to the 2001-2015 period and show that our findings are persistent.

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 ≈ 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 available 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]

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 some homes than for others?

4.1 Location in the House Price Distribution

In order 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 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 price distribution in the base year (in our case 2001). We then compute the change in house prices for these repeat sales. Under the assumption that the house did not undergo major changes, the repeat sales approach allows us to directly study the distributional dynamics of house prices while holding characteristics fixed.

The second solution uses an 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.[4] Next, using these loadings and the amenities of houses sold in 2006, we can rank each house within the distribution of 2001 home prices. We therefore ensure that statements made

[3]To further validate the ZTRAX data, we note that when we use the FHFA data only for the CZ's for which we have ZTRAX coverage, we estimate a manufacturing coefficient of -0.444 in column (3) of Online Appendix Table A2, which is almost identical to the -0.467 coefficient reported in column (2) of Table 1. We are therefore confident that the transactions contained in the ZTRAX dataset are representative within their geographies.

[4]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 A for further details.

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.

The tradeoffs between the two approaches are clear. The repeat sales approach does not require us to control for a pre-specified list of housing 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 smaller sample size. Hence, in order 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 A we verify that our conclusions are robust to the use of repeat sales only.

4.2 Results

We divide all transactions in our 2001 benchmark year into three equally sized price terciles or segments: low-value, mid-value, and high-value. 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. The growth of average prices from 2001 to 2006 within each CZ $\times$ segment cell provides our main outcome measure. Table 2 presents estimates at the CZ $\times$ segment level. Our first specification is given by

$$\Delta p_{c,s,t} = \alpha + \daleth_s + \beta M_{c,2000} + \rho \left(s \times M_{c,2000}\right) + \gamma X_{c,2000} + \delta_{div} + \varepsilon_{c,t}. \tag{2}$$

In the equation above, $s \in \{1, 2, 3\}$ denotes the segment or tercile of the housing distribution, and $\daleth_s$ denotes the segment fixed effect. We continue to control for all the variables discussed in the context of equation (1). In this specification, we interact the manufacturing employment share $M_{c,2000}$ with the house price tercile s. This parametric 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) reports the results. Houses in all terciles appreciated more slowly on average in high-manufacturing areas. Moreover, the positive and precisely estimated interaction term reveals that exposure to manufacturing predicts even lower price growth for the lowest-value segment.

Column (2) provides a more flexible non-parametric specification, interacting manufacturing shares at the CZ-level with indicator variables for each house-price segment or tercile. Our second regression is then

$$\Delta p_{c,s,t} = \alpha + \daleth_s + \sum_s \beta_s 1_s \times M_{c,2000} + \gamma X_{c,2000} + \delta_{div} + \varepsilon_{c,t}. \tag{3}$$

where 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. This non-parametric approach to measuring heterogeneous house price dynamics leads to the same qualitative conclusion as column (1): while low-value homes display sharply lower growth in the face of manufacturing exposure, this difference is more muted for their high-value neighbors. To summarize, 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, column (2) reveals 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.

Our analysis up to this point has focused on the 2001-06 pre-Great Recession period in order to avoid picking up factors specific to the financial crisis associated with the large disruption in housing markets from 2007 onward. Columns (3) and (4) in Table 2 show our results when we expand our sample period by nine years to 2001-15. One might expect that the predictive power of past manufacturing intensity would dissipate fairly quickly as structural adjustment occurs at the local level. Remarkably, we instead find that the lowest-value homes in manufacturing-heavy areas continue to experience lower cumulative house price growth one and a half decades later. We estimate both our parametric and nonparametric specifications on the longer 2001-15 sample in columns (3) and (4) of Table 2, respectively. As expected, the exposure to manufacturing predicts more muted differences over the longer horizon. However, our estimates reveal persistent and long-lasting differences in the price growth of the lowest-value homes in manufacturing-heavy areas. In contrast, over this longer time 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.

5 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. We then document and discuss empirical evidence consistent with these assumptions, providing a framework that rationalizes our results.

