Manufacturing Busts, Housing Booms, and Declining Employment: A Structural Explanation

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Abstract

This paper studies the extent to which the housing boom and subsequent housing bust within the U.S. during the 2000s masked (and then subsequently unmasked) the sharp, ongoing decline in the manufacturing sector. We exploit cross-city variation in manufacturing declines and housing booms during the 2000-2007 period, and we jointly estimate the effect of both types of shocks on local employment and wages. Focusing on the 2000-2007 period, we find that a one standard deviation negative manufacturing shock increases the non-employment rate of non-college-educated men by 1 percentage point, and we find that a one standard deviation positive housing price shock reduces the non-employment rate for this group by 1.2 percentage points, enough to fully offset the effects of the adverse manufacturing shock. Roughly half of the "offsetting" appears to come from increased construction employment, with the remainder coming through other sectors that are affected by shocks to local housing prices. We find that other demographic groups are affected by both of these shocks to a lesser extent. Finally, we use these estimates to construct counterfactuals assessing how aggregate employment would have evolved during the 2000s absent the housing boom/bust cycle, and we find that roughly 40 percent of the increase in non-employment between 2007 and 2011 can be attributed to the decline in manufacturing employment that occurred within the U.S. during the 2000s. In particular, we find that much of the recent increase in non-employment would have occurred earlier had it not been for the large temporary boom in local housing prices. (JEL J21, E24, E32)

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1 Introduction

The dramatic decline of the manufacturing sector that began in the 1970s has continued, and perhaps slightly accelerated, through the 2000s. Previous research has established a relatively sharp negative relationship between sectoral decline in manufacturing and wage and employment outcomes for men, particularly for men without a college degree.[2] However, from 2000-2007 and from 2007-2011, this negative relationship departed from what might have been predicted based on the historical pattern. Between 2000 and 2007, manufacturing employment declined by 3.5 million jobs. A change this dramatic might have been expected to cause massive increases in non-employment and reductions in wages for less-skilled men. In fact, non-employment rates for prime-aged men without a college degree (the group we define as "less-skilled" throughout the paper) only increased by 2.8 percentage points during this period, and their median wages stabilized and slightly increased after decades of consistent decline.[3] By contrast, between 2007 and 2011, manufacturing employment fell by about 2.5 million jobs, while the non-employment rate of less-skilled men surged by 8.6 percentage points, a change that was much *larger* than might have been predicted from the historical relationship between manufacturing changes and employment outcomes.[4]

This paper argues that the sectoral decline in manufacturing between 2000 and 2007 *would have otherwise* lowered employment and wages of less-skilled (and possibly other) workers, but these adverse effects were obscured by the employment opportunities for less-skilled men associated with the unprecedented boom in the housing market during these years, when house prices rose nearly 37%. The collapse of the housing market between 2007 and 2011 – during which almost all of the price gains from the boom were erased – removed from the economy the less-skilled employment opportunities associated with the preceding boom. Moreover, less-skilled men were now confronted with a labor market where there was much less demand for their skills than there had been at the start of the housing boom, due to the continuing decline in manufacturing between 2000 and 2011. In this sense, the housing bust "unmasked" the effects of the ongoing decline in manufacturing employment.

The temporary boom and bust cycle in the housing market could have independently affected the employment opportunities of less-skilled men through a number of channels. For example, changes in household wealth associated with house price variation likely changed households' consumption.[5] Perhaps a more direct channel, though, is the change in construction activity caused by changes in the housing market. Figure 1 uses data from the Current Population Survey (CPS) to plot the share of all less-skilled men employed

[2] See Bound and Holzer (1993) for analysis of the labor market effects of manufacturing decline in the 1970s and 1980s.

[3] Data for changes in manufacturing are from the the Bureau of Economic Analysis. Wages and employment for lower skilled men come from the authors' calculations from Current Population Survey (CPS) data. See Appendix Figure A1 for depiction of the median wage series.

[4] Changes in non-employment for less-skilled men were large relative to those among higher-skilled men during the latter part of the 2000s but were nearly identical during the 2000-2007 period.. The non-employment gap between prime-aged men without and with a college degree, which had been basically flat or growing very slightly since the late 1990s, nearly doubled after 2007, jumping to 16 percentage points.

[5] See Mian and Sufi (2012) for a discussion and evidence of this mechanism.

in manufacturing and construction.[6] The figure provides suggestive evidence regarding the masking and unmasking effect of the boom and bust in housing when coupled with a persistent, ongoing decline in the manufacturing sector. The patterns are all the more striking because construction is only *one* mechanism by which a housing market boom or bust affects labor market outcomes for these men.

The broken line in the figure, which plots the share of less-skilled men working in either manufacturing or construction, shows that these two sectors have historically combined to account for a very large fraction of the employment of these men. In 1979, 37 percent of less-skilled men worked in one of these two sectors, and more than 20 percent continue to work in these sectors in 2010.[7] The figure shows that the steady decline in manufacturing, discussed earlier for the population as a whole with BEA data, was even more significant for less-skilled men. The share employed in manufacturing fell from 27 percent to 20 percent between 1977 and 1997, then from 20 percent to 15 percent between 1997 and 2007, and has continued falling after 2007. By contrast, construction employment among less-skilled men was constant at around 10 percent between 1977 and 1997, then increased to over 15 percent during the housing boom, before collapsing after the bust in housing in 2007.[8] During the boom, higher employment from construction alone (ignoring any likely increase in the provision of local services from a housing wealth effect) sharply offset the employment declines from manufacturing for less-skilled men. When construction employment collapsed between 2007 and 2011, there was a dramatic change in the sum of employment in construction and manufacturing, as the accumulated losses from manufacturing which had been masked by construction during the housing boom were exposed.

In this paper, we formally investigate how the decline in manufacturing and the housing boom and bust during the 2000s *separately* affected changes in non-employment and wages for less-skilled men. Determining separate effects for housing market changes and manufacturing decline allows to us to estimate how labor market outcomes would have evolved in response to one of these changes, had the other not occurred. In addition, producing these estimates allows us to provide a quantitative assessment of the size of the "masking"/"unmasking" phenomenon. We regard the housing boom and bust as inseparably linked parts of the same phenomenon; it is, for example, difficult to conceive of the bust without the preceding boom. We are therefore interested in understanding changes over the entire 2000-2011 period, not just the housing boom and housing bust periods.

Our analysis focuses on comparisons across metropolitan areas (MSAs), and we exploit variation in both the size of the manufacturing decline in the MSA during the 2000s and in the size of the housing boom during the same period. Our estimation focuses on the period from 2000-2007 (prior to the 2008 recession). We use

[6] We define the CPS sample more precisely later in the paper. Throughout, we treat prime-aged men as those between 21 and 55 (inclusive), and define less skilled individuals to be those without a college degree. Although we focus in this initial section on less-skilled men, we later examine the results for less skilled women as well as higher skilled men and women.

[7] The wages of less skilled men is also strongly correlated with employment in manufacturing plus construction. The simple correlation between the two series over the period depicted is 0.91.

[8] There was a smaller housing boom and bust cycle in the U.S. from 1984 through 1993. This can also be seen in the construction shares. In ongoing work, we are exploring the extent to which this earlier housing boom masked the manufacturing declines during the 1980s and contributed to the higher levels of non-employment in the 1990 recession.

total manufacturing employment to proxy for the decline in manufacturing demand in an MSA. To isolate exogenous variation in MSA manufacturing labor demand that is derived from the long-term secular decline of the industry, we follow the widely-used procedure of Bartik (1991) and Blanchard and Katz (1992), and we instrument for changes in MSA manufacturing employment share using the interaction between MSA's initial industry mix and national changes in manufacturing employment. The logic of the Bartik instrument we construct is that the national decline in the manufacturing sector differentially impacted MSAs based on the *pre-existing* importance of manufacturing in the area as measured by manufacturing share and pre-existing differences in specific manufacturing industries that experienced different trends over time. Consistent with previous work, the Bartik instrument strongly predicts changes in local manufacturing employment in our analysis.[9]

We use housing prices to proxy for changes in labor demand within an MSA. Since house prices are determined in part by the strength of local manufacturing industry, and since we wish to *separately* identify the effects of manufacturing declines, we residualize local house prices of the effect of predictable changes in local manufacturing employment, as captured by the Bartik instrument. Variation in this residualized house price measure reflects changes in demand and supply of housing arising from (at least) two possible sources: (1) shocks to sectors other than manufacturing within the MSA, which change workers' wages or lead to an in-migration of workers which in turn increases the demand for housing within the MSA; and (2) changes to the demand for housing resulting from innovations in the lending industry or changes in interest rates. The house price changes produced by either of these can be temporary or relatively permanent. The house price within the MSA is a good proxy for labor demand associated with the housing market because many activities, such as construction booms or changing demand for local service workers because of changes in household wealth, will vary positively with the level of the (residualized) price.

We ideally would like to isolate the effect of *temporary* changes in local labor demand caused by housing market activity. These temporary changes, we argue, are what masked and then unmasked the changes in manufacturing. We therefore instrument for housing prices using estimates of the local housing supply elasticity, which captures the ease with which construction can be changed in the MSA because of zoning, geography, or other restrictions. These elasticity measures capture the extent to which housing supply is restricted in the short run. Short-term changes, such as those associated with the transitory housing boom and bust at the national level, should produce larger increases in housing prices (and associated changes in local demand from a wealth effect) in places where the housing supply was more inelastic. It is important to recognize that higher housing prices will lead to increased construction activity even in places where the supply of *new* construction was restricted, as house price increases cause households to tear-down, remodel, or renovate existing structures. Indeed, this is precisely what we document empirically, as the housing

[9] We are aware of the potential general equilibrium effects of a housing boom on manufacturing demand. If people feel richer from their increase in housing wealth, spending on all goods - including manufactured goods - will increase. As we discuss later, such general equilibrium effects will cause us to underestimate the extent to which the housing boom masked the decline in manufacturing during the 2000-2007 period.

elasticity instrument we use in our analysis strongly predicts total construction activity in an MSA during the 2000-2007 period.

Using OLS and Two Stage Least Square (TSLS) models, we find that the predicted manufacturing bust during 2000-2007 in an MSA: (1) reduced actual manufacturing employment, (2) reduced construction employment, (3) decreased wages, (4) increased non-employment, and (5) decreased population. In particular, a one standard deviation increase in an MSA's predicted manufacturing bust led to a 1 percentage point increase in the non-employment rate for less-skilled men within the MSA during the 2000-2007 period. We find that a positive housing price shock during the 2000-2007 period: (1) had no effect on manufacturing employment, (2) increased construction employment, (3) increased non-manufacturing, non-construction employment, (4) increased wages, and (5) decreased non-employment. In particular, a one standard deviation increase in magnitude of housing boom led to a 1.2 percentage point decrease in the non-employment rate for less-skilled men, enough to fully "offset" the effects of an adverse manufacturing shock. Our estimates imply that only about half the effect of employment resulting from a housing boom comes from increased construction employment. The remainder comes from other sectors, including local retail and services. While our estimates of labor market effects in response to the manufacturing and housing shocks are largest for less skilled men, we find non-trivial effects for higher-skilled men and less-skilled women.

Interestingly, the estimated effects of house price booms during the 2000-2007 period are very similar across the OLS and TSLS specifications. This suggests that the variation in residualized housing prices at the MSA level between 2000 and 2007 was primarily transitory. Indeed, almost all of the MSAs experiencing large house price increases during the 2000-2007 period experienced large decreases during the 2007-2010 period. This pattern helps reconcile our last set of empirical results, which show no evidence that a negative housing price shock during the 2007-2010 period significantly affected longer run changes in non-employment over the *entire* 2000-2010 time period. While the housing bust strongly predicts within-MSA changes in non-employment during 2007-2010, it does not predict longer run changes over the 2000-2010 time period, most plausibly because the housing bust "unmasked" non-employment growth that was suppressed by the housing boom that preceded it.

Using our preferred estimates of the responsiveness of non-employment and wages to the manufacturing and housing boom measures, we conduct a series of counterfactuals analyses. In particular, we trace out how the non-employment rate in the U.S. would have evolved over the 2000-2007 period if the economy had not experienced a housing boom. We find that the non-employment rate for less-skilled men (women) would have increased by an additional 1.9 (1.6) percentage points between 2000 and 2007 in that hypothetical case.[10] More importantly, we conclude that roughly 40 percent of the increase in non-employment for all groups in the U.S. between 2007 and 2011 can be attributed to the decline in manufacturing demand during the 2000s. The decline in manufacturing between 2007 and 2011 accounts for part of this, but a much larger portion

[10] As we discuss later, these estimates are likely lower bounds of the true effect given that the housing boom in the U.S. may have actually inflated manufacturing demand more than it would have been otherwise.

can be attributed to the decline in manufacturing from 2000 to 2007 that was masked by the housing boom. In summary, we estimate that the decline in manufacturing explains roughly 40 percent of the increase in non-employment between 2000 and 2011 (the entire decade) while house prices explain essentially none of the increase in non-employment over this longer time period.[11] This is because over the longer period from 2000-2011, housing prices were essentially flat (in real terms) in the U.S.

We believe that our results are relevant to the ongoing debate about whether there is a structural component to the current high levels of non-employment in the U.S. Despite much speculation by academics and policymakers, to our knowledge there is little credible research showing that structural factors explain a significant portion of current non-employment.[12] Most discussion of structural forces focuses on labor market mismatch, which empirically seems to account for little of current unemployment.[13] The structural forces that we highlight are inherently different than the mismatch mechanism, in that they exist in a standard labor market account where workers choose whether to work based on the market wage they command and their reservation wage. When the demand for their skills falls, wages fall and some workers choose to exit employment. These forces are an extension of the same phenomenon that has been occurring in the U.S. economy for the last thirty years, but which were obscured during the 2000s by a temporary and large boom-bust cycle in housing. We stress that we are *not* suggesting that cyclical forces do not play an important role with respect to high levels of non-employment in the U.S. Our estimate that 40 percent of the rise in non-employment between 2007 and 2011 is due to the secular decline in manufacturing that the U.S. economy experienced in the last decade implies that fully 60 percent of the non-employment rise could be due to cyclical forces, other structural forces (like mismatch), or to labor supply response from changing government policies.

The remainder of the paper of the paper proceeds as follows. In the next section we outline a simple model that will frame our empirical work, which highlights the interaction between permanent declines in labor demand in one sector (e.g., manufacturing) and cyclical booms and busts in labor demand in another sector (e.g., housing related sectors). We use the model to show that to the extent that booms and busts in the overall economy are correlated with booms and busts in one sector (like housing), labor force participation will be more stable during aggregate booms and more responsive in recessions when there is simultaneously a persistent decline in another sector (like manufacturing). The model provides intuition for the empirical results later in the paper. We discuss the data in Section 3. In Section 4, we outline the empirical model, describing our estimation equations and identification strategy. In this section we also present our main

[11] We show that our results are not substantially affected by accounting for a migration response to the manufacturing and housing shocks. If anything, allowing for a migration response *increases* the estimated importance of the manufacturing shock in explaining the current levels of non-employment. Additionally, in section 5 below, we also discuss how other general equilibrium effects could affect our results. If anything, we argue that the most relevant general equilibrium effects of the housing boom on manufacturing demand during the 2000-2007 period likely lead our results to be biased downwards.

[12] See, for example, the recent op-ed in the Financial Times by Rajan (2012)(http://www.ft.com/cms/s/2/17166454-a366-11e1-988e-00144feabdc0.html#axzz1yjIeXK18), and a speech by Minneapolis Federal Reserve President Kotcherlakota (2010) (http://www.minneapolisfed.org/news_events/pres/speech_display.cfm?id=4525 #_ftnref2).

[13] See, for example, Sahin et al. (2012).

empirical results. In Section 5, we construct counterfactuals, based on our regression estimates, of how labor market outcomes would have evolved since 2000 had there been no boom and bust in the housing market. We conclude in Section 6.

2 Conceptual Framework

2.1 Setup

This section develops a stylized model of a local labor market. We use the model to provide simple intuition regarding the determinants of substitution elasticities across occupations and between employment and non-employment. We also use our model to illustrate how persistent declines in one sector interact with a temporary "boom-bust" cycle in another sector over time. We consider an economy with workers who choose to work in one of three sectors. Two sectors (A and B) are "employed" sectors, and the third sector (H) represents non-employment in the "home sector". In our specific empirical application below (which focuses on labor market outcomes for less-skilled men), sector A corresponds to the manufacturing sector (which is undergoing persistent decline), and sector B corresponds to sectors that are affected by the housing boom.[14]

The mass of workers in the economy have heterogeneity in skill endowments and reservation wages, which are jointly distributed according to the PDF $f(s, r)$. Workers with skill endowment s can either choose to supply s efficiency units of labor in sector A, $(1-s)$ efficiency units of labor in sector B, or choose to work in the "home" sector H.[15] Workers will choose to work in the home sector if the highest wage they would receive across the two sectors is lower than their reservation wage – i.e., workers with skill endowment s and reservation wage r will choose employment if $r < \max\{sw_A, (1-s)w_B\}$ and non-employment otherwise.

Aggregate market output is given by the following production function:

$$Y = \alpha L'_A + \beta L'_B$$

where α and β are productivity/demand shifters in each sector and L'_A and L'_B are total labor supplies for sectors A and B (denominated in efficiency units). Cost minimization implies that wages per efficiency unit are pinned down by the productivity/demand shifters, so that $w_A = \alpha$ and $w_B = \beta$. The total labor supplies are determined by the endogenous self-selection of workers given the prevailing wages. A worker with (s, r) chooses to work in sector A if $sw_A > (1-s)w_B$ and $sw_A > r$. This condition leads to a marginal worker s^* who is indifferent between sectors A and B, given by $s^* w_A = (1-s^*)w_B$. Total labor supplies

[14] We discuss the sectors affected by the temporary housing booms in greater depth below.

