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

Kerwin Kofi Charles
University of Chicago
Harris School of Public Policy
and NBER

Erik Hurst
University of Chicago
Booth School of Business
and NBER

Matthew J. Notowidigdo
University of Chicago
Booth School of Business
and NBER

August 2012[1]

Abstract

We study the extent to which the U.S. housing boom and subsequent housing bust during the 2000s masked (and then unmasked) the sharp, ongoing decline in the manufacturing sector. We exploit cross-city variation in manufacturing declines and housing booms and jointly estimate the effects of both shocks on local employment and wages. Between 2000 and 2007, we find that a one standard deviation negative manufacturing shock increases the non-employment rate of non-college men by 0.9 percentage points, and a one standard deviation positive housing price shock is enough to fully offset this effect. We find that roughly half of the "offsetting" comes from increased construction employment and that other demographic groups are affected by both shocks, as well, though to a lesser extent. We also find that positive housing price shocks significantly reduce college enrollment, with the largest effects concentrated among community colleges and junior colleges. Finally, we use our estimates to assess how aggregate employment would have evolved absent the housing boom/bust cycle, and we find that roughly 35 percent of the increase in non-employment between 2007 and 2011 can be attributed to the decline in manufacturing employment 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)

[1] E-mail: kcharles@uchicago.edu; Erik.Hurst@chicagobooth.edu; noto@chicagobooth.edu.

We thank seminar participants at the Einaudi Institute, the NBER Summer Institute (Macro Perspectives), and the Chicago Federal Reserve Board for helpful comments. We are grateful to David Toniatti and Dan Zangri for excellent research assistance. We gratefully acknowledge the Initiative on Global Markets at the University of Chicago Booth School of Business for financial support. Hurst thanks the Peter Wall Institute for Advanced Studies at the University of British Columbia and Notowidigo thanks the Einaudi Institute for both their financial support and hospitality while working on this project.

1 Introduction

The dramatic decline of the manufacturing sector that began in the 1970s has accelerated through the 2000s. Between 2000 and 2007, manufacturing employment declined by 3.5 million jobs within the United States. This is compared to a loss of 1.8 million manufacturing jobs between 1980 and the late 1990s.[2] Previous research has established a relatively sharp negative relationship between the sectoral decline in manufacturing and wage and employment outcomes for men, particularly for men without a college degree (a group we label as "non-college men" throughout the paper).[3] However, from 2000-2007 and from 2007-2011, this negative relationship departed from what might have been predicted based on the historical pattern. Such a dramatic decline in manufacturing employment during the early 2000s might have been expected to cause massive increases in non-employment and reductions in wages for non-college men. In fact, non-employment rates for prime-aged, non-college men increased by 2.8 percentage points during this period, and their median wages stabilized and slightly increased after decades of consistent decline. By contrast, between 2007 and 2011, manufacturing employment fell by about 2.5 million jobs, while the non-employment rate of non-college 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 non-college workers (and possibly others), but these adverse effects were obscured by the employment opportunities associated with the unprecedented boom in the housing market during this time period, when house prices rose nationally by 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 employment opportunities associated with the preceding boom. Moreover, non-college workers 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 non-college workers through a number of channels. For example, changes in household wealth associated with house price variation likely changed households' consumption of goods and services provided by those workers.[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

[2] Data from the U.S. Bureau of Economic Analysis. The role that China played in explaining the sharp decline in manufacturing employment within the U.S. during the 2000s was recently examined by Autor et al. (2012).

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

[4] Changes in non-employment for non-college men were large relative to those among college 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.

plot the share of all non-college men employed 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; in fact, our main results suggest that increased construction employment is responsible for roughly half of the overall change in employment in response to the housing boom, with the remaining employment response coming from other sectors.

The broken line in the figure, which plots the share of non-college men working in either manufacturing or construction, shows that these two sectors have historically jointly accounted for a very large fraction of the employment of these men. In 1979, 37 percent of non-college men worked in one of these two sectors, and more than 20 percent continue to work in these sectors in 2010.[7] 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 non-college 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. 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 non-college 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 non-college 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). We exploit variation across MSAs during the 2000s in both the size of the manufacturing decline and in the size of the housing boom. Our primary estimation focuses on the period from 2000-2007 (prior to the 2008 recession). We use total manufacturing

[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). Although we focus in this initial section on non-college men, we later examine the results for non-college women as well as men and women with at least a college degree.

[7] Appendix Figure A1 shows the trend in median wages for non-college men between the late 1970s and 2010 using CPS data. The wages of non-college men is strongly correlated with the share of their employment in manufacturing plus construction. The simple correlation between the two series over the period depicted is 0.91.