Model 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

$$Y_{A,L} = \frac{\alpha}{2} Pop_A^{MFG} \times Y^{MFG} + \left(0.5 - \frac{\alpha}{2} Pop_A^{MFG}\right) \times Y^{Other},$$

while income in the H segment is

$$Y_{A,H} = \left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG} \times Y^{MFG} + \left(0.5 - \left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG}\right) \times Y^{Other}.$$

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.[5]

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 $X_{A,L} >$

[5]Specifically,

$$X_{A,L} = \frac{\frac{\alpha}{2} Pop_A^{MFG} \times Y^{MFG}}{\frac{\alpha}{2} Pop_A^{MFG} \times Y^{MFG} + \left(0.5 - \frac{\alpha}{2} Pop_A^{MFG}\right) \times Y^{Other}},$$

$$X_{A,H} = \frac{\left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG} \times Y^{MFG}}{\left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG} \times Y^{MFG} + \left(0.5 - \left(1 - \frac{\alpha}{2}\right) Pop_A^{MFG}\right) \times Y^{Other}},$$

$$X_{B,L} = \frac{\frac{\alpha}{2} Pop_B^{MFG} \times Y^{MFG}}{\frac{\alpha}{2} Pop_B^{MFG} \times Y^{MFG} + \left(0.5 - \frac{\alpha}{2} Pop_B^{MFG}\right) \times Y^{Other}}, \text{ and}$$

$$X_{B,H} = \frac{\left(1 - \frac{\alpha}{2}\right) Pop_B^{MFG} \times Y^{MFG}}{\left(1 - \frac{\alpha}{2}\right) Pop_B^{MFG} \times Y^{MFG} + \left(0.5 - \left(1 - \frac{\alpha}{2}\right) Pop_B^{MFG}\right) \times Y^{Other}}.$$

$X_{B,L}$ 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 $Pop_A^{MFG} > Pop_B^{MFG}$. Below we discuss evidence 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. Below we show that manufacturing workers are indeed disproportionately represented in the lowest tercile of the housing distribution.

Exposure to Manufacturing and Labor Market Outcomes in the Data Previous work studying manufacturing documents that areas with more steeply declining manufacturing shares experienced lower employment growth (Charles et al., 2019; Ramey, 2018). In Online Data Appendix Table A4, we document similar patterns at our level of spatial and time coverage. In particular, we show that manufacturing-heavy CZ's experienced lower average wage growth, a higher likelihood of non-employment, a lower likelihood of working in manufacturing, no increased likelihood of working in the alternative construction sector, and a declining likelihood of work in all other sectors.

Manufacturing Workers and House Price Tiers Using self-reported Census house price valuations, we compute the fraction of manufacturing workers in each home-price tercile, at the CZ level.[6] As is evident from Figure 2, manufacturing workers are disproportionately represented in the lowest tercile of the housing distribution and much less present in the highest tier.

Thus, the empirical patterns we show in this 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.

6 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. In order to isolate the role of the lowest-value homes for the observed rising inequality of house prices, we engage in a series of simple counterfactual accounting exercises.

The top panel of Table 3 reports that inequality in house prices rose from a log standard deviation of 87.9% in 2001 to 92.8% in 2015, an increase in cross-sectional variance of $(0.928/0.879)^2$-1 $\approx$ 11.5%. Increased inequality manifested itself mostly for low-value homes, while dispersion in mid-value and

[6]We do not have information in the ZTRAX dataset regarding the occupation of the sellers.

high-value homes remained fairly flat or declined over the same period. 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. In particular, 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 values $\varepsilon_{h,c,s,t}$ represent the normalized home prices, 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.

In our first scenario, we shut down all heterogeneity in the growth of mean house prices $\mu_{c,s,t}$ across c or s over the 2001-15 period. The first counterfactual in the bottom panel of Table 3 reveals that the 2015 standard deviation of log prices under this scenario is 85.4%, implying an overall *decline* in house price inequality in this period absent heterogeneous growth rates across cells. In other words, differences in the average growth of home prices across regions and home-value segments more than fully account for increased overall house price inequality.

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. The bottom panel of Table 3 reveals that the 2015 standard deviation of log prices under this scenario is 87.3%, again implying an overall *decline* in house price inequality absent heterogeneity in the average growth of the lowest-value homes across regions. In other words, differences in the average growth of *only* the lowest-value home prices across regions more than fully account – on their own – for increased overall house price inequality.