[15] Given this, s represents the productivity of the worker in sector A relative to their productivity in sector B. In this sense, s indexes a workers comparative advantage between the two sectors. The main implications of the model carry through if we also allow workers to have an absolute advantage in any of the sectors.

are therefore given by the following:

$$L'_A = \int_{s^*}^{1} \int_0^{s\alpha} s f(s,r) dr ds$$
$$L'_B = \int_0^{s^*} \int_0^{(1-s)\beta} (1-s) f(s,r) dr ds$$

Empirically, it is simpler to measure population shares in each sector (rather than total labor supplies in efficiency units), so we solve for the population shares in each sector by noting that individuals must choose to be in one of the three sectors, implying that $L_A + L_B + L_H = 1$:

$$L_A = \int_{s^*}^{1} \int_0^{s\alpha} f(s,r) dr ds \tag{1}$$
$$L_B = \int_0^{s^*} \int_0^{(1-s)\beta} f(s,r) dr ds \tag{2}$$
$$L_H = 1 - L_A - L_B \tag{3}$$

With a specific functional form assumption for $f(r,s)$ and values for α and β, one can solve for equilibrium values of s^*, L_X, L_Y, L_H.

2.1.1 Graphical Solution

The solution to the model can be represented graphically, which illustrates how workers self-select into sectors for all possible combinations of skill endowments and reservation wages. In these figures, the y-axis is the reservation wage (r) and the x-axis is the skill endowment (s), with the entire plane representing all possible (s,r) combinations. The density ($f(s,r)$) would be represented as contour lines on the plane.

Figure 2a shows an initial equilibrium, with workers endowed with $s > s^*$ choosing to work in sector A as long as $s\alpha > r$. Workers endowed with $s < s^*$ and $s\beta > r$ will work in sector B. Those workers with a high reservation wage or who have no relative skill advantage in either sector are more likely to work in the home sector.

Figure 2b shows the equilibrium response to a negative productivity shock to sector A. The negative shock causes a reduction in share of individuals in L_A. Notice, as the figure illustrates, this decline comes from two margins: workers switching from sector A to sector B, and workers who leave sector A and enter non-employment (sector H). The relative importance of these two margins depends on the mass of workers along each margin.

If the negative shock to A is simultaneously accompanied by a positive shock to sector B, the resulting equilibrium is shown in Figure 2c. Relative to the previous figure, there are three additional margins. First, there are workers who leave non-employment and enter sector B. Second, there are additional switchers who move from sector A to sector B, but who would have remained in sector A in the absence of a positive

shock to sector B. Lastly, there are workers who switch from A to B, but who would have entered non-employment in the absence of a positive shock to B. As before, the relative importance of these margins depends on mass of workers along each margin, and the figure helps to immediately see several possibilities. For example, if most workers have very low reservation wages, then most of the response to sector-specific shocks will occur among workers switching between sectors A and B and there will not be an observed change in non-employment. This would correspond to the case of inelastic labor supply as in occupational choice models such as Autor, Levy, and Murnane (2003), where the sector-specific shocks reallocate workers across sectors but do not change aggregate non-employment. By contrast, if the reservation wages of most workers are close to their market wages, then most of the adjustment to the sector-specific shocks will come through changes in non-employment rather than through reallocation across sectors. In this case, the combination of sector-specific shocks (a decline in A and an increase in B) reallocates workers from sector A to sector B, but these workers would have ended up in non-employment (sector H) in the absence of the positive shock to sector B.

To summarize, this simple model illustrates that the effect of sector-specific shocks on non-employment will depend on the mass of workers who are on the margin between sectors and the mass of workers on the margin between employment and non-employment. In our empirical work below, we will construct sector-specific shocks and estimate the extent to which non-employment responds to each of these shocks. As the model makes clear, the estimated responses shed light on the relative importance of reservation wages and skill endowments in determining aggregate changes in non-employment. In particular, the extent to which negative shocks to sector A can be "offset" by booms in sector B is determined by the amount of skill substitutability among the set of marginal workers who are displaced as a result of the negative shock to A.

2.2 Time Series Implications of Model

We also extend the stylized model to generate time series predictions regarding the effects of sector-specific shocks over time. We consider numerical simulations of the stylized model under two scenarios to illustrate the time series predictions; the details of the simulations are provided in the Appendix.

Figure 3a shows results for the first scenario, where sector A is experiencing a steady decline while sector B is stable over time (i.e., α is steadily declining and β is constant over time). In this case, results of simulation show a steady increase in the non-employment rate (L_H) over time and a gradual reallocation of workers from sector A to sector B. By contrast, Figure 3b shows results of the second scenario, when sector A is again experiencing a steady decline but sector B is experiencing a transitory "boom-bust" cycle instead. In this case, when sector B is experiencing a "boom", it offsets the decline in sector A, and the non-employment rate remains roughly constant. When sector B enters the "bust" period, then both sectors are declining and the non-employment rate sharply increases. By construction, the non-employment rates end up identical at the end of the time period in both figures, but in Figure 3b the time path of non-employment

more closely resembles a "hockey stick", as the temporary boom masks the ongoing deterioration in the labor market arising from the continuing declines in sector A.[16]

Although the above simulation is highly stylized, it highlights the underlying intuition of the model. Moreover, the simple model gives potential insights into business cycle dynamics of labor market outcomes. If the aggregate business cycle is linked to booms and busts in Sector B, aggregate employment dynamics at a business cycle frequency will differ depending upon whether sector A is stable or whether it is experiencing a persistent sectoral decline.[17] If there is a persistent sectoral decline occurring in sector A, the labor market outcomes will be muted during the aggregate expansion (due to the boom in sector B) relative to the case where there is no persistent structural decline in sector A. Likewise, the response of labor markets to the bust in sector B would be amplified when sector A is also in decline. This is precisely what we illustrate in our empirical work below. During the aggregate expansion of 2000-2007, the employment propensities of less-skilled men did not rise substantially despite the very large housing boom. However, during the recent recession, we saw a very large decline in the employment propensities for less-skilled men. Once the boom and bust in sector B (housing related sectors) finished, employment still remains depressed in the overall economy because of the ongoing decline in labor demand in sector A.

3 Data

This section briefly describes the data. The Data Appendix gives more detail on how the data set was created.

Census and American Community Survey (ACS) The basic panel of metropolitan area data comes from the 2000 Census and 2005-2007 and 2009-2010 ACS individual-level and household-level extracts from the Integrated Public Use Microsamples (IPUMS) database (Ruggles et al., 2004). The baseline data are limited to individuals and households living in metropolitan areas. The IPUMS data are used to construct estimates of average wages, non-employment, employment shares in various occupations, and total population in each metropolitan area. The primary advantage of the Census and ACS data is the ability to construct reliable estimates of city-level labor market outcomes disaggregated by skill. Our primary sample consists of non-institutionalized men age 21-55 (inclusive), without a college degree. In alternative specifications, we study non-college women, college-educated men, and college-educated women. For these groups, we also focus on the non-institutionalized population between the ages of 21 and 55. We also use the Census and ACS data to construct the manufacturing instrumental variable following Bartik (1991) by using the industry categories of the individuals in the labor force. We discuss this instrument in greater detail below. The Data Appendix provides additional details pertaining to the sample construction.

[16] Note that the absence of intertemporal linkages make the model particularly easy to simulate. The dynamics of the model are completely pinned down by the dynamics of the α and β parameters.

[17] There is a growing literature showing that housing boom bust cycles and the aggregate business cycle are closely linked (see, for example, Leamer 2007). While we focus on the boom-bust cycle in housing for our empirical work, the intuition we are developing in this paragraph applies to a boom-bust cycle in any sector that is correlated with the aggregate business cycle.

Federal Housing Finance Agency (FHFA) House Price Indexes We use metropolitan area housing price data from the FHFA to construct measures of changes in local area housing prices, focusing primarily on house price growth measures during the 2000s. The FHFA index is a repeat-sales housing price index and is available for most metropolitan areas. We mapped the FHFA metro areas to the Census/ACS metro areas by hand. A discussion of our matching procedure can be found on the authors' websites. To mirror the ACS data, we construct average house price growth between 2000 and the pooled 2005-2007 years. To do this, we took the simple average of the house price index in the first quarter of 2005, 2006, and 2007. Likewise, we computing house price changes between 2007 and 2010, we are using the pooled FHFA data in 2005, 2006, and 2007 and the pooled FHFA data from 2009 and 2010. Our main results are similar if we compute housing price growth directly from the Census and ACS instead of using the FHFA house price indices.

Local Housing Supply Elasticity For some specifications, we use instruments to isolate temporary variation in housing prices at the local level. When doing so, we use estimates of metropolitan area housing supply elasticity from Saiz (2010). As we discuss below, the use of housing supply elasticities can isolate the temporary variation in housing prices that we wish to identify. These model-based elasticity estimates exploit pre-existing cross-sectional differences in land availability (arising from topological differences across MSAs) as well as (endogenous) differences in regulatory constraints, which jointly affect the cost of expanding the housing supply. See Saiz (2010) for a full discussion of how these elasticities were calculated.

Regional Economic Information System (REIS) We construct measures of metropolitan area expenditures on public assistance programs by aggregating county-level data in the REIS database. The REIS data contain annual county-level data on total expenditures broken down by transfer program (e.g., food stamps, income maintenance programs, public medical benefits, veterans benefits, etc.).[18] Counties are aggregated into metropolitan areas using the 1990 Metropolitan Statistical Area (MSA) definitions. All transfer program measures are adjusted per capita based on the non-college adult population.

Table 1 reports descriptive statistics for the baseline sample. In total, our baseline sample contains 235 metropolitan areas with non-missing labor market and housing market data. The top part of the table shows the distribution of changes in housing prices for 2000-2007 period and 2007-2010 period. Most MSAs experienced house price growth during 200-2007 period and house price declines during 2007-2010 period. Moreover, as shown in Figure 4, these changes are closely related. Figure 4 shows that MSAs experiencing the sharpest increases in house prices during the boom also generally experienced the sharpest decreases during the bust. The R-squared of a simple regression relating the bust in an MSA's housing prices 2007-2010 on its run-up in housing prices during 2000-2007 yields a point estimate of -0.64 (standard error = 0.06), with an R-squared of 0.73. This figure supports our interpretation that most of the variation in house

[18] See Notowidigdo (2011) and Autor, Dorn, and Hanson (2012) for other recent examples using REIS data to study the effect of shocks to local labor demand on aggregate transfer program expenditures.

price growth across MSAs between 2000 and 2007 appears to have been transitory.[19]

The next section of Table 1 reports labor market outcomes. On average, MSAs experienced modest declines in non-employment and average wages for the non-college men. Also, most MSAs experienced increase in construction employment share and a decrease in manufacturing employment share between 2000 and 2007.

4 Empirical Model

4.1 Setup

Our conceptual framework highlights how sector-specific shocks affect wages and employment, and our specific empirical setting exploits local shocks to the manufacturing sector and local shocks to sectors which are affected by temporary housing price booms. Our primary outcomes of interest are the local labor market outcomes for men without a college degree, which motivates the following empirical model for changes in local labor market outcomes, ΔL_i (e.g., changes in non-employment rate, average wages, etc.):

$$\Delta L_i = \alpha + \beta_1 \Delta D_i^M + \beta_2 \Delta p_i^H + X_i \Gamma + \Delta \varepsilon_i \tag{4}$$

where i indexes MSAs, ΔD_i^M is an observable shock to labor demand in the manufacturing sector, Δp_i^H is the percentage change in housing prices in the MSA, X_i is a vector of control variables, and $\Delta \varepsilon_i$ represents all other unobserved shocks. In most of our results, the changes are defined between 2000 and 2007. We focus on the 2000 to 2007 reason for two reasons. First, although the housing boom in the U.S. started in 1997, our analysis starts in 2000 because of data limitations. There is no large scale survey with enough sample size to track labor market outcomes at the metropolitan area during this time period aside from the 2000 Census and the recently started American Community Survey (2001-2010). Given this, we start our analysis in 2000. Second, we wanted to perform our baseline analyses prior to the recent recession, to ensure that our estimates are unaffected by factors associated with the recession. This is the period in which we think the masking of the housing boom on the manufacturing decline took place. Given this, all of our baseline estimates are made using cross-MSA variation prior to the 2008 recession.[20]

Since the above empirical model is defined in first differences, it implicitly controls for time-invariant differences across MSAs, so the controls in X_i capture differences in trends across MSAs that are correlated with MSA characteristics. In most of our specifications, the X vector includes the year 2000 population of the MSA, the share of women in the labor force within the MSA in 2000, and the share of employed workers

[19] If we regress house price bust over the 2007-2011 period (as opposed from 2007 through the pooled 2009/2010 period), we get even more mean revision in housing prices. In other words, the places where housing prices fell most between 2009/2010 pooled years and 2011 were places that had the largest run-up between 2000 and 2007.

[20] To be more concrete, for our ending period, we pool together the American Community Survey data from the 2005-2007 period. We do this to increase the power of our analysis at the metropolitan area level. When we restrict our analysis to prime age lower skilled men and then cut the data by 3-digit occupation, some cells were really small if we restricted our attention to only the 2007 data. Throughout the paper, all 2007 data refer to pooled data between 2005 and 2007.

with a college degree within the MSA in 2000. In this model, β_1 estimates the effect of local manufacturing shocks on local labor market outcomes, while β_2 estimates the local labor market effects of shocks to housing prices. If the (standardized) effect of β_2 is similar to the (standardized) effect of β_1, then we will conclude that housing booms substantially "offset" the effects of manufacturing busts.

It is useful to discuss at this point the logic by which housing prices are considered an appropriate proxy for changes in labor demand that are associated with changes in the housing market. First, positive labor demand shocks in any local industries (whether in manufacturing or non-manufacturing) will cause workers in those industries to demand more housing and lead to increases in housing prices. Alternatively, a change in national lending technology or interest rate policy which affected the demand for housing would affect household wealth. This change in wealth, which is plainly a function of the degree to which housing prices rise, could increase demand for local, non-tradable services. In either of these scenarios, the extent to which local demand increased would be reflected in the change in the housing price. Notice, however, that the associated housing price change could be either short-term or more permanent, depending on the nature of the shock that occasions it. Our research question, which involves the comparison of permanent shocks to one sector to a temporary boom-bust cycle in another, requires that we isolate variation in housing prices that is *short-term* rather than long-run. In addition, since we wish to separately estimate the effect of changes in the manufacturing sector and housing market changes on labor market outcomes, we must isolate variation in housing prices that is purged of the effect of predictable changes in manufacturing. The temporary variation we are interested in could result because of a temporary productivity boom and a subsequent bust within some other non-manufacturing sector in the MSA, or because housing prices themselves (and the associated wealth effect on spending) were temporarily high within the MSA and then receded.

Given this discussion, there are three key challenges to implementing the empirical approach summarized in the estimating equations above. First, using observed changes in manufacturing employment as a proxy for ΔD_i^M is problematic because this measure is likely correlated with other unobserved determinants of labor market outcomes such as local labor supply shifts within the manufacturing sector. Using observed manufacturing changes would bias OLS estimates of β_1. We therefore use an instrumental variable as a proxy for ΔD_i^M, which we form by interacting pre-existing cross-sectional differences in employment shares across narrowly defined manufacturing industries with national employment trends in these industries (Bartik 1991). This widely-used instrumental variable is typically justified by assuming that the variation in national trends in industry employment is plausibly uncorrelated with local labor supply shifts (see Blanchard and Katz 1992; Autor and Duggan 2003; Luttmer 2005; Notowidigdo 2011 for examples). As in Notowidigdo (2011), we include the manufacturing instrument in a reduced form way to capture the fact that the instrument affects multiple endogenous variables simultaneously (e.g., housing prices, wages, and employment).

The second challenge, as discussed above, is that we want to interpret the effect of Δp_i^H on local labor markets as the effect of a temporary, unanticipated shock to local labor demand. Therefore, we need to

isolate variation in Δp_i^H that represents transitory variation in local labor demand. As shown in Figure 4, most of the variation in house prices turned out, ex-post, to in fact be temporary. This suggests that using actual house price changes is likely an appropriate way to isolate temporary variation in local labor demand during this period.[21] However, there is no way to guarantee that all of the observed variation in house prices during this time period is the result of temporary changes in local labor demand. For example, if unobserved permanent shifts in local labor market demand or local amenities are (at least partially) capitalized into housing values, then we would need to purge this variation from Δp_i^H. To account for this possibility, we instrument for Δp_i^H with variables which have been shown to strongly predict transitory changes in city housing prices during the past decade. Specifically, we report results using local housing supply elasticity estimates from Saiz (2010) as an instrument for local housing price changes. These estimates are intended to represent differences across MSAs in the local housing supply elasticity, which arise through a combination of pre-determined differences in geography and endogenous differences in housing supply regulations.

To justify the use of the local housing supply elasticity estimate as an instrument for temporary housing price variation, we note that (almost by definition) these supply elasticities capture how hard it is to expand housing supply in the short-term. In response to a national shock to housing demand (e.g., low interest rates, an increase in the extension of credit to home buyers, etc.), the effect on house prices will differ across MSAs based on how hard it is to adjust housing supply the MSA in the short term, which is precisely what the elasticity measures capture. In places where it is harder to adjust housing supply, more of the effect of the increase in national housing demand will show up in house prices and less in changes in housing quantities. As the national demand shock recedes (e.g., interest rates rise, lending dries up) or as housing supply eventually adjusts, house prices will fall. A second reason these elasticity measures work as instruments is that they exploit pre-determined, exogenous features of the geographic environment. Finally, as discussed above, we know that housing price variation was over the period studied was temporary, both nationally and within MSAs. We can therefore be confident that the underlying variation driving MSA changes in housing prices during the boom period of 2000-2007 is short-term.