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 an MSA's initial industry mix and national changes in industry employment within narrowly-defined manufacturing industries. 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 as well as 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.[8]

We use housing prices to proxy for housing market shocks in MSA. The house price within the MSA is a good proxy for housing market shocks in an MSA because key mechanisms by which housing sector shocks affect local labor market outcomes, such as increased construction activity or the provision of other goods and services because of an increase in household wealth, likely operate through house prices. Unfortunately, it is possible that not all observed variation in housing prices is exogenous with respect to unobserved determinants of labor market outcomes. In particular, variation in the housing price across MSAs might arise from different unobserved shocks either to sectors other than manufacturing or to workers' labor supply. Since these unobserved shocks may also directly affect labor market outcomes, the naive use of the housing price as a measure of the effect a housing shock may be biased. We therefore estimate Instrumental Variables (IV) models, in which we isolate exogenous variation in housing prices using pre-determined measures of the share of land that is available for development ("land availability") from Saiz (2010). We argue that the degree to which house prices respond to an increase in national demand for housing (perhaps due to increases in lending technology or changes in interest rate policy) should be a function of these topographic characteristics of the MSA. Importantly, this instrument is constructed based on pre-existing characteristics of the local labor market, which allows us to assume that any variation in housing boom captured by the instrument is plausibly uncorrelated with unobserved labor supply shifts during the housing boom. It is important to recognize that higher housing prices will lead to increased construction activity even in places where the supply of *new* construction is difficult, as house price increases cause households to tear-down, remodel, or renovate existing structures. Indeed, this is precisely what we document empirically, as the land availability instrument that we use in our analysis strongly predicts increases in both housing prices as well as construction employment within an MSA during the 2000-2007 period.[9]

Using OLS and IV models, we find that the predicted manufacturing bust during 2000-2007 in an MSA:

[8] We are aware of the potential general equilibrium effects of a housing boom on manufacturing demand, and we acknowledge that these will not be captured by our research design. For example, if people feel richer from their increase in housing wealth, then spending on all goods - including manufactured goods - will increase. As we discuss in detail below, such general equilibrium effects will likely cause us to underestimate the extent to which we can account for the increase in non-employment between 2007 and 2011 due to declining manufacturing.

[9] This finding is consistent with recent findings in Mian and Sufi (2011) and Davidoff (2012).

(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 0.9 percentage point increase in the non-employment rate for non-college 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 1.0 percentage point decrease in the non-employment rate for non-college men, enough to fully "offset" the effects of an adverse manufacturing shock. Additionally, our estimates imply that roughly half of the non-employment effect resulting from a housing boom comes from increased construction employment, with the remainder comes from other sectors, such as local retail and services. While our estimates of labor market effects in response to the manufacturing and housing shocks are largest for non-college men, we also find significant (though smaller) effects for college-educated men and non-college women, as well. Lastly, we explore differences across different age groups, and we find similar effects of the housing boom for younger and older non-college men, though we find that the manufacturing shocks increase non-employment significantly more for older men.

Interestingly, the estimated effects of house price booms during the 2000-2007 period are very similar across our preferred OLS and IV specifications. This suggests that the variation in housing prices at the MSA level between 2000 and 2007 is not substantially confounded by unobserved labor supply shifts. Additionally, we show that 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. This contrasts sharply with our manufacturing results, which show lasting employment effects over the longer run. 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. Specifically, 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, extrapolating our local labor market estimates to the national context. We find that the non-employment rate for non-college men would have increased by an additional 1.3 percentage points between 2000 and 2007 in that hypothetical case. More importantly, we conclude that roughly 35 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 can be attributed to the decline in manufacturing from 2000 to 2007 that was masked by the housing boom. Overall, we estimate that the decline in manufacturing explains roughly 45 percent of the overall increase in non-employment between 2000 and 2011.[10]

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 research showing that structural factors explain a significant portion of current non-employment.[11] Most discussion of structural forces focuses on labor market mismatch, which empirically seems to account for little of current unemployment.[12] 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 large, temporary 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 35 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 65 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.

Lastly, we conclude by investigating the relationship between housing booms and college enrollment, using the same local labor market strategy used to study wage and employment outcomes. This exercise is motivated by the striking patterns in Figure 2. This figure shows the share of men and women age 18-29 who have attended any college for the years 1980-2011 from the CPS, and alongside each data series is a gender-specific linear predictor estimated during 1980-1996 (the period before the housing boom) and extrapolated thereafter. Starting in 1997 when housing prices start to rise nationally, the college share begins to lag trend, and the lagging continues all the way until the housing bust begins, when both series begin to quickly revert back to trend. By 2007, the share of men who have attended any college lags trend by 2.2 percentage points, and for women the share lags by 3.4 percentage points. We find that our local labor market estimates are broadly consistent with these time series trends. Using rich survey day on college and university enrollments, we show that local housing booms significantly reduce first-time undergraduate enrollment, with the largest effects concentrated among community colleges, junior colleges, and technical colleges. When we apply our

[10] 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 many of the relevant general equilibrium effects of the housing boom on manufacturing demand during the 2000-2007 period likely lead our results to be biased downwards.