Our two initial decompositions lead to the striking conclusion that regional differences, and in particular those for the very lowest-value homes, prove critical for understanding increased house price inequality. In our third counterfactual, motivated by our manufacturing regressions, we narrow the analysis even further. We 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 all heterogeneity in the growth rates of the lowest-value segment of homes predicted by our regressions in column (4) of Table 2. The third counterfactual in the bottom panel of Table 3 reveals that the 2015 standard deviation of log prices under this scenario is 92.1%. Therefore, house price inequality would still have increased absent the variation predicted by manufacturing exposure at the bottom of the housing distribution. However, the resulting increase in variance would be only $(0.921/0.879)^2$-1 $\approx$ 9.7 percentage points, which is 15 percent smaller than the observed increase. In other words, heterogeneity in average growth rates for the lowest-value homes predicted only by their exposure to manufacturing accounts for around a sixth of the increase in total house price inequality over this period.

To summarize, our analysis suggests that any analysis of house price inequality must grapple with important heterogeneity in the growth rate of home prices across regions, especially for the lowest-value homes in manufacturing-heavy areas.

7 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. 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, a pattern which matters for total house price inequality.

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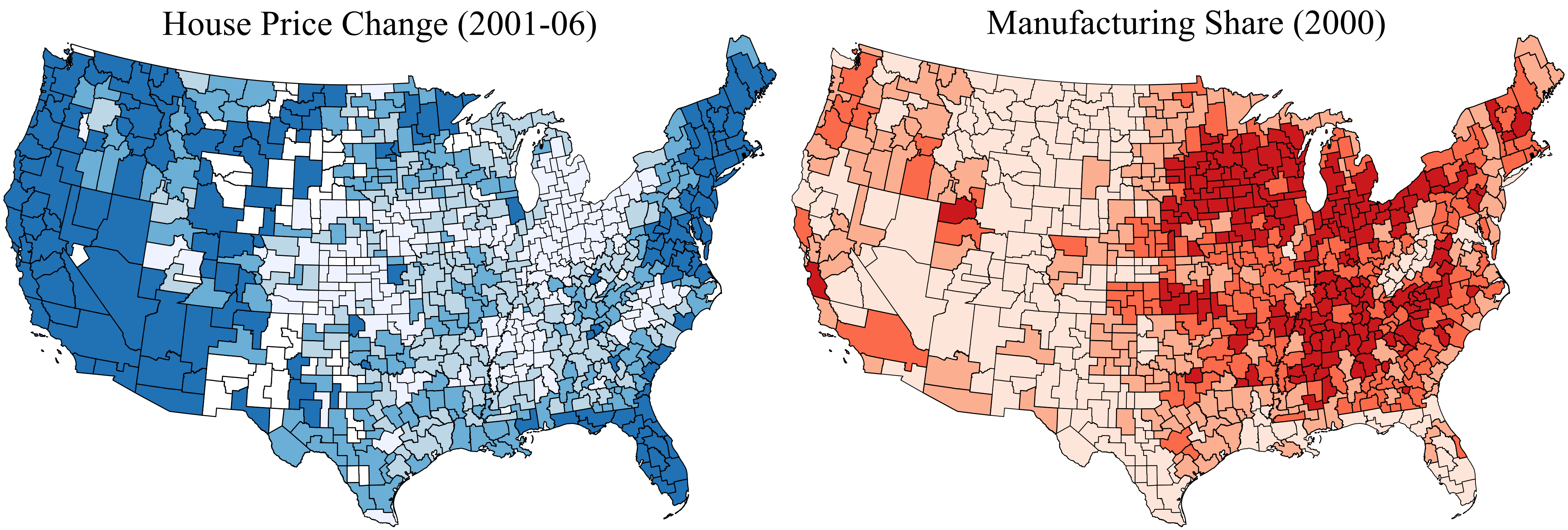
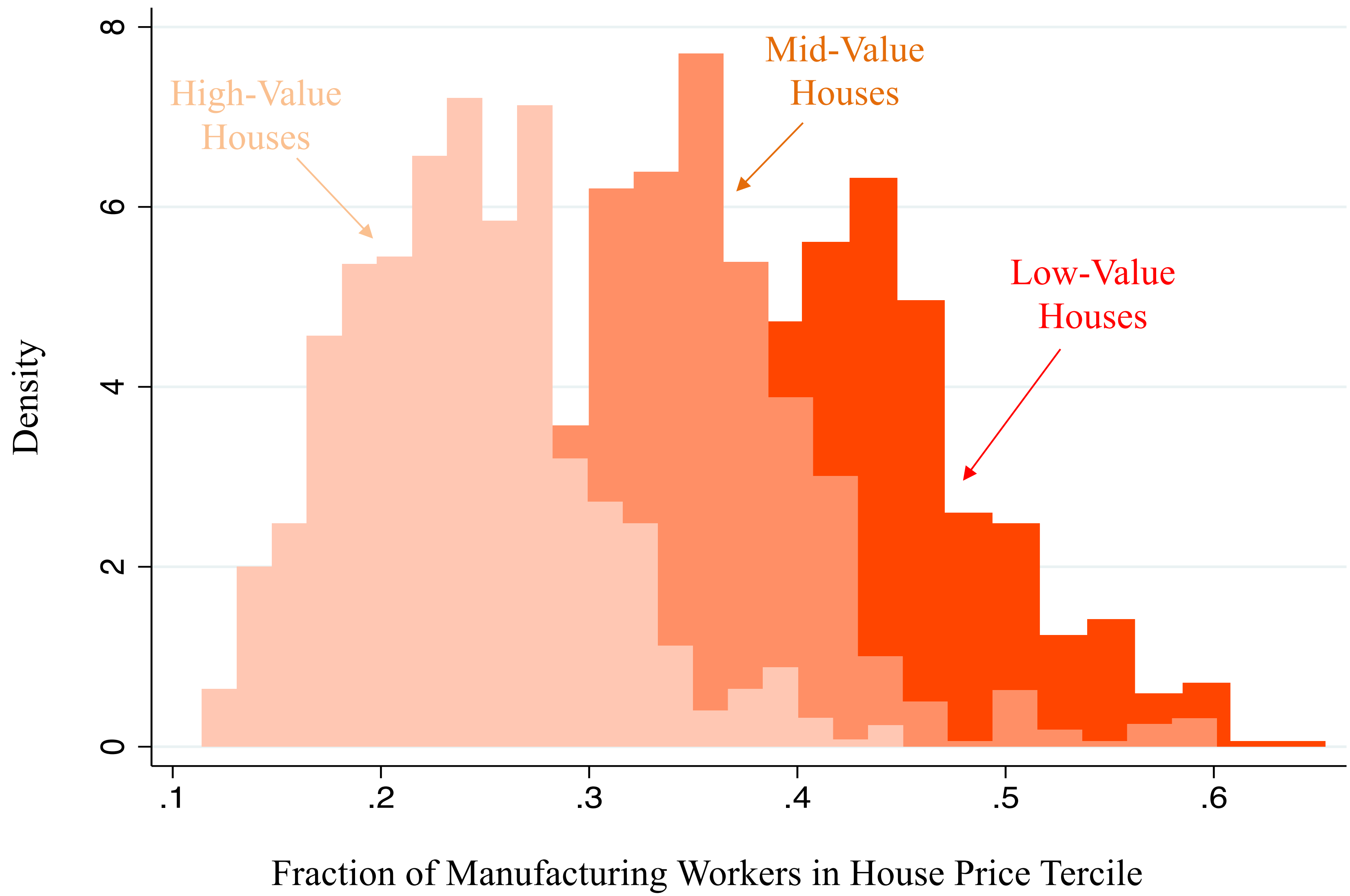
Figure 1: House Prices and Manufacturing



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)	(2)
Manufacturing Share	-0.488***	-0.467***
	(0.142)	(0.137)
Controls	Yes	Yes
Fixed Effects	No	Census Division
Underlying House Transactions	19,670,168	19,670,168
Commuting Zone Observations	179	179
Years	2001-06	2001-06
Adjusted R^2	0.227	0.249

Note: Regressions run at the commuting zone level with the average percentage house price growth over 2001-06 on the manufacturing employment share in 2000. Controls include the Saiz (2010) housing supply elasticity, the percent 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 2: House Prices and Manufacturing across the Distribution