The third challenge to confront in our empirical approach is the fact that Δp_i^H may (at least partially) capitalize permanent shifts in local labor demand implies that ΔD_i^M will directly affect Δp_i^H, just as would be predicted by a standard spatial equilibrium model (Roback 1982). Although this would not necessarily bias our estimates of β_1 and β_2, it does affect our interpretation of these coefficients. To address this, we

[21] We understand that it is likely not appropriate to use actual house price changes in an MSA as being the result of a temporary change in local labor market condition over most periods. Quite to the contrary, actual changes in house prices are often the result of permanent changes in local labor market demand (see, for example, Blanchard and Katz (1991) and Guerrieri, Hartley, and Hurst (2012) for some recent examples). However, during the 2000s, the assumption that local MSA house price growth was picking up temporary demand shocks seems much more appropriate.

therefore extend the simple empirical model above by specifying the following simultaneous equations model:

$$\Delta p_i^H = \gamma + \delta_1 \Delta D_i^M + \delta_2 Z_i + X_i \Pi + \Delta \nu_i \tag{5}$$

$$\Delta L_i = \alpha + \beta_1 \Delta D_i^M + \beta_2 \Delta p_i^H + X_i \Gamma + \Delta \varepsilon_i \tag{6}$$

where Z_i represents an instrumental variable for housing prices that is used to identify β_2, and the other variables are the same as above. In this model, exogenous shocks to the manufacturing sector (ΔD_i^M) affect local labor market outcomes directly (through β_1) as well as indirectly through their effect on housing prices (through $\beta_2 \delta_1$). Therefore, when reporting "the effect" of a manufacturing shock ($d\Delta L_i / d\Delta D_i^M$), we will include both the direct and the indirect effects, as follows:

$$\frac{d\Delta L_i}{d\Delta D_i^M} = \frac{\partial \Delta L_i}{\partial \Delta D_i^M} + \frac{\partial \Delta L_i}{\partial \Delta p_i^H} \frac{d\Delta p_i^H}{d\Delta D_i^M} = \beta_1 + \beta_2 \delta_1 \tag{7}$$

By contrast, when reporting "the effect" of a housing boom, we will report the following:

$$\frac{d\Delta L_i}{d\Delta p_i^H} = \beta_2 \tag{8}$$

This asymmetry comes from assuming that there are no direct or indirect effects of a housing boom on local manufacturing demand; we test this assumption below and find strong empirical support for it in our data. Therefore, the goal of the empirical model is to produce estimates of δ_1, β_1, β_2 by jointly estimating equations (5) and (6). We estimate the simultaneous equations model using simple two-step procedure. In the first step, we run an OLS regression of equation (5) and retain the estimate of $\hat{\delta}_1$. In the second step, we estimate equation (6) using 2SLS using Z_i as an instrument for Δp_i^H and ΔD_i^M as an instrument for itself. In this second step regression, the estimated coefficient on ΔD_i^M will correspond to $\hat{\beta}_1$ and the estimated coefficient on Δp_i^H will correspond to $\hat{\beta}_2$. After these two steps we can construct estimates $d\Delta L_i / d\Delta D_i^M = \hat{\beta}_1 + \hat{\beta}_2 \hat{\delta}_1$ and $d\Delta L_i / d\Delta p_i^H = \hat{\beta}_2$. In all results we cluster standard errors by state, and we compute standard errors on $d\Delta L_i / d\Delta D_i^M$ using standard methods for two-step estimators (Greene 2000).[22]

4.2 First stages for manufacturing bust and housing boom instruments

Before presenting the main results, we summarize how well the instrumental variables used in our analysis predict variation in permanent manufacturing declines and temporary changes in housing prices within MSAs. We begin with the instrumental variable for changes in housing prices, the housing supply elasticity estimates provided by Saiz (2010). As shown in Figure 5, the reciprocal of the housing supply elasticity

[22] We could also estimate our empirical model in equations (5) and (6) using 3SLS. Our inference is very similar using a 3SLS estimator rather than the two-step estimator described in the main text. Our standard errors are also very similar when we bootstrap the standard errors across the two-step procedure, resampling states with replacement. Finally, when we report OLS results, we report estimates constructed from separate OLS regressions of both equations (5) and (6), which is analogous to estimating a Seemingly Unrelated Regressions (SUR) model of the two-equation system.

strongly predicts within-city growth in housing prices between 2000 and 2007.[23] Additionally, Figure 6 shows that this same variable predicts housing price declines between 2007 and 2010. Table 2 reports OLS regression results analogous to Figures 5 and 6 in columns (1) through (5), and the results show that the reciprocal of the housing supply elasticity strongly predicts housing price changes between 2000 and 2007 as well as housing price declines between 2007 and 2010. The patterns across the boom-bust cycle as well as the robustness to a standard set of controls support our interpretation that the instrumental variable properly isolates transitory variation in local housing prices.[24]

Column (3) of Table 2 includes the manufacturing shock instrument alongside the local housing supply elasticity measure. As described above, this manufacturing instrument is formed by interacting pre-existing cross-sectional differences in manufacturing employment with national trends in manufacturing industry employment shares. The full details of construction of the instrument are provided in the Appendix, and the units of the instrument are in (predicted) percentage point changes in share of population employed in manufacturing. As expected, the results in column (3) show that the manufacturing demand instrument also predicts changes in housing values, consistent with housing values (at least partially) capitalizing permanent shifts in local labor demand. This pattern is also shown in Figure 7, which shows the positive correlation between housing prices and the manufacturing demand instrument.

Lastly, Figure 8 shows that the manufacturing instrument strongly predictions actual changes in manufacturing employment. Columns (6) through (8) of Table 2 show that the relationship is very precise and robust to standard controls. Additionally, the results in column (8) show that the housing supply elasticity instrument does not predict changes in manufacturing employment. This strongly supports the assumption underlying equation (8) above, which is that the housing booms and busts do not directly or indirectly affect local labor demand in the manufacturing sector. By contrast, the fact that the manufacturing demand shock affects housing values implies that there will be both direct and indirect effects, which the simultaneous equations model above is intended to capture.[25]

[23] In all our specifications, we use the reciprocal of housing supply elasticity. We do this for two reasons. First, as shown in Figure 5, it results in a fairly linear relationship between the two variables; by contrast, the relationship between house price growth and the elasticity is highly non-linear when plotted. Second, we argue that this better captures the economic interpretation of our instrument, since the reciprocal of the housing supply elasticity captures the percentage increase in price that would be predicted for a given housing demand shock. In any case, all our results are very similar using the housing supply elasticity rather than the reciprocal.

[24] We use the following controls in our baseline specifications (all variables refer to year 2000 values): the log of the city population, the share of employed workers with a college degree, and the share of women employed in labor force.

[25] We also show the correlation between the manufacturing shock instrument the reciprocal of the housing supply elasticity in Appendix Figure A2. The figure shows that these instruments are not significantly correlated.

4.3 Main Results

4.3.1 Graphical Evidence

We begin by presenting our main results graphically. To do this, we divide the sample based on 2000-2007 house price growth.[26] We categorize the top 1/3 of sample as "housing boom MSAs", and we group the other MSAs in bottom 2/3 together. We then graph 2000-2007 changes in various local area economic outcomes alongside the manufacturing shock instrument, and we plot the two groups of MSAs separately. Figure 9 shows the results for the change in the non-employment rate for non-college men. The grey line shows the (weighted) OLS regression line for the bottom 2/3 of sample that did not experience a housing boom.[27] The negative slope implies that negative manufacturing shocks are associated with increases in non-employment rate for this group. This is consistent with the theoretical framework set out in Section 2.[28] Moreover, the magnitude of the slope is large and precisely estimated (-1.490, s.e. 0.167). The key result in the figure is the relationship between the black circles (which represent the housing boom MSAs) and the regression line from the non-boom MSAs. In Figure 9, most of the black triangles lie below the regression line, implying that MSAs with a housing boom experienced relative declines in non-employment rate for less-skilled men, and this is true even when comparing across MSAs experiencing the same local shock to manufacturing employment. We can quantify the "housing boom" effect by estimating the following regression:[29]

$$\Delta L_i = \alpha' + \beta_1' \Delta D_i^M + \beta_2' \mathbf{1}\{\text{Housing Boom}\}_i + \Delta\varepsilon_i$$

This is similar to (9) above except that there are no X controls in the above specification and Δp_i^H was replaced with the dummy variable for high housing boom MSAs. In this model, the estimate of β_2' represents the average difference in change in outcome ΔL_i across MSAs that did and did not experience a large hosing boom. Figure 9 reports the estimate of β_2', or the "shift", as -0.018 (s.e. 0.004). This implies that housing boom MSAs experienced 1.8 percentage point reduction in non-employment rate of less-skilled men, holding the MSA manufacturing shock constant. The magnitude is quantitatively large and precisely estimated, and it is consistent with the regression results below.

Figures 10 through 12 repeat the same exercise with alternative local area outcomes: changes in average wages for non-college men (Figure 10), changes in share of non-college male population employed in construction (Figure 11), and changes in share of non-college male population employed in manufacturing (Figure

[26] In grouping cities based on house price growth, we first residualize the manufacturing shock out of the house price growth variable in order to increase the share of cross-city variation in house price growth that is transitory.

[27] Unless otherwise noted, all of our regression results are weighted regressions using the initial (year 2000) population of prime-aged less-skilled men as weights. The weighting is intended to reduce attenuation bias from measurement error in the MSA labor market outcome estimates.

[28] Many researchers have documented the effect of manufacturing demand on increased non-employment of lower skilled men during the 1970s and 1980s. See, for example, Bound and Holzer (1993).

[29] Note that in this model, the effect of the manufacturing instrument is constrained to be the same across all cities; we test for this and do not reject that the effect of the manufacturing instrument is the same across cities that did and did not experience housing booms for all of the local labor market outcomes in our data.

12). The patterns for average wages are similar to the results for non-employment: negative manufacturing shocks are associated with declines in average wages. However, as in Figure 9, areas with a housing boom experienced relative increases in average wages. Figure 11 shows the same pattern for construction employment share. Unsurprisingly, housing booms appear to be associated with relative increases in construction employment share. Interestingly, the manufacturing instrument is also associated with construction employment; specifically, negative manufacturing shocks are associated with relative declines in construction employment, consistent with the results above showing the manufacturing shocks also affect housing prices. Lastly, Figure 12 shows that the manufacturing instrument is strongly correlated with actual changes in manufacturing employment. However, consistent with the results in column (8) of Table 2, MSAs with housing boom are no more or less likely to experience changes in manufacturing employment.

We conclude with two figures looking at longer run changes in non-employment. In these figures (Figure 13 and Figure 14), we report changes in non-employment between 2000 and 2010 for the same set of MSAs, and we define the manufacturing shock across this longer time period. In Figure 13, we divide MSAs based on housing boom, as in the previous figures (i.e., top 1/3 of house price growth between 2000 and 2007). In Figure 14, we divide MSAs based on severity of housing bust, defining "housing bust MSAs" as the top 1/3 of sample according to magnitude of housing bust between 2007 and 2010. According to this definition, 45 of the 62 MSAs categorized as "housing boom MSAs" based on 2000-2007 house price changes are also defined as "housing bust MSAs" based on 2007-2010 house price changes. This reflects the fact that MSAs experiencing large housing booms were also those most likely to experience substantial housing busts (see Figure 5 above for this graphical relationship). In both figures, the picture that emerges is that neither the housing boom MSAs nor the housing bust MSAs experience relatively different longer run changes in non-employment between 2000 and 2010. In contrast, the manufacturing shock strongly predicts longer run changes in non-employment. Therefore, while the housing boom predicts non-employment changes during the boom period, and the housing bust predicts non-employment changes during the bust period, neither boom nor bust predicts non-employment changes over the longer time period. These results are consistent with the housing boom masking local manufacturing busts, and the subsequent housing bust unmasking non-employment growth that would have occurred earlier in absence of the boom.

The remainder of this section quantifies the amount of "offset" using the two-step model described above. Additionally, the regression results below explicitly addresses the concern that housing prices are endogenous to both observed and unobserved shocks.

4.3.2 Main Results

Table 3 presents the main results from jointly estimating equations (5) and (6) using the two-step IV estimator described in Section 3.1. The columns are grouped based on the labor market outcome. The first two columns report two-step OLS and IV estimates (respectively) which show how the manufacturing and

housing shocks affect the non-employment rate of men without a college degree. The estimates show that both shocks significantly affect non-employment. To interpret the magnitudes, the rows below the estimated coefficients rescale to a one standard deviation shock.[30] Below the standardized effects, we report the first stage F-statistic from the second-step 2SLS estimation of equation (6). As would be expected based on the results in Table 2, there is no evidence of weak instrument concerns with any of our main results.

The results in columns (1) and (2) show that the manufacturing shock strongly affects non-employment. A one standard deviation negative manufacturing shock increases non-employment by 1 percentage point. The IV estimate in column (2) shows that a one standard deviation positive housing shock increase non-employment by 1.2 percentage points, which is enough to fully offset the effect of the negative manufacturing shock. The results in columns (1) and (2) are similar, implying there is not substantial bias from treating house price growth as exogenous (conditional on the manufacturing shock and the other controls).

The remainder of the table reports OLS and two-step results for other local labor market outcomes. Columns (3) and (4) report results for average wages for this sample of men without a college degree. The results show that manufacturing shocks reduce average wages while housing booms increase wages; additionally, the standardized effects show similar magnitudes, again implying that a one standard deviation change in housing prices is enough to offset the wage declines from a one standard deviation decline in labor demand in manufacturing sector. This offsetting in average wages is broadly consistent with the time series patterns presented in Figure 2. Columns (5) and (6) report results when the dependent variable is the percentage point change in share of the (non-college male) population employed in the construction sector. These results show that housing booms are associated with an increasing share of the population employed in construction, and the two-step estimates are approximately 60% of the magnitude of the estimates when total non-employment is the dependent variable. This implies that construction employment played a prominent (though not exclusive) role in offsetting the employment losses due to manufacturing shocks that would have occurred in the absence of the housing boom. The remaining offsetting must have come from other sectors besides construction, likely employment in services, transportation, or public administration.[31]

Overall, the results in this table show that temporary housing booms during 2000-2007 had a substantial offsetting effects on labor market outcomes for non-college men. Furthermore, this offsetting does not appear to be coming exclusively through changes in construction employment. The next subsection reports results from a wide range of alternative specifications to demonstrate the robustness of our main results; in general, we find results which are broadly consistent with the main results in Table 3.

[30] The coefficients are always standardized by the cross-city standard deviation in magnitude of manufacturing shock and housing shock during the time period analyzed.

[31] Finally, columns (7) and (8) report results when the dependent variable is the percentage point change in share of population employed in manufacturing sector. Similar to the results in Table 2, the manufacturing instrument strongly predicts actual changes in manufacturing employment, and the housing boom has no affect on manufacturing employment.

4.4 Robustness

The first two columns of Table 4 reproduce the first two columns of Table 4 for comparison, and the remainder of the columns show results from alternative specifications. In all columns, the dependent variable is the change in the non-employment rate. Appendix Tables A1 through A3 show analogous alternative specifications for the other dependent variables reported Table 3.

We begin by considering alternative instrumental variables for local housing price changes. The other instrument we consider is a dummy variable for whether the city belongs to the "sand states" of Arizona, California, Florida, and Nevada. This instrumental variable is motivated by the discussion in Davidoff (2012), and is also motivated by conceptual concerns about the appropriateness of the local housing supply elasticity estimate used in the baseline results.[32] Column (3) shows that the non-employment results are very similar using the "sand states" instrument instead of the housing supply elasticity variable, and column (4) shows that the results are also similar when both instruments are used together. Moreover, we report results from an over-identification test in column (4) when both instruments are used together, and the test does not reject the null hypothesis ($p = 0.940$).[33] The similarity across the OLS results and the IV results with any combination of the two instruments is consistent with most of the variation in local housing prices changes being driven by the transitory variation that the instruments are supposed to isolate.[34]

The remaining columns (5) and (6) report results which add Census region fixed effects to the baseline set of controls.[35] This forces all of the identification to come with within-region variation in the instrumental variables. Column (5) reports results using the local housing supply elasticity instrument. Although the point estimates are fairly similar, the instrument is somewhat weakened with the inclusion of region FEs (the first stage F-statistic falls from 26.86 to 12.40). Therefore, in column (6) we report results using both instruments (as in column (4)); this increases power of first stage and reduces weak instrument concerns. The results remain fairly similar to the baseline results in the first two columns, and the overidentification test for this specification with region fixed effects continues to fail to reject the null ($p = 0.420$). The

[32] These concerns, described in detail in Davidoff (2012), cast doubt that the correlation between housing supply elasticity and the housing boom/bust cycle between 2000 and 2010 as actually arising through cross-city differences in shape of local housing supply curve. The results in Davidoff (2012) suggest that unobserved state-level demand factors (that are correlated with the local housing supply elasticity measure) may be actually responsible for much of the cross-city variation in housing booms. We argue that we do not need to take a stand on this debate, as long as the instrument isolates transitory house price variation, which appears to be the case (as shown in Figures 5 and 6).

The logic of using the sand state instrument is to isolate variation in house prices that others have shown were the result of temporary movements in housing demand. For example, Davidoff (2012) illustrates that movements in house prices during both the boom and bust in sand state MSAs were the result of temporary movements in local housing demand. Chinco and Mayer (2012) show that the MSAs in the sand states were more likely to show symptoms of housing bubbles (as proxied by a dramatic increase of out-of-town property owners). In fact, a temporary housing bubble would be one example of a temporary increase in housing demand illustrated by Davidoff.

[33] For all overidentification tests, we report the Sargan-Hansen test statistic and the associated p-value.

[34] An alternative interpretation that housing prices are not actually endogenous to other unobserved determinants of local labor market outcomes, but this seems much less likely. Additionally, it is inconsistent with the fact that the manufacturing instrument strongly predicts housing price changes.

[35] The four census regions are Northeast, Midwest, South, and West. In unreported results, we also explore specifications including the nine census divisions. The OLS results are similar with these additional controls, while the IV results are roughly similar in magnitude but very imprecise due to weak identification (first stage F-statistic is only 4.87).

similarity in results for non-employment across the columns of Table 4 is replicated for the other primary dependent variables (average wages, construction employment share, manufacturing employment share) in Appendix Tables A1 through A3. Therefore, we conclude that our main results are fairly robust to alternative specifications.