[11] 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).

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

local estimates nationally as was done in the counterfactual analyses for employment described above, our estimates can account for 64% of the "gap" (relative to trend) in 2007 for men and 37% for women.

The remainder of the paper proceeds as follows. In the next section we outline a simple model that will frame our empirical work. The model highlights the interaction between 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), and it provides intuition for the empirical results later in the paper. We outline the empirical framework in Section 3, describing our estimation equations and identification strategy. In Section 4, we discuss the data. This section discusses the predicted manufacturing measure and housing price changes - the proxies we use for manufacturing and housing market shocks. We present evidence showing that these proxies are high-quality measures of the shocks they are supposed to measure, and we also show how well each of the proxies are explained by plausibly exogenous instruments. In Sections 5-7, we present our main empirical results and in Section 8 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. In Section 9, we explore how the sectoral shocks affected college enrollments, and we conclude in Section 10.

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 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 non-college 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.

The mass of workers in the economy have heterogeneity in skill endowments and reservation wages, which are jointly distributed according to the PDF $f(s, r)$. To simplify the exposition of the model (and to highlight the primary self-selection mechanism that is the focus of our paper), we assume that both the skill endowment and the reservation wage are exogenous characteristics of the individual. 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.[13] 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

[13] 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.

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 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 $L_A + L_B + L_H = 1$:

$$L_A = \int_{s^*}^{1} \int_{0}^{s\alpha} f(s,r) dr ds \quad (1)$$
$$L_B = \int_{0}^{s^*} \int_{0}^{(1-s)\beta} f(s,r) dr ds \quad (2)$$
$$L_H = 1 - L_A - L_B \quad (3)$$

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 3a 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 3b 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 3c. 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.

3 Empirical Model

Our empirical analysis examines how shocks to the manufacturing and housing sectors across different labor markets (MSAs) during the 2000s affected labor market outcomes for different groups of workers. We assume that changes in labor market outcomes for workers in an MSA, k, are determined, in part, by shocks to the total demand for those workers, across all sectors in the MSA. The labor market outcomes, L_k, we explore include MSA employment rates, average wages, and employment rates in a given sector. We suppose that there are three sectors - manufacturing, M, housing, H, and "other", O - and denote the shocks to demand that originate in these sectors as ΔD_k^M, ΔD_k^H, and ΔD_k^O, respectively. Apart from these demand shocks, labor market outcomes are affected by labor supply elasticities or other labor supply parameters, and other latent features of workers in the labor market. Let the change in workers' labor supply parameters be summarized by unobserved factors θ_k. Observed changes in labor market outcomes for a given type of workers in a given MSA can thus be written as the general function:

$$\Delta L_k = \left(\Delta D_k^M, \Delta D_k^H, \Delta D_k^O, \theta_k\right). \tag{4}$$

Our empirical work seeks to estimate the two effects $\partial \Delta L_k / \partial \Delta D_k^M$ and $\partial \Delta L_k / \partial \Delta D_k^H$. One challenge with empirically implementing equation (4) to conduct this analysis is that shocks to demand, ΔD, are not directly observed. We must therefore use proxies for ΔD_k^M and ΔD_k^H. Ideally, there should be strong *a priori* reason to suppose that each of these proxy measures is systematically positively related to the shock to which it relates. In addition, these proxy measures would ideally be exogenous with respect to unobserved determinants of labor market outcomes for workers in market k, summarized by θ_k and ΔD_k^O.

A proxy measure for the local manufacturing demand shocks, which is likely to satisfy both of these conditions, is suggested by previous work. Following Bartik (1991), many previous authors (see Blanchard and Katz 1992; Autor and Duggan 2003; Luttmer 2005; Notowidigdo 2011, for examples) have observed that a *national* shock to manufacturing is arguably exogenous with respect to unobserved local factors such as the labor supply elasticities of particular type of worker in a particular labor market. At the same time, this national shock should differentially affect local demand from manufacturing based on the importance and distribution of manufacturing employment in the local market at some time preceding the shock. Formally, our proxy for the change in manufacturing at the MSA level between 2000 and 2007 is a predicted measure, which is computed as follows:

$$\widehat{\Delta D_k^M} = \sum_{g=1}^{G} \varphi_{k,g,2000} \left(\upsilon_{-k,g,2007} - \upsilon_{-k,g,2000}\right)$$

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

3-digit industries in manufacturing sector.