Percent Change in House Prices	(1)	(2)	(3)	(4)
Interaction	Parametric	Non-Parametric	Parametric	Non-Parametric
Years	2001-06	2001-06	2001-15	2001-15
Manufacturing Share	-0.816***		-0.174***	
	(0.179)		(0.051)	
Manufacturing Share	0.121***		0.079***	
* House Price Tercile	(0.037)		(0.013)	
Manufacturing Share		-0.690***		-0.088*
* Low-Value Houses		(0.151)		(0.047)
Manufacturing Share		-0.583***		-0.029
* Mid-Value Houses		(0.142)		(0.041)
Manufacturing Share		-0.448***		0.071
* High-Value Houses		(0.123)		(0.045)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Census Division	Census Division	Census Division	Census Division
Underlying House Transactions	19,670,168	19,670,168	43,686,431	43,686,431
Commuting Zone x Tercile Obs.	535	535	535	535
Adjusted R^2	0.288	0.286	0.387	0.388

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 percent 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	2015
All Houses	0.879	0.928
Low-Value Houses	0.920	1.132
Mid-Value Houses	0.853	0.876
High-Value Houses	0.862	0.726
Panel B: Counterfactuals		
Log Standard Deviation for All Houses in Year:	2001	2015
Observed	0.879	0.928
Removing All Regional and Segment House Price Growth Differences	0.879	0.854
Removing Low-Value House Price Growth Differences	0.879	0.873
Removing Mfg.-Predicted Low-Value House Price Growth Differences	0.879	0.921
Underlying House Transactions	2,664,242	2,255,561

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 Appendix

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 housing 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 first approach relies on hedonic regressions run only on the year-2001 portion of our sample. In particular, we estimate

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

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.

Our second 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 A3 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 a given 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.

Table A4 leverages this Census IPUMS micro data, demonstrating that manufacturing-heavy areas experienced lower wage and employment growth over our period of interest. In particular, column (1) reveals that average wages in a highly exposed area at the 75th percentile of manufacturing shares in 2000 grew by $0.495 \times 7.1 \approx 3.5\%$ less each year over 2001-06 than in a manufacturing-light region at the 25th percentile, a difference equal to 32% of the overall IQR of wage growth across regions. Using the same comparison, column (2) shows that the likelihood of an individual not working grew by $0.295 \times 7.1 \approx 2.1\%$ more in that same CZ, equal to 56% of the IQR of non-employment growth. Column (3) shows that the likelihood of working in manufacturing fell by $0.141 \times 7.1 \approx 1.0\%$ more, equal to 56% of the IQR of growth in the share of manufacturing work. Column (4) shows that the likelihood of working in construction was not precisely different in the manufacturing-heavy region. Column (5) documents that the likelihood of working in all other sectors fell by $0.157 \times 7.1 \approx 1.1\%$ more, equal to 33% of the IQR of the growth in the share of all other work. Note that by construction the sum of the coefficients in columns (2) - (5) must be zero.

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.

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 Wprl 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)	(3)
Sample	FHFA	FHFA	Zillow
Manufacturing Share	-0.379***	-0.387***	-0.444***
	(0.073)	(0.085)	(0.080)
Controls	Yes	Yes	Yes
Fixed Effects	No	Census Division	Census Division
Commuting Zone Observations	657	657	179
Years	2001-06	2001-06	2001-06
Adjusted R^2	0.583	0.708	0.715

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 two columns are estimated on the FHFA sample, while the third column restricts to the sample covered by the Zillow ZTRAX dataset. Controls include the Saiz (2010) housing supply elasticity, the percent 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: Repeat Sale House Prices and Manufacturing across the Distribution

Percent Change in House Prices	(1)	(2)
Interaction	Parametric	Non-Parametric
Years	2001-06	2001-06
Manufacturing Share	-0.326***	
	(0.088)	
Manufacturing Share * House Price Tercile	0.122***	
	(0.032)	
Manufacturing Share * Low-Value Houses		-0.229***
		(0.071)
Manufacturing Share * Mid-Value Houses		-0.032
		(0.055)
Manufacturing Share * High-Value Houses		0.015
		(0.055)
Controls	Yes	Yes
Fixed Effects	Census Division	Census Division
Underlying House Transactions	909,780	909,780
Commuting Zone x Tercile Obs.	132	132
Adjusted R^2	0.51	0.51

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 percent 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.

Table A4: Manufacturing Shares and the Labor Market

Percent Change in	(1) Wages	(2) Not Working	(3) Manufacturing Work	(4) Construction Work	(5) 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 percent 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.