4.5 Alternative Demographic Groups

Our main results have focused on the local labor market outcomes for men without a college degree (ages 21-55). This is a natural population to focus on given the time-series patterns in construction employment during the housing boom and the disproportionate decline in manufacturing employment experienced by this group during the past decade. However, we can also consider other demographic groups: specifically, women without a college degree, college-educated men, and college-educated men. Table 5 reports analogous results for the change in the non-employment rate for each of these demographic groups, as in the previous subsection.

Columns (1) and (2) of Table 5 reproduce the OLS and IV estimates from Table 3 for men without a college degree (for comparison), and columns (3) and (4) reproduce analogous estimates for college-educated men. The results for college-educated men show smaller effects of both the housing shock and manufacturing shock on non-employment, with magnitudes of estimated coefficient declining by more than 50%. Columns (5) through (6) report results for women without a college degree, with the results roughly in between the results for non-college men and college-educated men, and columns (7) and (8) report results for college-educated women, which show the smallest effects across all of the demographic groups. Next, columns (9) and (10) report results for the overall population (all men and women age 21-55). As expected, these estimates lie somewhere in between the estimates for the individual demographic groups, with magnitudes somewhat closer to the non-college estimates, which is expected as roughly two-thirds of the workforce does not have a college degree. In Table 6, we report analogous results for average wages, which mirror the results for non-employment; in particular, there is negligible effect of housing booms on wages for college-educated workers, and the effects for non-college workers is significant, with the largest effects for non-college men.

4.6 Other Local Labor Market Outcomes: Migration and Social Transfers

Appendix Tables A4 and A5 report results focusing specifically on migration and social transfers, which have both been shown to respond strongly to shifts in local labor demand (Blanchard and Diamond 1992; Notowidigdo 2011). Interestingly, the results in Appendix Table A4 suggest that manufacturing shocks are strongly associated with migration, while the results for housing shocks are more ambiguous and depend on the source of identifying variation.

The results in Appendix Table A5 use the REIS data to estimate the effect of manufacturing shocks and housing shocks on transfer payments. The table reports suggestive evidence that aggregate expenditures on

various social transfers (food stamps, income maintenance programs, and unemployment insurance payments) respond strongly to manufacturing shocks, and that housing booms offset this increase in transfer payments by a similar magnitude. Though the precision of the effects vary across the specifications, they are broadly consistent with the results in Notowidigdo (2011) and Autor, Dorn, and Hanson (2012), which show that transfer payments respond strongly to local labor demand shifts.

4.7 Housing Booms, Housing Busts, and Longer Run Outcomes

Finally, Table 7 reports estimates of longer run changes in non-employment which quantify the patterns in Figures 12 and 13 discussed above. As before, columns (1) and (2) reproduce the OLS and IV estimates from Table 3 on non-employment of non-colllege men. Columns (3) and (4) modify the OLS and IV models to instead use a longer run change in non-employment as the dependent variable – from 2000 to 2010 rather than 2000 to 2007 Strikingly, the results show that the magnitude of the housing boom no longer significantly predicts longer run change in non-employment. The most likely explanation for this is given in columns (5) and (6) which show results for the housing bust period (2007-2010); in this case, the magnitude of housing bust during this time period is associated with non-employment changes over this time period. These results are summarized in columns (7) through (10) which show that longer run changes in non-employment are not affected by either the magnitude of housing boom nor magnitude of housing bust, despite the fact that both the boom and bust themselves predict short-run changes in non-employment. In contrast, our manufacturing shock consistently predicts large changes in non-employment across both the boom period, the bust period, and the longer run (2000-2010) period. We therefore conclude that the oft-discussed relationship between housing bust and non-employment growth is likely an unmasking of non-employment growth that would have occurred earlier in the absence of the housing boom. The next section tries to quantify this unmasking at a national level using our local labor market estimates.

5 Estimating Structural non-employment: Counterfactual Analysis

In this section, we apply our local labor market estimates on the effect of manufacturing shocks and housing booms/busts to provide counterfactual estimates of aggregate non-employment nationally during the 2000-2010 period. To do this counterfactual calibration, we use national time series changes in the non-employment rate, housing prices, and manufacturing employment shares, and combine these with our main estimates in Tables 3 and 5 to compute the contribution of manufacturing and housing shock on aggregate non-employment. With our estimates, we asked how non-employment would have evolved during over the 2000-2011 period had their only been the decline in manufacturing and no housing boom and bust.

Panel A of Table 8 reports the exercise for non-college men and Panel B of Table 8 reports results for the entire adult population (age 21-55). For non-college men, the share of population employed in manufacturing

declined by 5 percentage points between 2000 and 2007, which according to the estimates in column (2) of Table 3 would correspond to a predicted change in non-employment of 3.5 percentage points.[36] During this same time period, house prices increased nationally by 37%, which according to the same model estimates (Table 3, column (2)) would correspond to a predicted change in non-employment of -1.4 percentage points. Therefore, on net the change in aggregate non-employment is predicted to be 2.1 percentage points, which is very close to the actual increase of 2.2 percentage points observed during this time period.

Continuing with non-college men, during the housing bust (2007-2010), house prices fell by 37% (returning to 2000 levels on average) and the share of non-college male population employed in manufacturing continued to fall by another 2.1 percentage points. Applying the same coefficients, this corresponds to predicted increases in non-employment of 5.5 percentage points, whereas actual increase in non-employment was 8.6 percentage points. In other words, the combination of manufacturing shocks plus "unmasking" of earlier manufacturing decline contributes to roughly 36% of total non-employment growth during 2007-2010 and 48% during 2000-2010. We therefore conclude that a substantial fraction of non-employment growth is ultimately traceable to longer run shifts in manufacturing demand rather than the housing market itself.

As Panel B shows, in absolute terms, the importance of manufacturing shocks and housing shocks is attenuated for the general population (as would be expected based on the results in Table 6); however, the results are broadly similar in percentage terms, suggesting a prominent role for structural non-employment in explaining overall non-employment rate growth both during the Great Recession as well as over the longer run.

We conclude with several important caveats with this calibration exercise. It is always difficult to apply "local general equilibrium" estimates to a national context, so we will address several key concerns with such an exercise. First, our local estimates allow for migration as an endogenous outcome to manufacturing and housing shocks, and we find significant migration in response to manufacturing shocks. These results are shown Appendix Table A4. In our main results, we find that a one standard deviation manufacturing and housing shock both affect non-employment by roughly 1 percentage point. However, the same manufacturing shock also appears to affect population by roughly 3 percent. Using these estimates, we can bound how much migration will affect our counterfactual predictions. To get one bound, we assume that all of the migrants would have been non-employed had they been forced to stay. In this instance, the aggregate non-employment rate in response to a one standard deviation manufacturing shock would have increased by an additional 3 percentage points (from 1 to 4). In that case, our counterfactual estimates above would be severely *underestimated*. If all the migrants would have remained unemployed in the MSA, the effect of the manufacturing shock would have been much greater than we actually estimated. By contrast, if we assume that all of the migrants would have been employed had they been forced to stay, then are estimated response

[36] For the national trends in non-employment and manufacturing over the 2000-2007 period, the 2007-2011 period, and the 2000-2011 period, we use data from the CPS. The sample for this data is the same as the ones used in Figure 1. We use the CPS data as opposed to the Census/ACS data because non-employment rates seem too high in the 2000 Census (relative to the 2000 CPS and relative to the 2001 ACS. This fact has been documented Clark et al. (2003).

to a one-standard deviation manufacturing shock would fall by roughly 0.03 percentage points (from 1.0 to 0.97). The reason the effect is so small is the number of people migrating out of the MSA in response to manufacturing shock is very small relative to the number of people who are employed in the MSA. Therefore, assuming that migrants are either more employable the average non-migrant or roughly similar to average non-migrant has a negligible effect on our results. If, however, the marginal migrant is much less employable, then our above counterfactual estimates are very conservative.[37]

A second potential limitation of our results is that we are isolating only local responses and ignoring any potential general equilibrium responses to the manufacturing and housing shocks. In particular, changes in house prices may have a direct effect on U.S. manufacturing demand. For example, Mian and Sufi (2011) show that households that experienced large increases in housing prices not only increased their purchase of local services, they also increased their nondurable expenditures. In this case, local housing booms can affect the national demand for manufacturing goods. This type of feedback will again cause us to underestimate the extent of masking that occurred during the 2000-2007 period. Put another way, the decline in manufacturing between 2000 and 2007 would have been even greater had it not been for the housing boom within the U.S. Like with the migration results, ignoring this general equilibrium channel makes our counterfactual estimates from the 2000-2007 period conservative.

Another potential concern is that the decline in manufacturing during the 2000-2007 period caused the housing/construction boom. Our results suggest such a channel is implausible. The implausibility stems from two reasons. First, declines in manufacturing put downward pressure on house prices. Given that house prices rose during this time period, such a channel cannot be a first-order explanation for the housing price movements. Second, given that the manufacturing shocks and the residualized house price changes are essentially orthogonal, it is hard to explain the regional variation in housing prices being caused by the manufacturing shocks.

Finally, for reasons similar to the general equilibrium effects during the boom years, we may be overstating the decline in manufacturing during the bust years. If declines in housing prices dampened the demand for manufactured goods during the 2007-2011 period, the change in manufacturing between 2007 and 2011 for our counterfactuals may be too large. We do two additional things to account for this possibility. First, we redo our counterfactuals assuming that the trend in manufacturing between 2000 and 2007 continued through 2011. This assumption strikes us as reasonable, given that there has been a relatively stready decline in manufacturing within the U.S. for 40 years (see Figure 1). Linearly extrapolating the trend in manufacturing through 2011, we find nearly identical results to what was reported in Table 8, since the actual decline in manufacturing employment between 2007 and 2011 is very close to what one would extrapolate based on the 2000-2007 trend. As a second robustness check, we also redid all of our counterfactuals assuming that there was no further decline in manufacturing during the 2007-2011 period. Under the extreme assumption

[37] Similar to the logic used to discuss local area estimates of immigration (Borjas 2003), local area estimates may also be attenuated due to spatial arbitrage.

that none of national decline in manufacturing employment between 2007-2011 is due to same economic forces behind the 2000-2007 decline, we compute 17% of non-employment growth between 2007-2011 and 32% during 2000-2010 as ultimately traceable to longer run shifts in manufacturing industry (as compared to 36% and 48%).

In summary, with all these various caveats in mind, we conclude that a significant share of non-employment growth during the 2007-2011 period represents structural non-employment, with non-college-educated men as those primarily affected.

6 Conclusion

In this paper, we investigate the extent to which the boom and bust in the housing sector during the 2000-2011 period masked and then unmasked the effect of a declining manufacturing sector during the same time period. Manufacturing employment within the U.S. fell sharply during the 2000-2007 period and then fell further between 2007-2011. These changes during the 2000s merely extended declines in manufacturing that occurred within the U.S. since the late 1970s. As many researchers have documented, manufacturing declines reduce both the wages and employment propensities of lower skilled individuals. Housing booms, all else equal, result in both increased construction and in increased demand for local service employment because of increased spending induced by higher housing wealth (Mian and Sufi 2011).

Using comparisons across MSAs, we find that roughly 40 percent of the increase in non-employment during the 2007-2011 period can be attributed to the decline in manufacturing during the 2000s. Much of this increase in non-employment would have occurred prior to 2007 had it not been for the temporary housing boom that occurred during the 2000-2007 period. Our estimated effects for non-employment are largest for less-skilled men, but we find nontrivial effects of the manufacturing decline and the extent to which the housing boom masked those effects for both less-skilled women and higher-skilled men. Accounting for inter-MSA migration and general equilibrium effects of the housing boom on manufacturing employment during the 2000-2007 period is difficult, but we argue that these adjustments would likely increase the extent to which the housing boom masked the manufacturing decline prior to 2007. Moreover, we find that local employment shares over the entire 2000-2010 period did not respond at all either to the house price run-up between 2000 and 2007 or to the house price decline between 2007 and 2010. This means that the effects of the house price run-up on employment during the boom years was completely undone by the house price collapse during the bust years. By contrast, manufacturing declines (measured in either subperiod) had persistent effects on local employment over the entire 2000 to 2010 time period.

It is useful to briefly discuss a few key ways in which our analysis differs from the recent work of Mian and Sufi (2012), who also use variation in housing prices across MSAs to draw conclusions about the current state of non-employment in the United States. First, in terms of implementation, we explore the effects of

house price movements on employment both during the boom period (2000-2007) as well as the bust period (2007-2011). Mian and Sufi (2012) only explore the response of house price on employment during the bust. This is important because, as we show, house price increases propped up employment during the boom years. To understand the effect of housing price movements on current non-employment, our results make clear that employment patterns during *both* the boom and the bust must be examined. Second, the main focus of our analysis is on the ongoing erosion of the manufacturing sector; the secular decline of manufacturing is not the focus of the Mian and Sufi analysis. As we show, the housing boom and bust obscured the effects of manufacturing declines on wages and employment propensities during the last decade.

Often, sectoral booms and busts are linked to aggregate business cycle dynamics. All else equal, a sectoral boom will increase wages and employment during the expansion and result in wages and employment falling during the contraction. Our results, however, highlight that sectoral booms and busts have very different aggregate employment dynamics when another sector in the economy is in decline. When another sector is experiencing a persistent decline, a boom and bust in the first sector results in muted labor market effects during the boom period and larger labor market effects during the bust. Such a phenomenon has been a defining feature of U.S. labor markets since the early 1980s. In particular, the labor force participation rate of men since 1980 has been relatively stable during U.S. expansions and has adjusted sharply around U.S. contractions. This point has been emphasized recently by Jaimovich and Sui (2012). Our results suggest that booms and busts in other sectors coupled with a sectoral decline in manufacturing could also generate these patterns.

To this end, some preliminary work that we have done has shown that the "mini housing boom" in the U.S. that proceeded the 1990 recession had a similar masking effect during the mid to late 1980s. Places that experienced housing booms and manufacturing declines during the 1984-1990 period had smaller declines in wages and employment than did otherwise similar places that experienced equally large manufacturing declines but no housing boom. Although we have not formally explored the mechanism, it is possible that the tech boom and bust starting in the mid 1990s had a similar masking effect on labor markets from the decline in manufacturing in the period surrounding the 2000 recession. Such an analysis seems ripe for future work. Finally, it is possible that a similar phenomenon took place during the Great Depression when there was a finance and housing boom-bust cycle, reminiscent of the current finance and housing cycle, that may have interacted with the large secular decline in agriculture. Between 1900 and 1930, the share of the U.S. workforce employed in agriculture fell from 41 percent to 21.5 percent. The agricultural employment share fell by an additional 5.5 percentage points between 1930 and 1945.[38] One further area for future research could be the extent to which the sectoral boom in finance and housing during the 1920s masked the sectoral decline in agriculture during the time period proceeding the Depression.

Historically, one of the responses to the decline in demand for less-skilled workers was to induce a higher

[38] See Dimitri, Effland, and Conklin (2005). http://www.ers.usda.gov/media/259572/eib3_1_.pdf

level of skill acquisition. Consequently, as the decline in manufacturing demand occurred throughout the 1980s and 1990s, the propensity for men to attend at least one year of college steadily increased. However, as housing prices increased between the late 1990s and 2007, the share of men under the age of 30 with at least one year of college education actually *fell*. As housing prices fell between 2007 and 2011, the propensity for men to accumulate at least one year of college education reversed course again and started increasing.[39] This time series trend raises the question whether the housing boom actually deterred human capital acquisition. When faced with better than normal labor market prospects, less-skilled men may have found it less beneficial, at least in the short run, to accumulate skills. We explored this possibility in our data. However, when we focused exclusively on young men (under the age of 30), we did not have enough power to conclude whether or not the housing boom actually deterred college attendance. A more formal analysis of this question, using data for which statistical power is less of an issue, would also be a good area for future research.

Lastly, we think that our results can inform the current policy debate about how best to stimulate employment. The type of non-employment we have identified is the result of the long run sectoral decline in manufacturing. Temporary boosts in labor demand due to hiring subsidies or infrastructure investments are not likely to have permanent effects on the labor demand of less-skilled individuals. As those hiring subsidies and infrastructure investments expire, the labor demand for less-skilled labor will still be depressed because of the decline in manufacturing. In this sense, our paper is among the first to document a significant role for structural forces in explaining the current high level of non-employment within the U.S. As noted above, over longer periods of time, current nonemployed workers (or subsequent generations of workers) may find it more beneficial to accumulate skills. Addressing barriers to skill acquisition may have the most lasting effect on increasing the employment prospects of those workers who have become nonemployed as a result of the ongoing decline in the manufacturing sector.

[39] Authors' calculations from the Current Population Survey.

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Appendix A: Data Appendix

We follow the empirical strategy of Bartik (1991) and construct a measure of plausibly exogenous manufacturing shock by interacting cross-sectional differences in industry employment shares with national changes in manufacturing industry employment. We use this demand index to predict actual changes in manufacturing employment. The identifying assumption is that changes in industry shares at the national level are uncorrelated with city-level labor supply shocks and therefore represent plausibly exogenous (demand-induced) variation in metropolitan area employment. Formally, the manufacturing instrument is computed as follows:

$$\Delta D_i^M = \sum_{k=1}^{K} \varphi_{i,k,2000} \left(\upsilon_{-i,k,2007} - \upsilon_{-i,k,2000} \right)$$

where $\varphi_{i,k,2000}$ is the share of relevant population employed in industry k in city i in the year 2000 and $\upsilon_{-i,k,t}$ is the national employment of industry k excluding city i in year t. The set of industries in K includes all industries in manufacturing sector.

Appendix B: Details of Numerical Simulation

We numerically simulate the stylized model of Section 2 under two scenarios to illustrate the time series implications of the model. In both scenarios, skills (s) and reservation wages (r) are jointly uniformly distributed. The productivity/demand shifters in sectors A and B (α and β, respectively) are the only forcing variables in the model. In both scenarios, α is steadily declining from $a = 1.2$ to $a = 1.0$ between $t = [0, 10]$. In scenario 1, β is constant at 1.2 throughout the time period, while in scenario 2, β experiences a temporary "boom" from $\beta = 1.2$ to $\beta = 1.3$, before sharply falling back down to 1.2.