To proxy for demand shocks arising from the housing market (such as those caused by a national change in lending technology or interest rate policy) we use the change in the local price of housing, ΔP_k^H. This decision is motivated by the observation that two likely important channels by which shocks to housing affect labor market outcomes for workers of a given type in an MSA, which we denote, respectively, the wealth effect and construction channels, $W_k(\Delta P_k^H)$ and $C_k(\Delta P_k^H)$, are likely to operate through housing prices. By changing housing prices, a local demand shock in the housing market changes households' wealth and, by extension, their demand for goods and services that workers in the market produce. This specific mechanism is explored in detail by Mian and Sufi (2011). Additionally, a change in housing prices stemming from a shock to the housing market likely affects various activities related to housing construction (e.g., building new homes, tear-downs of old structures, renovations and other improvements to existing home), which also depend on the labor of workers in the market.

We use the two proxy measures to create an empirical specification based on equation (4):

$$\Delta L_k = \beta_0 + \beta_1 \widehat{\Delta D_k^M} + \beta_2 \Delta P_k^H + \alpha X_k + \Delta D_k^O + \theta_k + \epsilon_k, \tag{5}$$

where X_k is a vector of observable controls, ΔD_k^O and θ_k are unobserved, and ϵ_k is a mean-zero regression error. In regression equation (5), the parameter β_1 measures the partial effect of an exogenous predicted shift in local manufacturing demand on labor market outcomes. The parameter β_2 measures the *overall* effect of a housing demand shocks that operate through the housing prices. That is, β_2 corresponds to:

$$\beta_2 = \frac{d\Delta L_k}{d\Delta P_k^H} = \frac{\partial \Delta L_k}{\partial \Delta W_k}\frac{d\Delta W_k}{d\Delta P_k^H} + \frac{\partial \Delta L_k}{\partial \Delta C_k^H}\frac{d\Delta C_k}{d\Delta P_k^H}.$$

It is worth emphasizing that *any* effect of housing shocks on ΔL_k that operate (even partially) through housing prices will be captured by the housing price proxy, but the framework will not capture the effects of housing shocks that are orthogonal to housing prices.

OLS regression on (5) will yield consistent estimates of β_1 and β_2 so long as the predicted manufacturing shocks and the change in housing prices are not related to unobserved determinants of labor market outcomes. For reasons already noted, we believe this condition almost surely holds for the predicted manufacturing shock, which is based on national trends and the pre-existing distribution of employment in the local area across different manufacturing industries. The case for the exogeneity of housing price changes in a market is less obvious, but we think highly probable that, because we regress labor market outcomes of *particular* groups of worker on the change in the housing price across the local market, market-wide housing price changes are unlikely to be endogenous with respect to unobserved shocks to labor supply for that group of workers.

To see why there might nonetheless be a concern that housing price changes might be endogenous in a regression of labor market outcomes, suppose that changes in local housing prices can be written as follows:

$$\Delta p_k^H = \gamma + \delta_1 \widehat{\Delta D_k^M} + \delta_2 f\left(\Delta D_k^H; Z_k\right) + \alpha + X_k + \Delta D_k^O + \theta_k + Z_k + \nu_k, \tag{6}$$

where ν_k is an error term. Equation (6) captures the idea that ΔD_k^M directly affects house price changes, as predicted by a standard spatial equilibrium model (Roback 1982). Similarly, housing price changes also depend, in general, on unobserved shocks to sectors other than manufacturing or housing, ΔD_k^O. As before, θ_k denote latent labor supply shocks of workers in the local market. The fact that unobserved shocks from other sectors and to labor supply appear in both equations (5) and (6) is the reason for the concern that the estimate of the effect of the price change in (5) might be biased in OLS regression.

The variables Z_k in (6) reflects exogenous observed features of the local housing market which have been shown by Saiz (2010) and others to affect housing prices. These variables are measures of physical limits to geographical expansion in the city, as summarized by land availability and the city's basic topography more generally. These variables affect house price variation either directly, or by affecting the degree to which national housing market shocks, like interest rate or lending policy, translate in house price changes, as captured by the general function $f(.)$. Since the variables Z are pre-determined, exogenous features of local markets, we use the variables Z as instrumental variables for housing price changes, and we estimate Instrumental Variables (IV) models based on (5) and (6). In these models, the variation used to identify the effect of housing price changes is exogenous to unobserved sources of variation in price changes that would be the source of bias in the OLS estimates, if any such bias exists. Effectively, since the predicted manufacturing proxy is entered directly, it can be regarded as serving as an instrument for itself. We therefore sometimes refer to the predicted manufacturing shock variable as the "manufacturing instrument".