The model is solved by first solve for s^*, which is given by $s^*\alpha = (1 - s^*)\beta$. Next, s^* is used to compute L_A, L_B, L_H given equations (1) through (3) in the main text.

The absence of any intertemporal linkages implies that the wage and employment outcomes are identical across the two scenarios at the start and the end of the time period. The differences arise solely due to the different dynamics of β across the two scenarios. As shown in Figure 4a, in scenario 1 the aggregate non-employment (i.e., share of workers in the "home" sector H) steadily increases and average wages steadily decrease. In Figure 4b, by contrast, the boom/bust cycle in sector B causes a "hockey stick" pattern, as aggregate non-employment first remains stable (as the declines in sector A are "offset" by sector B), but eventually the non-employment rate sharply increases as the bust "unmasks" non-employment that occured earlier in Figure 4a in the absence of a boom in sector B.

Table 1
Summary Statistics

	N	Mean	Standard Dev.	Min	Percentiles 25th	50th	75th	Max
Housing market variables								
Change in Housing Prices, 2000-2007	235	0.442	0.362	-0.059	0.119	0.358	0.688	1.145
Change in Housing Prices, 2007-2010	235	-0.263	0.270	-1.279	-0.361	-0.176	-0.056	0.094
Change in Housing Prices, 2000-2010	235	0.179	0.192	-0.343	0.056	0.170	0.327	0.572
Labor market variables (2000-2007 changes for non-college men)								
Change in Nonemployment Rate	235	-0.016	0.039	-0.122	-0.034	-0.012	0.012	0.094
Change in Average Wages	235	-0.061	0.042	-0.184	-0.095	-0.066	-0.034	0.113
Change in Share of Population Employed in Construction	235	0.026	0.018	-0.028	0.013	0.026	0.037	0.092
Change in Share of Population Employed in Manufacturing	235	-0.027	0.018	-0.145	-0.037	-0.023	-0.015	0.039
Baseline control variables (2000 values)								
Log Population	235	14.42	1.20	11.53	13.48	14.47	15.31	16.07
Share of Employed with College Degree	235	0.240	0.058	0.091	0.207	0.232	0.272	0.405
Share of Women Employed	235	0.699	0.052	0.496	0.670	0.709	0.738	0.850
Instrumental variables								
Predicted Change in Share of Non-College Men Employed in Manufacturing [Manufacturing Bust Instrument]	235	-0.022	0.011	-0.071	-0.028	-0.019	-0.013	-0.001
Housing Supply Elasticity [Housing Boom Instrument]	235	1.699	1.033	0.595	0.811	1.496	2.302	7.940

Notes: This table reports the summary statistics for the baseline sample of 235 metropolitan areas (MSAs). The reported sample statistics all computed using the 2000 population of prime-aged non-college men in the MSA as weights, as are used in all the regressions that follow. All data from the 2000 Census and 2005-2007 American Community Survey except for the Housing Supply Elasticity, which comes from Saiz (2010). The Manufacturing Bust Instrument is constructed following the procedure in Bartik (1991) and is defined in more detail in the Appendix, which also contains more details on the other variables.

Table 2
First Stages for Housing Boom and Manufacturing Bust Instrumental Variables

Dependent variable:	Change in House Prices, 2000-2007			Change in House Prices, 2007-2010		Change in Share of Non-College Men Employed in Manufacturing, 2000-2007		
Specification:	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reciprocal of Housing Supply Elasticity	0.566	0.530	0.531	-0.345	-0.362			0.003
[Housing Boom Instrument]	(0.055)	(0.128)	(0.108)	(0.068)	(0.136)			(0.004)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.011]			[0.343]
Predicted Change in Share of			10.592			1.125	1.025	1.025
Non-College Men Employed in Manufacturing			(2.482)			(0.072)	(0.071)	(0.077)
[Manufacturing Bust Instrument]			[0.000]			[0.000]	[0.000]	[0.000]
Housing effect (standardized)	**0.172**	**0.161**	**0.161**	**-0.105**	**-0.110**			**0.001**
Manufacturing effect (standardized)			**0.143**			**0.015**	**0.014**	**0.014**
N	235	235	235	235	235	235	235	235
R^2	0.465	0.526	0.614	0.272	0.375	0.481	0.532	0.535
Include baseline controls		y	y		y			y

Notes: This table reports OLS results of estimating the first stage relationships. The control variables in columns (2), (3), (5), and (8) are initial (year 2000) values of log population, share of women in labor force, and the share of employed workers with a college degree. See Table 1 for more information on the instrumental variables. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 3
Manufacturing Busts, Housing Booms, and Declining Employment of Non-College Men

Dependent variable:	Change in Nonemployment Rate, 2000-2007		Change in Average Wage, 2000-2007		Change in Share of Non-College Men Employed in Construction, 2000-2007		Change in Share of Non-College Men Employed in Manufacturing, 2000-2007	
Specification:	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Housing Prices	-0.034	-0.039	0.059	0.048	0.024	0.023	0.001	0.007
[Housing Boom]	(0.011)	(0.018)	(0.010)	(0.011)	(0.006)	(0.010)	(0.004)	(0.008)
	[0.002]	[0.028]	[0.000]	[0.000]	[0.000]	[0.026]	[0.889]	[0.397]
Predicted Change in Share of	-0.724	-0.726	1.545	1.548	0.450	0.451	1.025	1.025
Non-College Men Empl. in Manuf.	(0.245)	(0.222)	(0.369)	(0.306)	(0.178)	(0.163)	(0.074)	(0.083)
[Manufacturing Bust]	[0.005]	[0.002]	[0.000]	[0.000]	[0.016]	[0.008]	[0.000]	[0.000]
Housing price effect (1σ)	**-0.011**	**-0.012**	**0.018**	**0.015**	**0.007**	**0.007**	**0.000**	**0.002**
Manufacturing effect (1σ)	**-0.010**	**-0.010**	**0.021**	**0.021**	**0.006**	**0.006**	**0.014**	**0.014**
First stage F-statistic		24.289		24.289		24.289		24.289
N	235	235	235	235	235	235	235	235
R^2	0.741	0.739	0.444	0.439	0.492	0.491	0.532	0.523
Include baseline controls	y	y	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y		y		y

Notes: This table reports results of estimating equations (2) and (3) by either OLS or IV, as indicated. A one unit in Change in Housing Prices represents a one log point increase in housing prices; 0.1 units in Manufacturing Bust instrument corresponds to a 10 percentage point change in predicted share of population employed in manufacturing. The rows in bold report standardized effects for one standard deviation changes. The baseline controls include the initial (year 2000) values of log population, share of women in labor force, and the share of employed workers with a college degree. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 4
Robustness to Alternative Specifications

Dependent variable:	Change in Nonemployment Rate of Non-College Men, 2000-2007					
Specification:	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Housing Prices	-0.034	-0.039	-0.037	-0.038	-0.045	-0.035
[Housing Boom]	(0.011)	(0.018)	(0.010)	(0.012)	(0.018)	(0.010)
	[0.002]	[0.028]	[0.000]	[0.001]	[0.012]	[0.001]
Predicted Change in Share of	-0.724	-0.726	-0.604	-0.632	-0.589	-0.516
Non-College Men Employed in Manufacturing	(0.245)	(0.222)	(0.203)	(0.206)	(0.199)	(0.172)
[Manufacturing Bust]	[0.005]	[0.002]	[0.005]	[0.004]	[0.005]	[0.005]
Housing price effect (1σ)	**-0.011**	**-0.012**	**-0.012**	**-0.012**	**-0.014**	**-0.011**
Manufacturing effect (1σ)	**-0.010**	**-0.010**	**-0.008**	**-0.009**	**-0.008**	**-0.007**
First stage F-statistic		24.289	41.116	43.991	10.945	37.471
Overidentification test statistic, $\chi^2(1)$				0.027		0.699
[p-value]				[0.869]		[0.403]
N	235	235	235	235	235	235
R^2	0.741	0.739	0.740	0.740	0.745	0.750
Include baseline controls	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y	y	y
Instrument with sand state indicator			y	y		y
Census region FEs (4 regions)					y	y

Notes: This table reports results of estimating equations (2) and (3) by either OLS or IV, as indicated. One unit increase in Change in Housing Prices represents a 100% increase in housing prices; 0.1 units in Manufacturing Bust instrument corresponds to a 10 percentage point change in predicted share of population employed in manufacturing. The rows in bold report standardized effects for one standard deviation changes. The baseline controls include the initial (year 2000) values of log population, share of women in labor force, and the share of employed workers with a college degree. The sand state indicator is an alternative instrumental variable suggested by Davidoff (2012) and is defined as the following states: Arizona, California, Nevada, Florida. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 5
Nonemployment Effects Across Other Demographic Groups

Dependent variable:	Change in Nonemployment Rate, 2000-2007									
Sample:	Non-College Men		College Men		Non-College Women		College Women		All Men and Women	
Specification:	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change in Housing Prices	-0.034	-0.039	-0.010	-0.018	-0.022	-0.032	-0.007	-0.003	-0.027	-0.031
[Housing Boom]	(0.011)	(0.018)	(0.005)	(0.008)	(0.005)	(0.007)	(0.005)	(0.009)	(0.005)	(0.008)
	[0.002]	[0.028]	[0.055]	[0.027]	[0.000]	[0.000]	[0.135]	[0.731]	[0.000]	[0.000]
Predicted Change in Share of	-0.724	-0.726	-0.330	-0.331	-0.515	-0.518	-0.196	-0.196		
Non-College Men Empl. in Manuf.	(0.245)	(0.222)	(0.104)	(0.091)	(0.157)	(0.159)	(0.124)	(0.125)		
[Manufacturing Bust]	[0.005]	[0.002]	[0.003]	[0.001]	[0.002]	[0.002]	[0.121]	[0.124]		
Predicted Change in Share of									-0.687	-0.729
Population Employed in Manuf.									(0.165)	(0.150)
[Manufacturing Bust]									[0.000]	[0.000]
Housing price effect (1σ)	**-0.011**	**-0.012**	**-0.003**	**-0.006**	**-0.007**	**-0.010**	**-0.002**	**-0.001**	**-0.008**	**-0.010**
Manufacturing effect (1σ)	**-0.010**	**-0.010**	**-0.004**	**-0.004**	**-0.007**	**-0.007**	**-0.003**	**-0.003**	**-0.007**	**-0.008**
First stage F-statistic		24.289		24.289		24.289		24.289		22.548
N	235	235	235	235	235	235	235	235	235	235
R^2	0.741	0.739	0.207	0.188	0.686	0.677	0.114	0.109	0.796	0.794
Include baseline controls	y	y	y	y	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y		y		y		y

Notes: This table reports results analogous to columns (1) and (2) in Table 3 for alternative demographic groups. See Table 3 for more details. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 6
Wage Effects Across Other Demographic Groups

Dependent variable:	Change in Average Wages, 2000-2007									
Sample:	Non-College Men		College Men		Non-College Women		College Women		All Men and Women	
Specification:	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change in Housing Prices	0.059	0.048	0.025	0.012	0.037	0.026	0.024	-0.004	0.045	0.042
[Housing Boom]	(0.010)	(0.011)	(0.015)	(0.027)	(0.008)	(0.012)	(0.013)	(0.022)	(0.010)	(0.015)
	[0.000]	[0.000]	[0.110]	[0.654]	[0.000]	[0.031]	[0.061]	[0.875]	[0.000]	[0.006]
Predicted Change in Share of	1.545	1.548	0.303	0.304	0.860	0.862	0.503	0.503		
Non-College Men Empl. in Manuf.	(0.369)	(0.306)	(0.450)	(0.403)	(0.251)	(0.206)	(0.279)	(0.256)		
[Manufacturing Bust]	[0.000]	[0.000]	[0.504]	[0.455]	[0.001]	[0.000]	[0.078]	[0.056]		
Predicted Change in Share of									1.051	1.107
Population Employed in Manuf.									(0.335)	(0.301)
[Manufacturing Bust]									[0.003]	[0.001]
Housing price effect (1σ)	**0.018**	**0.015**	**0.008**	**0.004**	**0.012**	**0.008**	**0.008**	**-0.001**	**0.014**	**0.013**
Manufacturing effect (1σ)	**0.021**	**0.021**	**0.004**	**0.004**	**0.012**	**0.012**	**0.007**	**0.007**	**0.011**	**0.012**
First stage F-statistic		24.289		24.289		24.289		24.289		22.548
N	235	235	235	235	235	235	235	235	235	235
R^2	0.444	0.439	0.088	0.080	0.486	0.478	0.153	0.113	0.455	0.454
Include baseline controls	y	y	y	y	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y		y		y		y

Notes: This table reports results analogous to columns (1) and (2) in Table 3 for alternative demographic groups. See Table 3 for more details. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 7

Manufacturing Busts, Housing Booms, and Housing Busts: Longer Run Effects

	Depent Variable: Change in Nonemployment Rate for Non-College Men for…									
	2000-2007		2000-2010		2007-2010		2000-2010		2000-2010	
Specification:	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change in Housing Prices, 2000-2007	-0.034	-0.039	-0.009	-0.010			-0.001	-0.008		
[Housing Boom]	(0.011)	(0.018)	(0.022)	(0.030)			(0.019)	(0.030)		
	[0.002]	[0.028]	[0.694]	[0.745]			[0.965]	[0.797]		
Change in Housing Prices, 2007-2010					-0.056	-0.044			-0.036	0.011
[Housing Bust]					(0.008)	(0.017)			(0.011)	(0.045)
					[0.000]	[0.009]			[0.002]	[0.804]
Predicted Change in Share of Non-College Men	-0.724	-0.726	-0.808	-0.809						
Employed in Manufacturing, 2000-2007	(0.245)	(0.222)	(0.433)	(0.422)						
[Manufacturing Bust]	[0.005]	[0.002]	[0.069]	[0.062]						
Predicted Change in Share of Non-College Men					-0.406	-0.416				
Employed in Manufacturing, 2007-2010					(0.297)	(0.270)				
[Manufacturing Bust]					[0.178]	[0.130]				
Predicted Change in Share of Non-College Men							-0.653	-0.651	-0.653	-0.651
Employed in Manufacturing, 2000-2010							(0.299)	(0.293)	(0.270)	(0.313)
[Manufacturing Bust]							[0.034]	[0.032]	[0.020]	[0.043]
Housing price effect (1σ)	**-0.011**	**-0.012**	**-0.003**	**-0.003**	**-0.016**	**-0.013**	**0.000**	**-0.002**	**-0.010**	**0.003**
Manufacturing effect (1σ)	**-0.010**	**-0.010**	**-0.011**	**-0.011**	**-0.006**	**-0.006**	**-0.018**	**-0.018**	**-0.018**	**-0.018**
First stage F-statistic		24.289		24.289		7.882		20.989		8.116
R^2	0.741	0.739	0.560	0.560	0.425	0.412	0.595	0.593	0.628	0.571
Include baseline controls	y	y	y	y	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y		y		y		y

Notes: N=235 in all columns. This table reports alternative specifications baesd on columns (1) and (2) of Table 3, which are reproduced in coluns (1) and (2) of this table. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 8

How Well do Manufacturing Busts and Housing Booms Explain the National Trends?

Panel A: Accounting for National Trends of Non-College Men

	Actual Change in Non-employment	Predicted Change due to Manufact. Shock	Predicted Change due to Housing Shock	Residual Change, (1) - (2) - (3)	Share of Actual Change Explained by Manufacturing + Housing
	(1)	(2)	(3)	(4)	(5)
2000-2007	0.022	0.035	-0.014	0.002	92.8%
2007-2011	0.086	0.017	0.014	0.055	36.2%
2000-2011	0.108	0.052	0.000	0.056	47.7%

Panel B: Accounting for National Trends of All Prime-Age Men and Women

	Actual Change in Non-employment	Predicted Change due to Manufact. Shock	Predicted Change due to Housing Shock	Residual Change, (1) - (2) - (3)	Share of Actual Change Explained by Manufacturing + Housing
	(1)	(2)	(3)	(4)	(5)
2000-2007	0.019	0.028	-0.011	0.002	89.3%
2007-2011	0.066	0.014	0.011	0.041	38.4%
2000-2011	0.085	0.042	0.000	0.043	49.7%

Notes: This table reports counterfactual estimates of predicted changes in aggregate non-employment. In Panel A, the coefficient estimates from column (2) in Table 3 are used in calibration; in Panel B, the estimates from column (10) in Table 5 are used. Actual changes in non-employment, housing prices, and manufacturing employment are taken from the CPS.