We produce estimates of δ_1, β_1, β_2 by jointly estimating equations (5) and (6) using a simple two-step procedure. In the first step, we run an OLS regression of equation (6) and retain the estimate of $\hat{\delta}_1$, which measures the direct effect of manufacturing changes on house price movements. In the second step, we estimate equation (5) using IV using the pre-determined land availability measures Z as instrumental variables for Δp_k^H. In this second step regression, the estimated coefficient on ΔD_k^M corresponds to $\hat{\beta}_1$ and the estimated coefficient on Δp_k^H corresponds to $\hat{\beta}_2$. After these two steps we construct estimates $d\Delta L_k/d\Delta D_k^M = \hat{\beta}_1 + \hat{\beta}_2\hat{\delta}_1$ and $d\Delta L_k/d\Delta p_k^H = \hat{\beta}_2$ for different groups of workers. The first of these measures the total effect of manufacturing shock on labor market outcomes: the direct effect β_1 plus an indirect effect operating through the effect of manufacturing on house prices. The total effect of the housing price shock on labor market outcomes is simply $\hat{\beta}_2$. Notice, we assume that housing prices do not affect predicted manufacturing directly - an assumption we test and confirm below. In all results we cluster standard errors by state, and we compute standard errors on $d\Delta L_k/d\Delta D_k^M$ using standard methods for two-step estimators (Greene 2000).[14]

[14] We can also estimate the empirical model using 3SLS. Our inference is very similar using a 3SLS estimator rather than the two-step estimator described in the main text. The estimated standard errors are also very similar when we bootstrap the

All of our estimation is conducted in first differences. As a result, our specifications implicitly control 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 with a college degree within the MSA in 2000.

Finally, for most of our results, we focus on changes between 2000 and 2007. We focus on the 2000 to 2007 period 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 American Community Survey (available annual between 2001 and 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.[15] However, we also provide estimates during the 2007-2010 period and over the entire 2000-2010 period below.

4 Data

4.1 Data Sources and Summary Statistics

We use data from various sources in the empirical work to follow.[16] We briefly summarize the main data sources.

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

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.

[15] To be more precise, for the endpoint in our sample period, we pool together the American Community Survey data from the 2005-2007 period. We do this to increase the precision of our analysis at the metropolitan area level. When we restrict our analysis to prime-age non-college men and then cut the data by 3-digit occupation, some cells were fairly 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. Likewise, the 2010 data pools together observations from 2009 and 2010.

[16] See Data Appendix for further details about how the data set was created.

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 predicted manufacturing shock measure, which is based on the approach due to Bartik (1991). When creating this measure, we use 3-digit industry categories of the individuals in the labor force.

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, when 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 Land Availability

As noted above, in some specifications, we use an instrumental variable for changes in local housing prices. When doing so, we use estimates of metropolitan area land availability from Saiz (2010). This measure is constructed from measures of the topography of the MSA; see Saiz (2010) for a full discussion of the computation of these measures.

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 2000-2007 period and house price declines during 2007-2010 period. Moreover, as shown in Appendix Figure A2, these changes are closely related. Appendix Figure A2 shows that MSAs experiencing the sharpest increases in house prices during the boom also generally experienced the sharpest decreases during the bust. The R^2 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^2 of 0.73. This figure shows that most of the variation in house price growth across MSAs between 2000 and 2007 appears to have been transitory.

The next section of Table 1 reports labor market outcomes. Most MSAs experienced increase in construction employment share and a decrease in manufacturing employment share between 2000 and 2007.

4.2 Quality of Proxy Measures and First Stage Results

In the discussion of the empirical strategy presented earlier, we argued that because the local manufacturing and housing market shocks experienced by MSAs are not directly observed, we proxy for these shocks using, respectively, two measures: a predicted manufacturing shock based on the interaction between national manufacturing trends and the pre-determined distribution of manufacturing employment in the MSA; and the change in local housing price. We argued that there is *a priori* reason to suppose that these measures varied systematically with the shocks for which they served as proxies in the empirical analysis. Table 2 presents more formal evidence to support this conclusion.

The table reports results from regressions that relate each of the proxy measures to a variable likely to be strongly positively affected by the shock to which the proxy measure is related. In the first two columns, we regress the change in the share of non-college men employed in manufacturing (an outcome which is unarguably positively related to the size of any unobserved actual manufacturing shock in the MSA) to the constructed predicted manufacturing shock measure. We present the estimated effects in standardized form, and show results with and without the X vector of controls. The point estimates imply that a one standard deviation change in the predicted manufacturing shock measure is associated with about a 1.4 percentage point decline in the share of the non-educated men employed in manufacturing. Notice that the R^2 for these regressions, including the one without controls, is quite high at around 0.5. In the third and fourth columns we conduct a similar exercise for the housing price proxy. Specifically, we relate the change in the share of non-college men employed in construction (a variable likely to be strongly affected by an unobserved housing shock) to the change in the local housing price. We estimate that a one standard deviation increase in the change in the housing price increases the share of non-college men employed in construction by about 1 percentage point, with R^2 in excess of 0.4.[17] On the whole, the results strongly support the use of the Bartik predicted manufacturing shock and change in housing prices as the two proxies.