Appendix Table A1
Robustness to Alternative Specifications

Dependent variable:	Change in Average Wage of Non-College Men, 2000-2007					
Specification:	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Housing Prices	0.059	0.048	0.034	0.039	0.054	0.043
[Housing Boom]	(0.010)	(0.011)	(0.010)	(0.008)	(0.022)	(0.014)
	[0.000]	[0.000]	[0.001]	[0.000]	[0.015]	[0.003]
Predicted Change in Share of	1.545	1.548	1.434	1.450	1.346	1.258
Non-College Men Employed in Manufacturing	(0.369)	(0.306)	(0.315)	(0.301)	(0.280)	(0.267)
[Manufacturing Bust]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Housing price effect (1σ)	**0.018**	**0.015**	**0.011**	**0.012**	**0.017**	**0.013**
Manufacturing effect (1σ)	**0.021**	**0.021**	**0.019**	**0.020**	**0.018**	**0.017**
First stage F-statistic		24.289	41.116	43.991	10.945	37.471
Overidentification test statistic, $\chi^2(1)$				0.857		0.754
[p-value]				[0.355]		[0.385]
N	235	235	235	235	235	235
R^2	0.444	0.439	0.418	0.427	0.459	0.448
Include baseline controls	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y	y	y
Instrument with sand state dummy			y	y		y
Census region FEs (4 regions)					y	y
Census division FEs (9 divisions)						

Notes: This table replicates robustness analysis in Table 4 for alternative dependent variable. See notes to Table 4 for more details. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Appendix Table A2
Robustness to Alternative Specifications

Dependent variable:	Change in Share of Non-College Men in Construction, 2000-2007					
Specification:	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Housing Prices	0.024	0.023	0.038	0.033	0.023	0.032
[Housing Boom]	(0.006)	(0.010)	(0.008)	(0.008)	(0.011)	(0.006)
	[0.000]	[0.026]	[0.000]	[0.000]	[0.031]	[0.000]
Predicted Change in Share of	0.450	0.451	0.327	0.370	0.294	0.219
Non-College Men Employed in Manufacturing	(0.178)	(0.163)	(0.144)	(0.142)	(0.124)	(0.118)
[Manufacturing Bust]	[0.016]	[0.008]	[0.028]	[0.012]	[0.023]	[0.071]
Housing price effect (1σ)	**0.007**	**0.007**	**0.012**	**0.010**	**0.007**	**0.010**
Manufacturing effect (1σ)	**0.006**	**0.006**	**0.004**	**0.005**	**0.004**	**0.003**
First stage F-statistic		24.289	41.116	43.991	10.945	37.471
Overidentification test statistic, $\chi^2(1)$				2.232		1.901
[p-value]				[0.135]		[0.168]
N	235	235	235	235	235	235
R^2	0.492	0.491	0.443	0.473	0.542	0.518
Include baseline controls	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y	y	y
Instrument with sand state dummy			y	y		y
Census region FEs (4 regions)					y	y
Census division FEs (9 divisions)						

Notes: This table replicates robustness analysis in Table 4 for alternative dependent variable. See notes to Table 4 for more details. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Appendix Table A3
Robustness to Alternative Specifications

Dependent variable:	Change in Share of Non-College Men in Manufacturing, 2000-2007					
Specification:	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Housing Prices	-0.001	0.009	0.005	0.006	0.009	-0.004
[Housing Boom]	(0.006)	(0.010)	(0.008)	(0.008)	(0.012)	(0.005)
	[0.824]	[0.392]	[0.553]	[0.415]	[0.486]	[0.458]
Predicted Change in Share of	1.026	1.027	1.015	1.015	1.023	1.034
Non-College Men Employed in Manufacturing	(0.073)	(0.084)	(0.075)	(0.076)	(0.069)	(0.048)
[Manufacturing Bust]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Housing price effect (1σ)	**0.000**	**0.002**	**0.001**	**0.002**	**0.002**	**-0.001**
Manufacturing effect (1σ)	**0.014**	**0.014**	**0.014**	**0.014**	**0.014**	**0.014**
First stage F-statistic		26.863	38.179	39.327	12.402	43.978
Overidentification test statistic, $\chi^2(1)$				0.199		3.904
[p-value]				[0.656]		[0.048]
N	234	234	234	234	234	234
R^2	0.532	0.519	0.527	0.525	0.549	0.564
Include baseline controls	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y	y	y
Instrument with sand state dummy			y	y		y
Census region FEs (4 regions)					y	y
Census division FEs (9 divisions)						

Notes: This table replicates robustness analysis in Table 4 for alternative dependent variable. See notes to Table 4 for more details. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Appendix Table A4
Robustness to Alternative Specifications

Dependent variable:	Change in Non-College male Population, 2000-2007					
Specification:	OLS	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Housing Prices	0.004	-0.188	0.077	-0.014	-0.274	-0.079
[Housing Boom]	(0.045)	(0.053)	(0.074)	(0.056)	(0.150)	(0.067)
	[0.935]	[0.000]	[0.299]	[0.799]	[0.067]	[0.236]
Predicted Change in Share of	2.395	2.383	2.149	2.430	1.865	1.958
Non-College Men Employed in Manufacturing	(0.704)	(1.250)	(0.751)	(0.686)	(1.217)	(0.758)
[Manufacturing Bust]	[0.001]	[0.063]	[0.007]	[0.001]	[0.133]	[0.013]
Housing price effect (1σ)	**0.001**	**-0.059**	**0.024**	**-0.004**	**-0.086**	**-0.025**
Manufacturing effect (1σ)	**0.032**	**0.032**	**0.029**	**0.033**	**0.025**	**0.027**
First stage F-statistic		24.289	41.116	43.991	10.945	37.471
Overidentification test statistic, $\chi^2(1)$				8.677		9.103
[p-value]				[0.003]		[0.003]
N	235	235	235	235	235	235
R^2	0.149	-0.234	0.094	0.146	-0.220	0.271
Include baseline controls	y	y	y	y	y	y
Instrument with (elasticity)$^{-1}$		y		y	y	y
Instrument with sand state dummy			y	y		y
Census region FEs (4 regions)					y	y
Census division FEs (9 divisions)						

Notes: This table replicates robustness analysis in Table 4 for alternative dependent variable. See notes to Table 4 for more details. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Appendix Table A5
Expenditures on Transfer Programs

	Dependent Variable: Percentage Change in Aggregate Expenditures on Transfer Programs (Adjusted Per Non-College Capita)							
	Food Stamps		Income Maintenance		Unemployment Insurance		Food Stamps + Income Maint. + Unemp. Insurance	
Specification:	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Housing Prices	-0.590	-0.701	-0.173	0.302	-0.155	-0.148	-0.220	-0.230
[Housing Boom]	(0.161)	(0.300)	(0.341)	(0.476)	(0.112)	(0.184)	(0.114)	(0.190)
	[0.001]	[0.020]	[0.615]	[0.526]	[0.173]	[0.420]	[0.059]	[0.226]
Predicted Change in Share of	-12.297	-12.343	-10.948	-10.928	-1.319	-1.328	-2.463	-2.478
Non-College Men Empl. in Manuf.	(4.033)	(3.852)	(4.888)	(5.710)	(1.988)	(1.883)	(2.120)	(2.011)
[Manufacturing Bust]	[0.004]	[0.003]	[0.030]	[0.062]	[0.511]	[0.484]	[0.252]	[0.225]
Housing price effect (1σ)	**-0.184**	**-0.220**	**-0.054**	**0.095**	**-0.049**	**-0.046**	**-0.069**	**-0.072**
Manufacturing effect (1σ)	**-0.166**	**-0.167**	**-0.148**	**-0.148**	**-0.018**	**-0.018**	**-0.033**	**-0.034**
First stage F-statistic		24.289		24.289		24.289		24.289
N	235	235	235	235	235	235	235	235
R^2	0.398	0.393	0.135	0.071	0.088	0.088	0.159	0.159
Include baseline controls	y	y	y	y	y	y	y	y
Instrument with $(\text{elasticity})^{-1}$		y		y		y		y

Notes: **XXX** Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Appendix Table A6

How Well do Manufacturing Busts and Housing Booms Explain the National Trends?

Panel A: Accounting for National Trends of Non-College Men

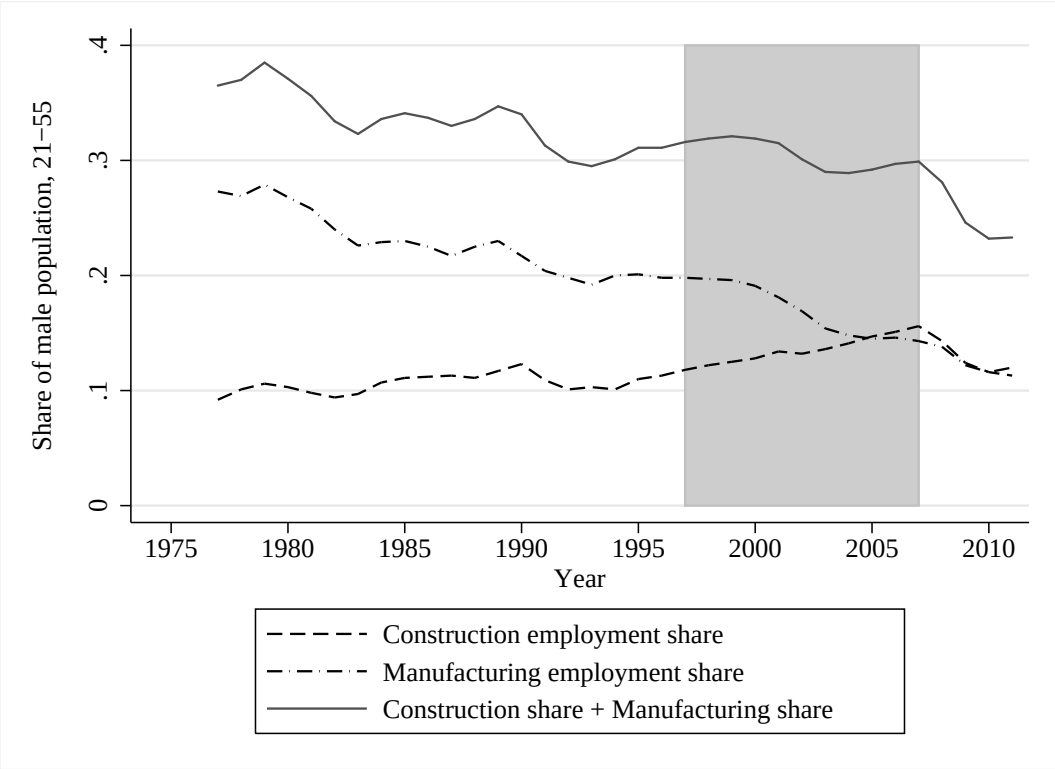
	Actual Change in Non-employment	Predicted Change due to Manufact. Shock	Predicted Change due to Housing Shock	Residual Change, (1) - (2) - (3)	Share of Actual Change Explained by Manufacturing + Housing
	(1)	(2)	(3)	(4)	(5)
2000-2007	0.022	0.035	-0.014	0.002	92.8%
2007-2011	0.086	**0.000**	0.014	0.072	16.8%
2000-2011	0.108	**0.035**	0.000	0.073	32.3%

Panel B: Accounting for National Trends of All Prime-Age Men and Women

	Actual Change in Non-employment	Predicted Change due to Manufact. Shock	Predicted Change due to Housing Shock	Residual Change, (1) - (2) - (3)	Share of Actual Change Explained by Manufacturing + Housing
	(1)	(2)	(3)	(4)	(5)
2000-2007	0.019	0.028	-0.011	0.002	89.3%
2007-2011	0.066	**0.000**	0.011	0.055	17.4%
2000-2011	0.085	**0.028**	0.000	0.057	33.4%

Notes: This table reports counterfactual estimates of predicted changes in aggregate non-employment. Unlike Table 9, in this calibartion the actual changes in manufacturing employment between 2007-2010 is replaced with 0; i.e., this calibration (conservatively) assumes that none of the decline in manufacturing employment between 2007-2010

Figure 1: Trends in Employment in Manufacturing and Construction for Non-College Men, 1974-2011



Notes: This figure uses data from the March CPS. The sample includes all men without a college degree that are noninstitutionalized and age 21-55.

Figure 2: Graphical Solutions of Sectoral Choice Model

Figure 2a: Initial Equilibrium

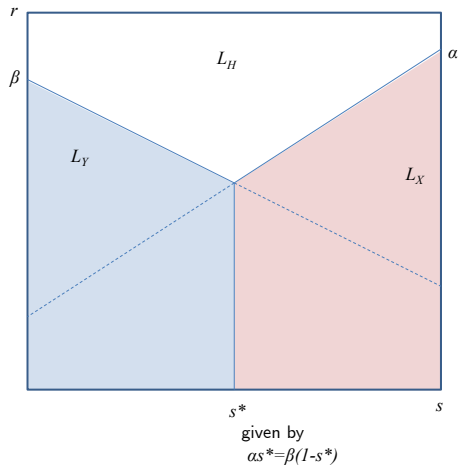


Figure 2b: Negative Shock to Sector A

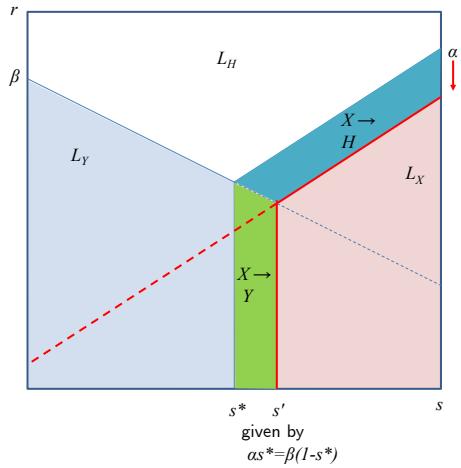
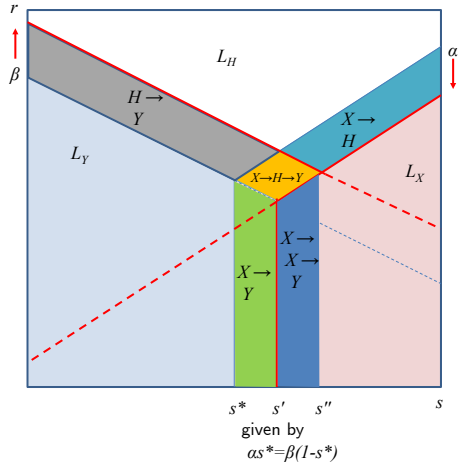


Figure 2c: Negative Shock to Sector A and "Offsetting" Positive Shock to Sector B



Notes: See text for details.

Figure 3: Time Series Implications of Model (Numerical Simulations)

Figure 3a: Scenario 1, steady decline in sector A

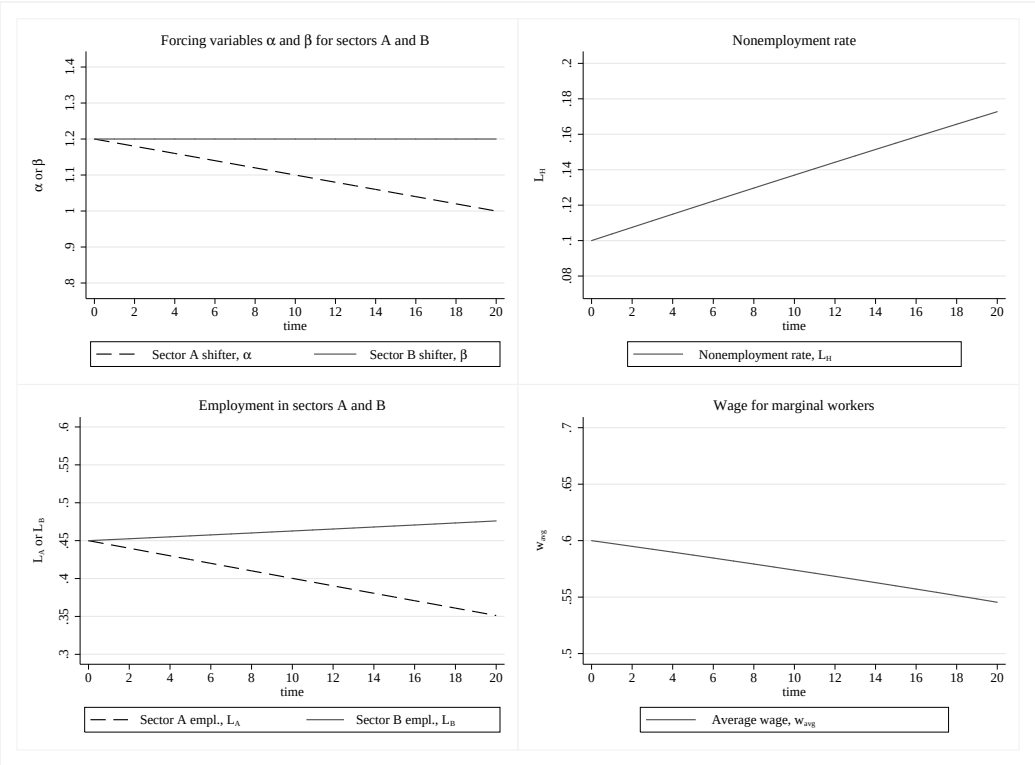
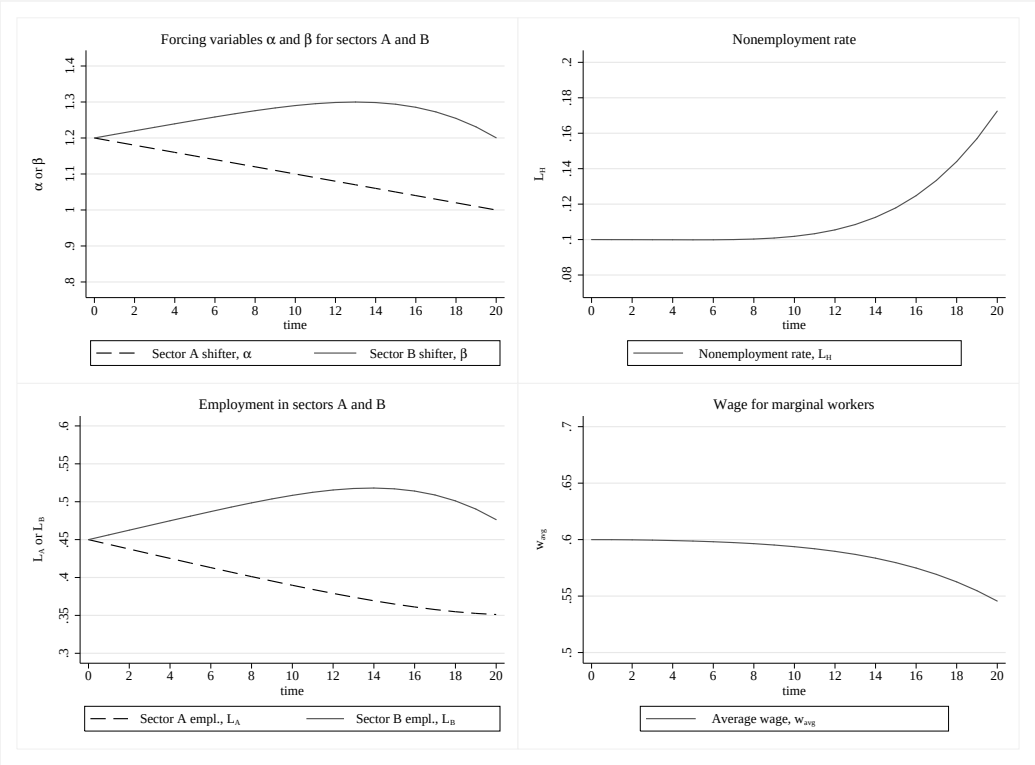
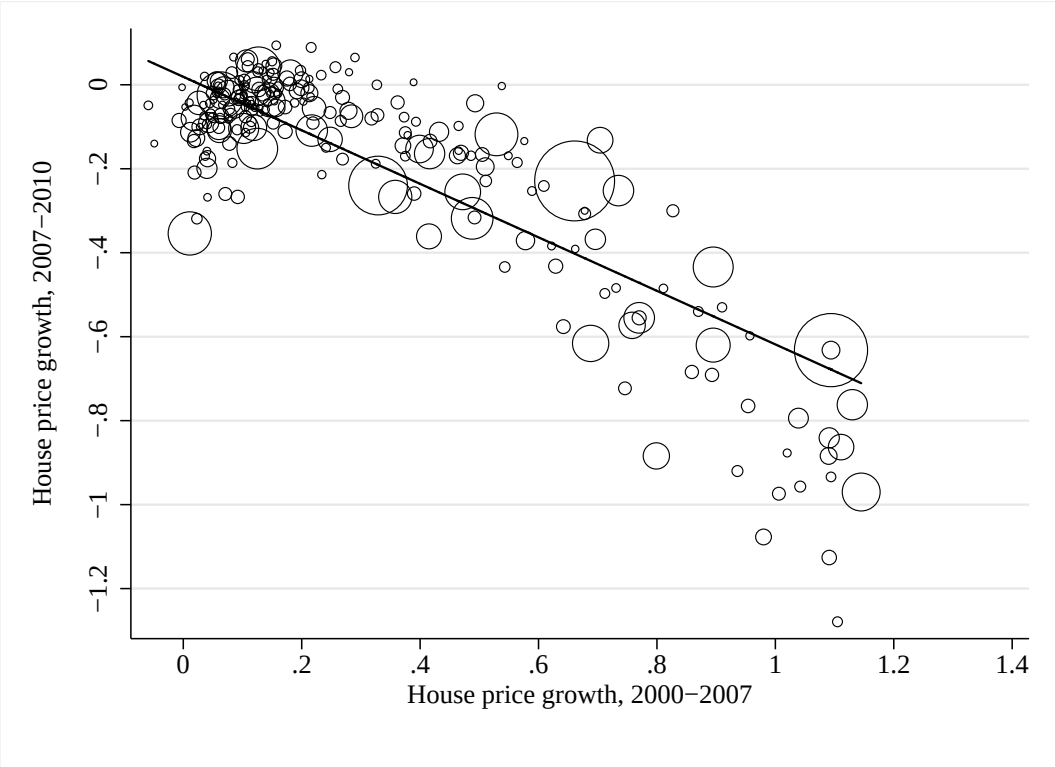


Figure 3b: Scenario 2, steady decline in sector A and "Boom/Bust" cycle in sector B



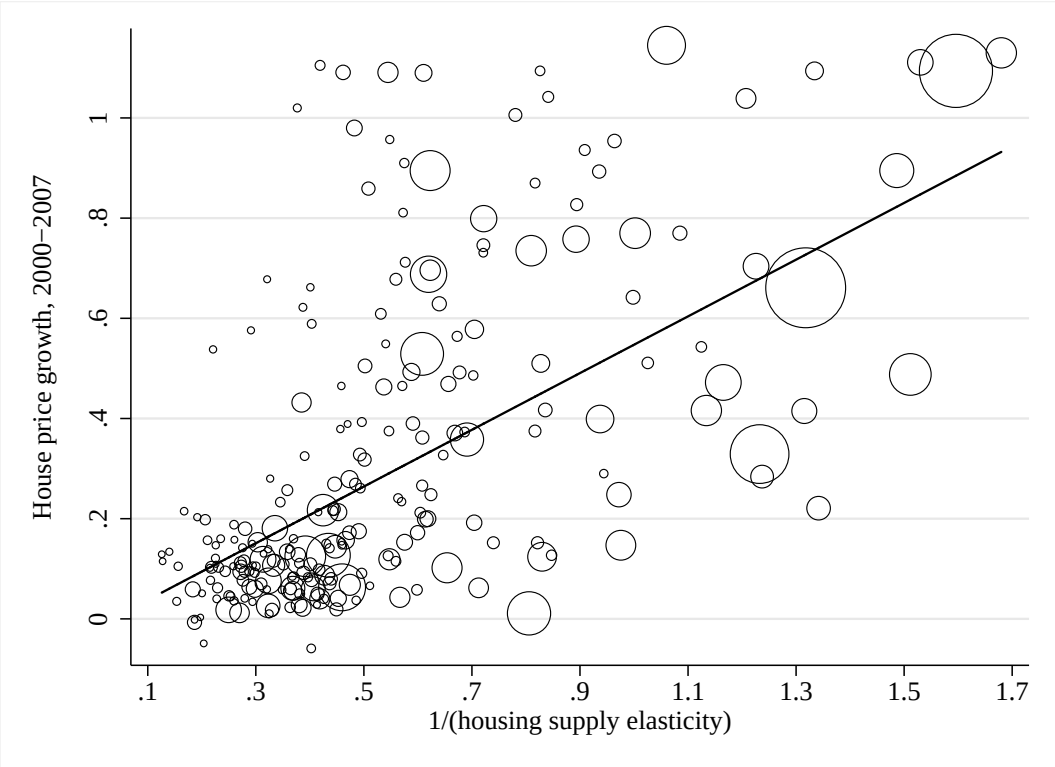
Notes: See text for details.

Figure 4: House Price Growth, 2007-2010 versus 2000-2007



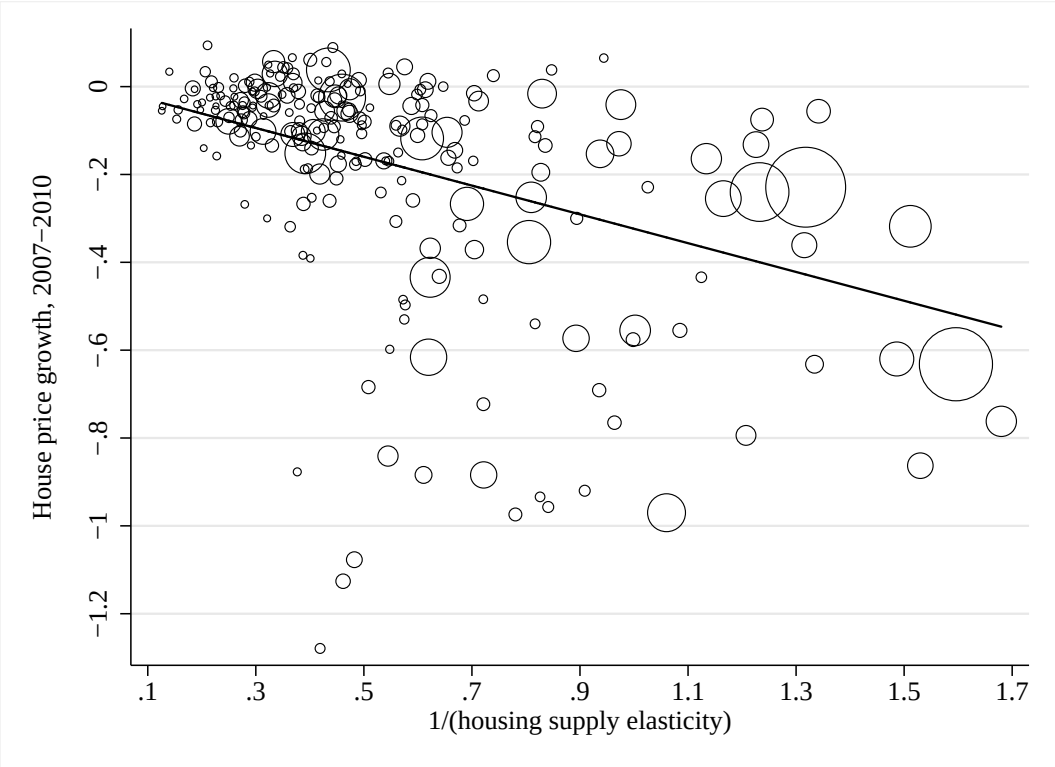
Notes: This figure reports the correlation across cities between house price changes in 2000-2007 and house price changes in 2007-2010. Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 25-54 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Figure 5: Housing Supply Elasticity and House Price Growth, 2000-2007



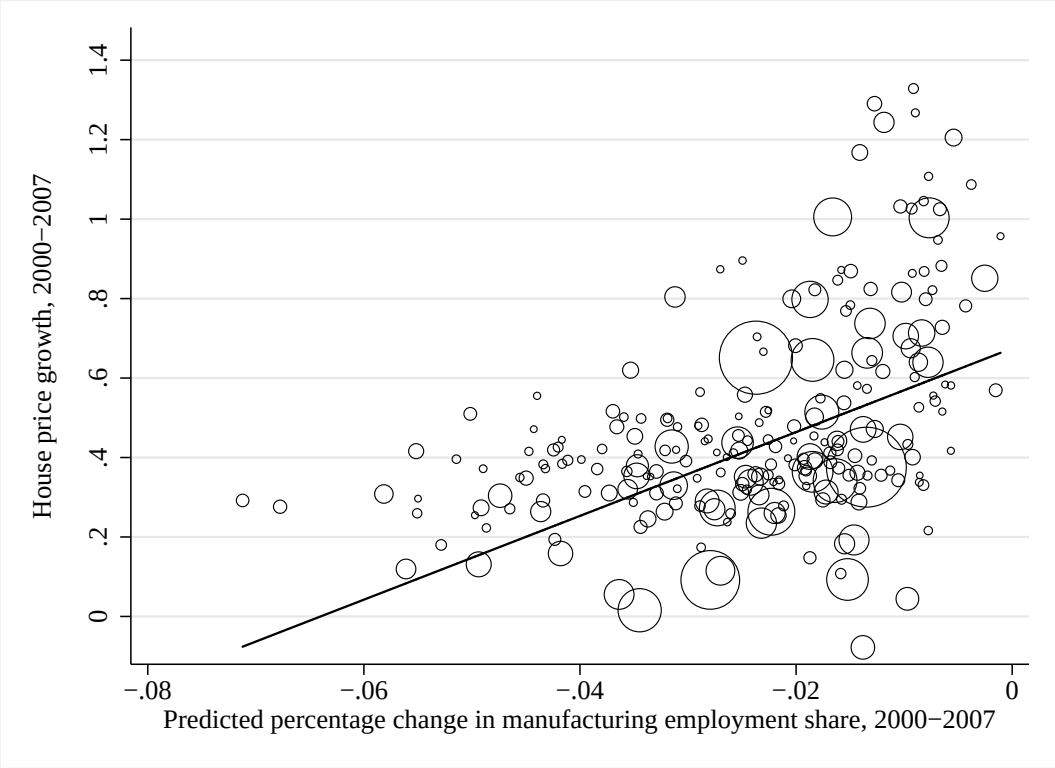
Notes: This figure reports the correlation across cities between 2000-2007 house price growth and the reciprocal of the housing supply elasticity from Saiz (2010). Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 25-54 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Figure 6: Housing Supply Elasticity and House Price Growth, 2007-2011



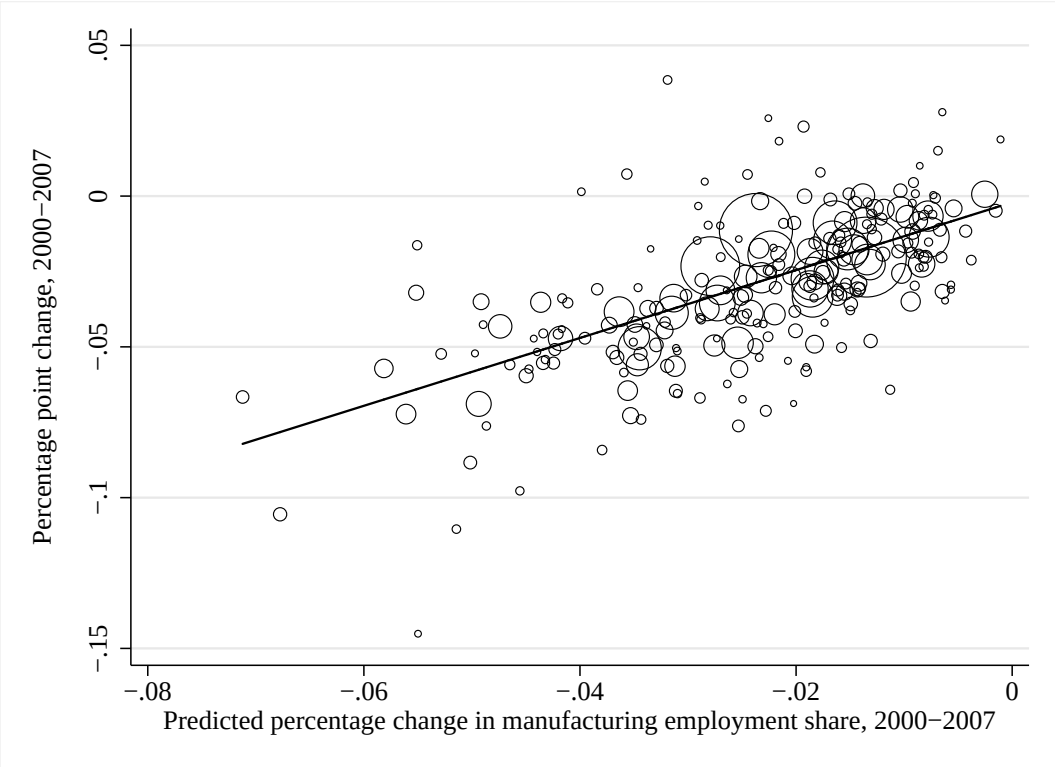
Notes: This figure reports the correlation across cities between 2007-2011 house price growth and the reciprocal of the housing supply elasticity from Saiz (2010). Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 25-54 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Figure 7: Manufacturing Shocks and (Residualized) House Price Growth, Non-College Men, 2000-2007



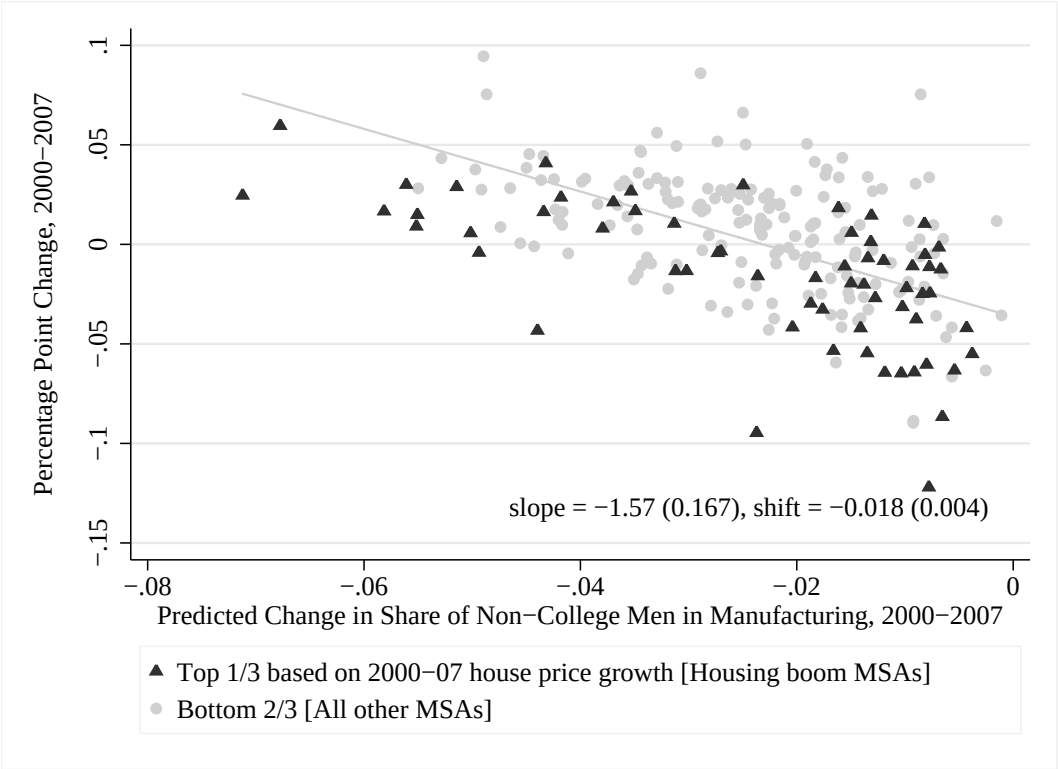
Notes: This figure reports the correlation across cities between shocks to local manufacturing industries and 2000-2007 house price growth. The manufacturing shock is constructed following Bartik (1991); see Appendix for details. Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 25-54 in the metropolitan area as computed in the 2000 Census. The reciprocal of the Housing Supply Elasticity instrument described in Figures 5 and 6 is residualized out of the House Price Growth variable. The solid line represents the weighted OLS regression line.