In the description of the empirical framework above, we also argued that since the predicted manufacturing shock is based on the interaction of national manufacturing employment trends and pre-existing distribution of manufacturing employment in the MSA, this proxy is arguably exogenous to unobserved local shocks that might bias the estimated effect of manufacturing on labor market outcomes. For the housing price change proxy, by contrast, we deal with possible endogeneity concerns by instrumenting the change in the housing price using pre-existing measures of land availability from Saiz (2010) in some analyses. How well do these variables predict variation in housing prices changes within MSAs?

Figures 4 and 5 plot a summary measure of land availability (the percentage of land in the MSA that is undevelopable) against the change in local housing prices between 2000-2007 and from 2007-2011, respectively, and show that the land availability measure appears to predict changes in housing prices during both the

[17] Appendix Figures 3 and 4 graphically present the relationship between the two proxy measures and the two outcomes related to the unobserved demand shocks, showing the strong positive relationship captured in the regressions.

housing boom and bust. Table 3 tests this relationship more formally. The table reports OLS results of regressions that relate the change in housing prices at the MSA level to the land availability instruments over the housing boom from 2000-2007 (columns (1) and (2)), and over the housing bust from 2007-2010 (columns (4) and (5)). The results show that the exogenous land availability measures strongly predict housing price changes between 2000 and 2007, as well as housing price declines between 2007 and 2010, in regressions with and without our standard controls. In particular, we find that places with relatively less land available for development experienced the largest price increases during the house price boom, and the largest declines during the collapse in housing prices. Importantly, the F-statistic on these exogenous land availability measures are comfortably above 10, which suggests that there is no "weak-instrument" concern when they are used as instruments in our IV analysis.

We next show in Figure 6 that construction employment increased more in MSAs with less land availability. The fact that the land availability measure predicts changes in both housing prices and construction employment is consistent with the variable capturing housing demand shocks during this time period. While it may seem counterintuitive that construction employment increased the most in places where land was most constrained, there are several explanations for this relationship. First, as documented by Mian and Sufi (2011), the strong wealth effect associated with house price appreciation causes a subsequent increase in housing demand within an MSA. This puts further upward pressure on housing prices and quantities, which in turn raises construction employment. Second, construction activity is not only associated with the building of new houses but also the remodeling and renovation of existing houses. The incentives to remodel or renovate an existing property is likely higher in areas where housing prices are appreciating. Third, the land availability measure may be correlated with unobserved local housing demand shocks during time period we study, with metropolitan areas with less land availability experiencing larger housing demand shocks. Regardless of the relative importance of these explanations, however, what is critical for the identification of our empirical model is that the land availability measure is uncorrelated with unobserved labor supply shocks.

Finally, in the third column of Table 3, we include the predicted manufacturing shock variable alongside the local land availability measures. As expected, the results show that the predicted manufacturing shock also predicts changes in housing values, consistent with housing values (at least partially) capitalizing shifts in local labor demand. Strikingly, columns (6) and (7) show that the land availability measure does *not* predict changes in manufacturing employment. This strongly supports the assumption in our empirical model that 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.

5 Results

5.1 Graphical Evidence

We begin with a graphical presentation of our main results. We first divide the sample based on 2000-2007 house price growth.[18] Next, 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 7 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. 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. 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 red triangles (which represent the housing boom MSAs) and the regression line from the non-boom MSAs. In Figure 7, most of the red 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:[19]

$$\Delta L_k = \beta_0 + \beta_1 \widehat{\Delta D_k^M} + \beta_2' \mathbf{1}\{\text{Housing Boom}\}_i + \Delta D_k^O + \theta_k + \epsilon_k,$$

This is similar to (5) above except that there are no X controls in the above specification and ΔP_k^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_k across MSAs that did and did not experience a large housing boom. Figure 7 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 8 through 12 repeat the same exercise with alternative local area outcomes: changes in average wages for non-college men (Figure 8), changes in share of non-college male population employed in construction (Figure 9), and changes in share of non-college male population employed in manufacturing (Figure 10). 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 seen in Figure 8, areas with a housing boom experienced

[18] In grouping cities based on house price growth, we first residualize the manufacturing shock out of the house price growth variable.

[19] 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.

relative increases in average wages. Figure 9 shows the same pattern for construction employment share. Not surprising, 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 10 shows that the manufacturing instrument is strongly correlated with actual changes in manufacturing employment. However, consistent with the results in column (8) of Table 3, 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 11 and Figure 12), 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 11 we divide MSAs based on housing boom as in previous figures (top third of house price growth between 2000 and 2007), while in Figure 12 we divide MSAs based on severity of housing bust. In this figure, the "top 1/3" of MSAs are those which experienced the most substantial housing bust; 45 of the 62 "housing boom MSAs" are also "housing bust MSAs" according to these definitions, reflecting the fact that MSAs experiencing large housing booms were those most likely to experience substantial housing busts (see Appendix Figure A2 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. In contrast, the manufacturing shock strongly predicts longer run changes in non-employment. Therefore, while housing boom predicts non-employment changes during boom period and housing bust predicts non-employment changes during bust period, neither boom nor bust predicts non-employment changes over longer time period. These results are consistent with the housing boom masking local manufacturing busts, and 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 will allow us to explicitly addresses the concern that housing prices are endogenous to unobserved labor demand and labor supply shocks by through instrumental variable regressions.

5.2 Main OLS and IV Estimates

Table 4 presents the main results from jointly estimating equations (5) and (6) using the two-step IV estimator described earlier. 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 re-scale to a one standard deviation shock.[20] Below the standardized effects, we report the first stage F-statistic from the

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

second-step IV estimation of equation (6). As noted earlier in the discussion of the first-stage results in Table 3, there is no weak instrument concern 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 0.9 percentage points. The IV estimate in column (2) shows that a one standard deviation positive housing shock increase non-employment by 1.1 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 similarity between the OLS and IV specifications is a feature of most of our specifications.

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 Appendix Figure A1; median wages stopped declining during the period of the housing boom. 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. 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 3, the manufacturing instrument strongly predicts actual changes in manufacturing employment, and the housing boom has no affect on manufacturing employment.

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. We next explore the robustness of these results to alternate specifications. The first two columns of Table 5 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 for non-college men. Columns (3) and (4) report OLS and IV results which add census region fixed effects (covering the four census regions) as additional controls. The remaining columns report IV estimates using alternative instruments constructed using the data from Saiz (2010); column (5) uses each of the constituent land availability measures as separate instruments (rather than the convenient land availability summary measure) while column (6) uses housing supply elasticity estimates from Saiz (2010) which account for (endogenous) land-use regulations in addition to land availability. In both of these columns, the results are extremely similar to the preferred OLS and IV estimates. The point estimates in columns (3) through (6) are fairly similar to the base results. It is worth noting, however, that the first stage from the IV specification in column (5) is weakened with the inclusion of the region fixed effects (F-statistic = 5.85).[21]

The similarity of the base results to alternate specifications is also shown for the dependent variables of wage changes (Appendix Table A1), changes in the construction employment share (Appendix Table A2), and changes in the manufacturing employment share (Appendix Table A3). Overall, we conclude that our main results are robust to alternative specifications.

Appendix Table A4 reports results focusing specifically on migration which has been shown to respond strongly to shifts in local labor demand (Blanchard and Katz 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 fact that migration responds to the manufacturing shocks is something we will account for when extrapolating our local estimates to assess the effect of aggregate declines in manufacturing employment on current non-employment within the U.S. as whole. Therefore, we will return to these results in Section 8.[22]

6 Results for Alternative Demographic Groups: Skill×Gender and Age

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 6 reports analogous results for the change in the non-employment rate for each of these demographic groups.

Columns (1) and (2) of Table 6 reproduce the OLS and IV estimates from Table 3 for men without a

[21] In the final column, we identify the effect of housing booms by relying on variation in housing prices net of the housing supply elasticity and the interaction of the housing supply elasticity with the manufacturing instrument. By controlling for the supply elasticity (and its interaction with the manufacturing instrument), we attempt to isolate house price variation that is primarily driven by variation in housing demand, though at the risk of re-introducing confounding labor demand and labor supply variation into the estimates. The results presented in this column using this alternative source of variation are extremely similar to columns (1) and (2). We interpret the striking similarity across these alternative sources of housing price variation as consistent with cross-city house price changes during 2000-2007 as being predominantly due to idiosyncratic shocks to local housing demand that are uncorrelated with other unobserved labor demand and labor supply shocks.

[22] In Appendix Table A7, we show the response of social transfers to changes in local labor demand. Specifically, the results in Appendix Table A7 use 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.

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, while 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 ages 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 (since roughly two-thirds of this population does not have a college degree). In Table 7, we report analogous results for average wages, which are consistent with the results for non-employment; in particular, we find a negligible effect of housing booms on wages for college-educated workers, while we find stronger wage effects for non-college workers, with the largest effects for non-college men.