Figure 8: Manufacturing Shocks and Manufacturing Employment, Non-College Men, 2000-2007



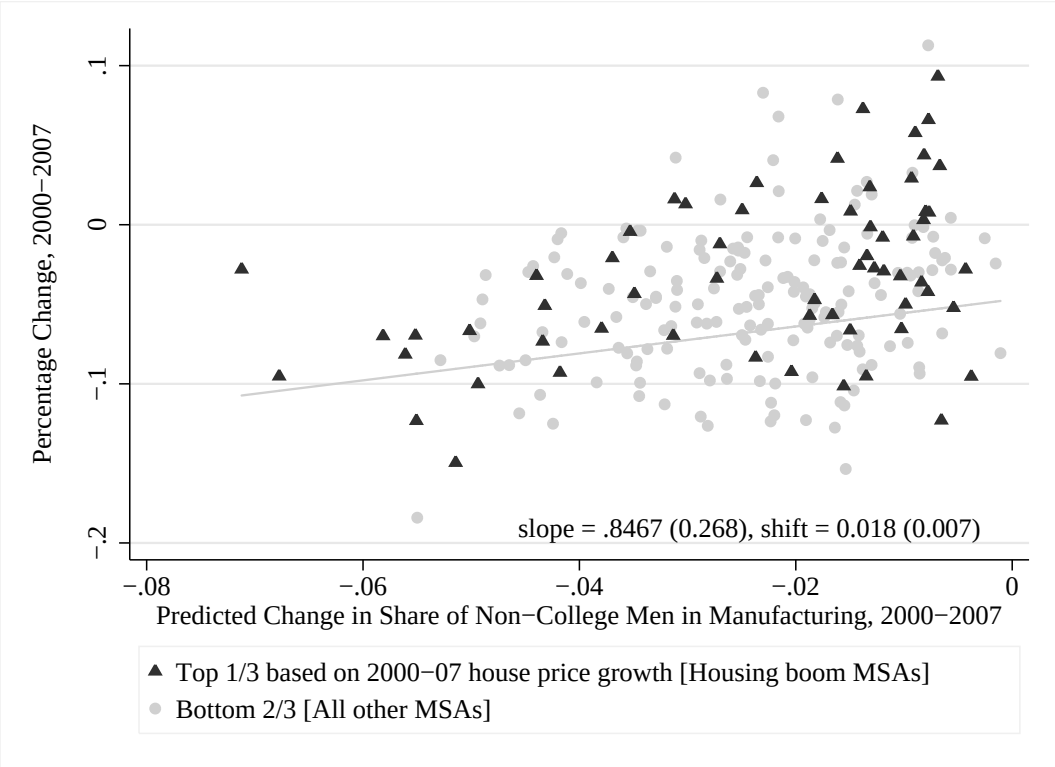
Notes: This figure reports the correlation across cities between shocks to local manufacturing industries and changes in manufacturing employment between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991); see Appendix for details. The change in manufacturing employment is defined as the change in the share of the total population of non-college men. Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 25-54 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Figure 9: Change in Non-Employment Rate of Non-College Men, 2000-2007



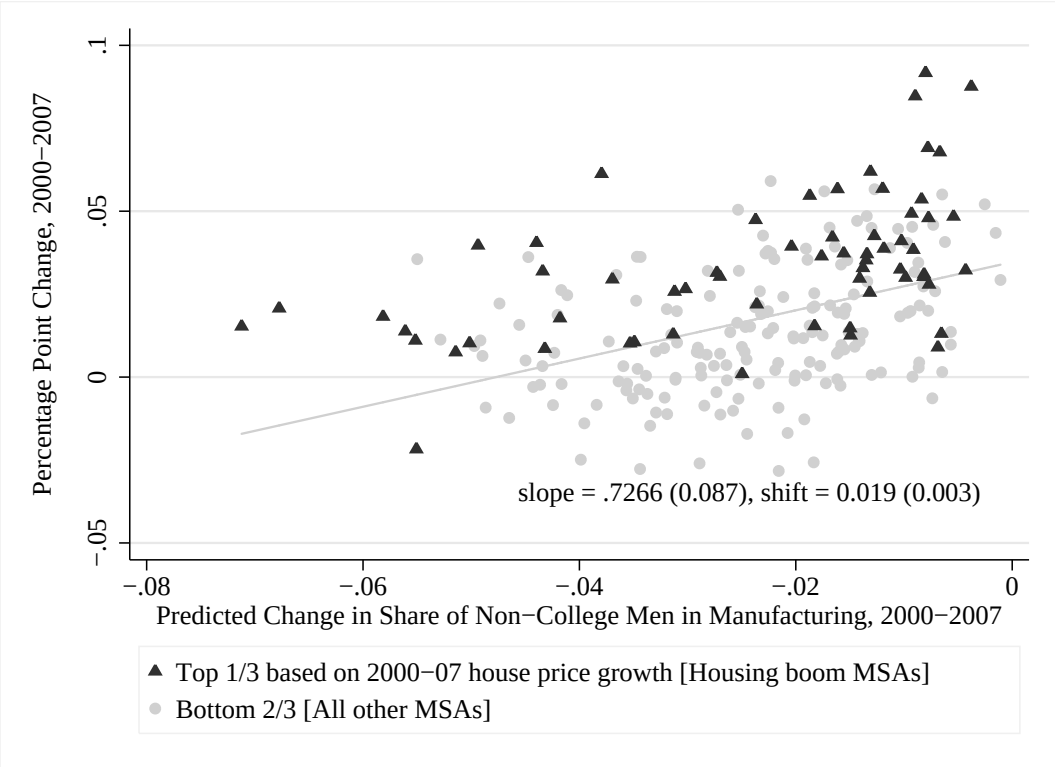
Notes: This figure reports the correlation across cities between shocks to local manufacturing industries and the change in the non-employment rate of non-college men (age 25-54) between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS; see the Appendix for more details. The change in non-employment rate is computed using data from the 2000 Census and the 2005-2007 ACS. The sample is divided based on the (residualized) house price growth in the metropolitan area between 2000 and 2007, where the local manufacturing shock has been residualized out of house price growth. The bottom two-thirds of the metropolitan areas based on the residualized house price growth are shown in grey circles; the top one-third are shown in black triangles. The solid grey line represents the weighted OLS regression line that is computed based on the bottom two-thirds sample.

Figure 10: Change in Average Wage of Non-College Men, 2000-2007



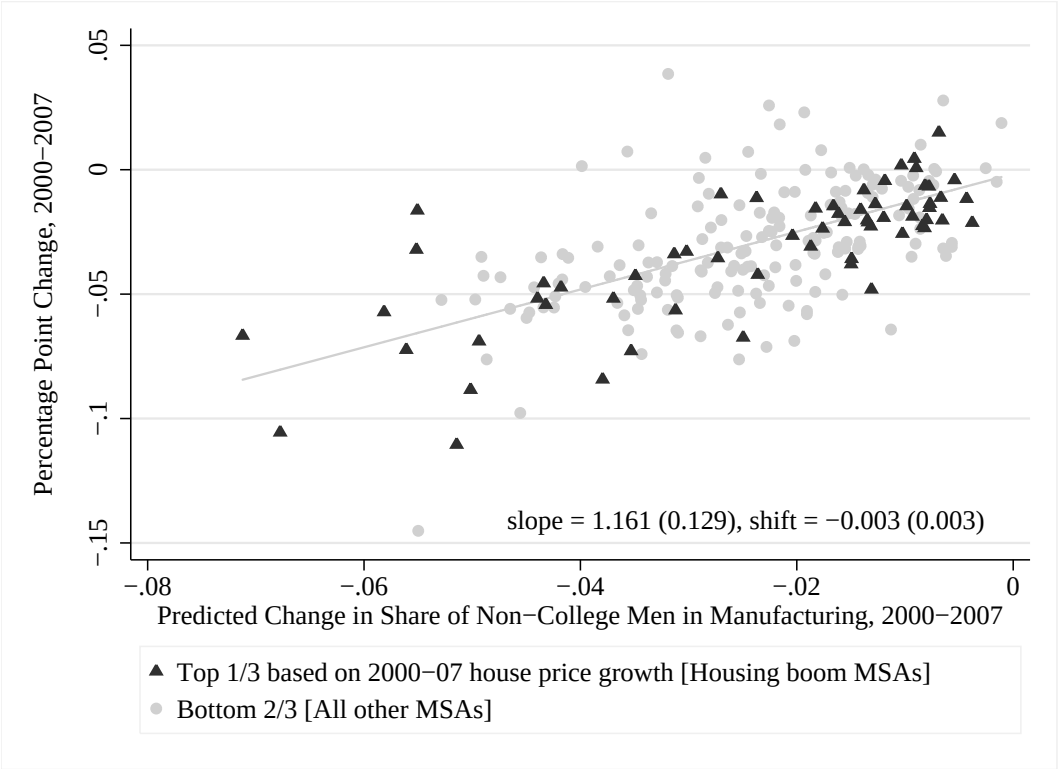
Notes: This figure reports the correlation across cities between local manufacturing shock and the change in the average wage of non-college men (age 25-54) between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS, and is described in more detail in the main text and in the Appendix. The change in average wage is computed using data from the 2000 Census and the 2005-2007 ACS. See Figure 5 for more information on the sample definition.

Figure 11: Change in Share of Population Employed in Construction, Non-College Men, 2000-2007



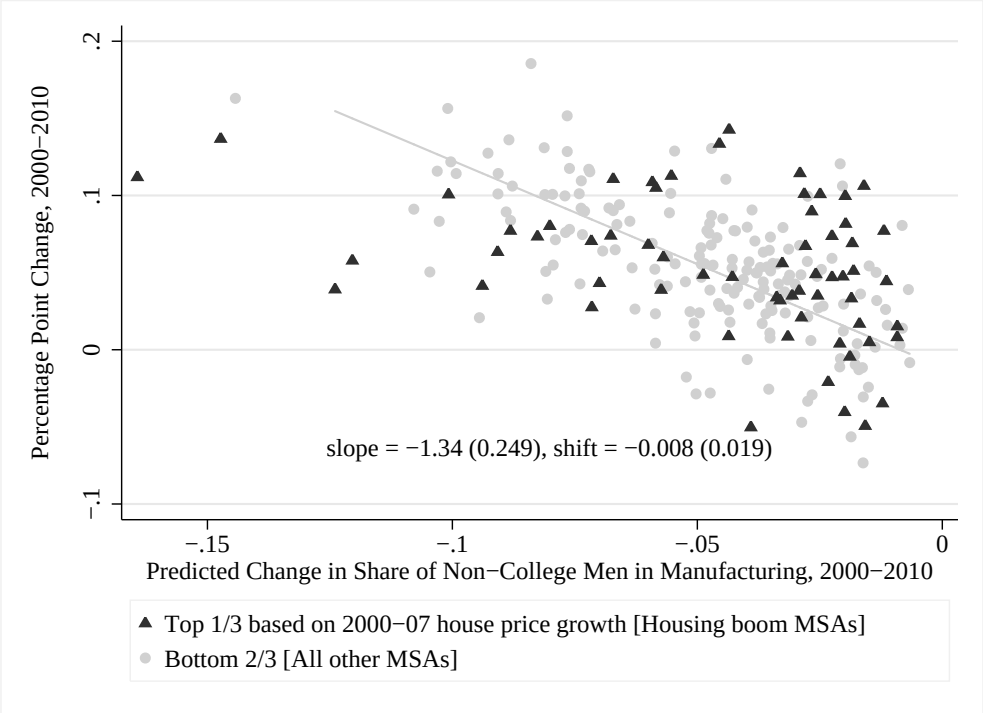
Notes: This figure reports the correlation across cities between local manufacturing shock and the change in the share of the non-college male population employed in construction (age 25-54) between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS, and is described in more detail in the main text and in the Appendix. The change in construction employment is computed using data from the 2000 Census and the 2005-2007 ACS. See Figure 5 for more information on the sample definition.

Figure 12: Change in Share of Population Employed in Manufacturing, Non-College Men, 2000-2007



Notes: This figure reports the correlation across cities between local manufacturing shock and the change in the share of the non-college male population employed in manufacturing (age 25-54) between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS, and is described in more detail in the main text and in the Appendix. The change in manufacturing employment is computed using data from the 2000 Census and the 2005-2007 ACS. See Figure 5 for more information on the sample definition.

Figure 13: Change in Non-Employment Rate of Non-College Men, 2000-2010 [Housing boom MSAs]



Notes: This figure reports the correlation across cities between local manufacturing shock and the change in the non-employment rate of non-college men between 2000 and 2010. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS, and is described in more detail in the main text and in the Appendix. The change in non-employment is computed using data from the 2000 Census and the 2009-2010 ACS. See Figure 5 for more information on the sample definition.

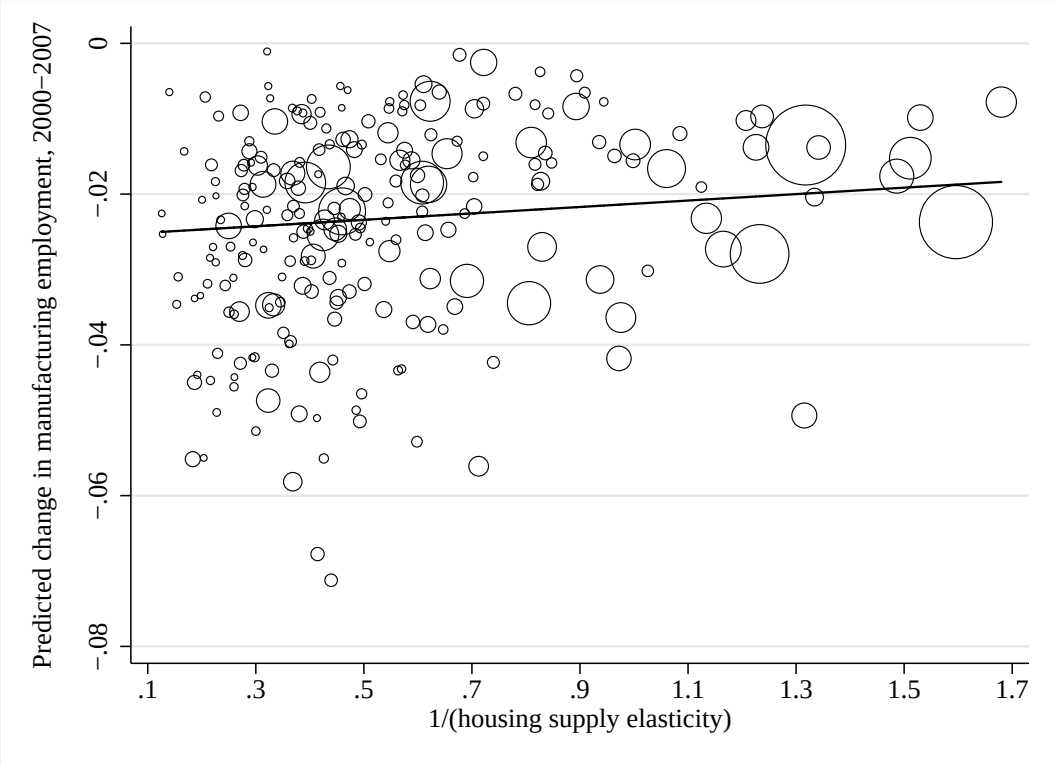
Figure 14: Change in Non-Employment Rate of Non-College Men, 2000-2010 [Housing bust MSAs]

Notes: This figure reports the correlation across cities between local manufacturing shock and the change in the non-employment rate of non-college men between 2000 and 2010. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS, and is described in more detail in the main text and in the Appendix. The change in non-employment is computed using data from the 2000 Census and the 2009-2010 ACS. See Figure 5 for more information on the sample definition.

Appendix Figure 1: Median Wages for Non-College Men, 1974-2011

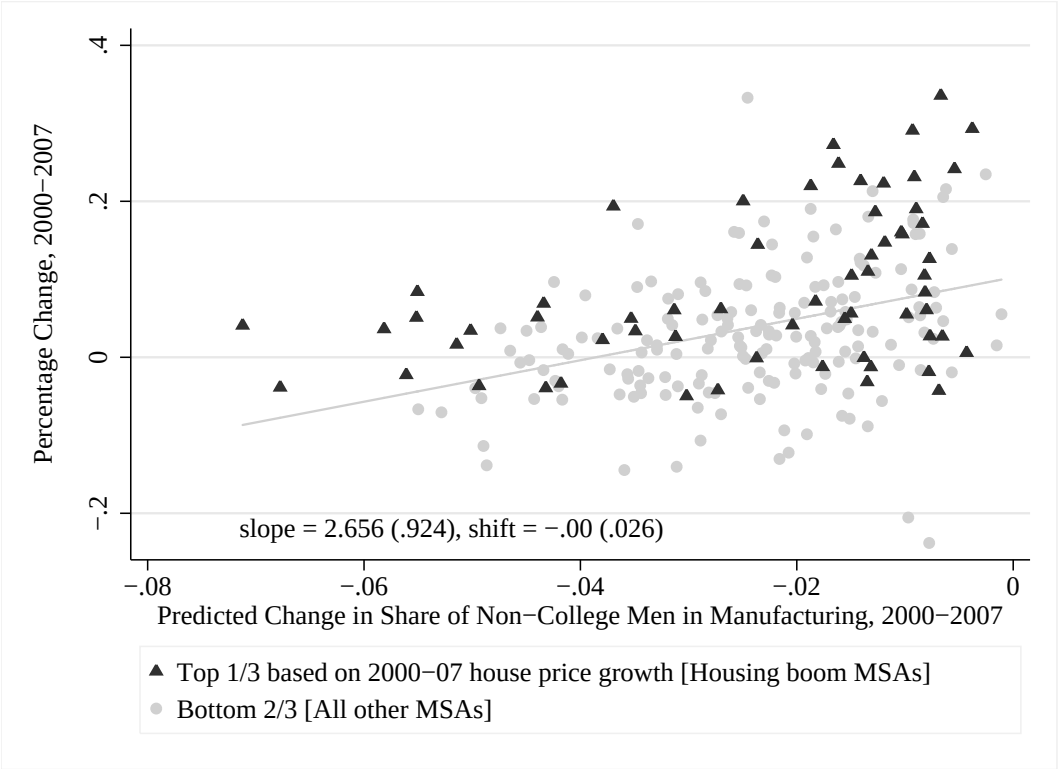
Notes: This figure uses data from the March CPS. The sample includes all men without a college degree that are noninstitutionalized and age 21-55.

Appendix Figure 2: Correlation Between Housing Supply Elasticity and Local Manufacturing Shock



Notes: This figure reports the correlation across cities between the reciprocal of the housing supply elasticity (from Saiz (2010)) and the local manufacturing shock. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS, and is described in more detail in the main text and in the Appendix. Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 25-54 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Appendix Figure 3: Correlation in Population of Non-College Men, 2000-2007



Notes: This figure reports the correlation across cities between local manufacturing shock and the change in the non-college male population employed in manufacturing (age 25-54) between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS, and is described in more detail in the main text and in the Appendix. The change in manufacturing employment is computed using data from the 2000 Census and the 2005-2007 ACS. See Figure 5 for more information on the sample definition.