In Table 8, we report results which divide our main sample of non-college men into two age groups (ages 21-35 and ages 36-55). For each age group, we re-defined the manufacturing instrument for that group using the age-group-specific industry employment. The results in the left panel report results using the non-employment rate as the dependent variable; columns (1) and (2) report results for the full sample for reference. Columns (3) and (4) report OLS and IV results for the younger age group, while columns (5) and (6) report analogous results for older workers. The results show estimated house price effects that are similar across the two age groups, while the estimated manufacturing effects are nearly twice as large for older workers. This implies that older workers are significantly more likely than younger workers to end up in non-employment following manufacturing shocks. The remaining columns (in the right panel) replicate the same set of results using the change in share of population employed in construction as the dependent variable. These results show that construction employment in both age groups responds similarly to both housing and manufacturing shocks. This implies that the differential non-employment responses to manufacturing shocks is not primarily due to differential construction employment responses.

In Appendix Table A5, the same exercise is repeated for the other main outcomes of interest (Average Wages and Manufacturing Employment Share). The results for manufacturing employment share verify that manufacturing shocks affect manufacturing employment in both age groups similarly, which is a reassuring confirmation that the manufacturing shock is being measured similarly across age groups. In particular, these results confirm that the differential non-employment results by age group are not primarily due to differential severity of the estimated manufacturing shock. Rather, the differential responses are more plausibly due to differences in labor supply responses by age group (arising, perhaps, due to differences in skill substitutability or reservation wages).[23]

[23] We also investigated differences within the group of non-college men across native-born men and immigrants. In Appendix Table A6, we replicate the results of Table 3 using the subs-ample of native-born non-college men. The results are broadly similar across all outcomes; in particular, construction employment for this group also strongly responds to housing shocks, by roughly the same magnitude as in the overall sample. This suggests that the overall "masking" of non-employment growth during housing

7 Housing Booms, Housing Busts, and Longer Run Outcomes

We next report estimates of longer run changes in non-employment in Table 9, 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-college men. Columns (3) and (4) modify the OLS and IV models to instead use changes in non-employment from 2007 and 2010.[24] The results suggest that housing busts are associated with sharp increases in non-employment; however the magnitude is extremely similar to the magnitudes estimated during boom period. Therefore, when estimating models using longer run (2000-2010) changes in as the dependent variable as in columns (5) through (10), we find that longer run changes in non-employment are neither affected by the magnitude of housing boom nor the magnitude of housing bust, despite the fact that both the boom and bust themselves predict short-run changes in non-employment. By contrast, our manufacturing shock predicts lasting longer run changes in non-employment. In all of the different time periods we investigated, we find that the manufacturing shock has a lasting effect on local employment.

Thus far, we have exclusively focused on changes in non-employment rate. When interpreting our results during housing boom and housing bust time periods, it is useful to decompose our non-employment results into the two broad categories of non-employment: unemployment and non-participation (i.e., not in the labor force). Appendix Tables A8 and A9 report results analogous to Table 9 replacing the non-employment rate with the unemployment rate and the non-participation rate, defining all three measures relative to the same base population (so that we can use the estimates from these tables to compute the share of non-employment effect coming through changes in unemployment and changes in non-participation). Using the estimates from these tables, we find that during 2000-2007, roughly 55% of non-employment growth arising from manufacturing shocks came through changes in labor force participation, while for housing shocks, this number is roughly 65%. In other words, the housing boom primarily "masked" non-employment growth by keeping non-college men in the labor force. By contrast, during the housing bust period, we find that virtually all of the non-employment effects of the housing bust came from changes in unemployment (with very little changes in labor force participation). These results are consistent with much of the current unemployment growth occurring among individuals who would have otherwise dropped out of the labor force earlier in the absence of the housing boom.

In summary, we conclude that the oft-discussed relationship between the housing bust and non-employment growth likely represents an unmasking of non-employment growth that would have occurred earlier in the absence of the housing boom. In the next section, we try to quantify this unmasking at a national level using our local labor market estimates.

booms is not primarily being driven by immigrant employment in the construction sector.

[24] For each specification in this table, we always (re-)define the manufacturing shock across the time period being analyzed (as indicated in the column heading).

8 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 10 reports the exercise for non-college men and Panel B of Table 10 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 3.3 percentage points.[25] 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 -1.3 percentage points. Therefore, on net the change in aggregate non-employment is predicted to be 2.0 percentage points, which is very close to the actual increase of 2.0 percentage points observed during this time period.

Continuing with non-college men, during the housing bust (2007-2011), 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 1.6 percentage points. Applying the same coefficients, this corresponds to predicted increases in non-employment of 2.9 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 34% of total non-employment growth during 2007-2011 and 46% during 2000-2011. 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.

In Table 11, we repeat the same exercise for non-college men separately by age group, using the estimates from Table 7. While our estimates for non-college men overall suggested that 34% of non-employment growth during bust can be ultimate traced to earlier manufacturing shocks, we find a larger role of manufacturing shocks for older workers (47%), and a somewhat smaller role for younger workers (22%). In both cases,

[25] 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).

the housing shock estimates suggest significant "masking", but (as noted above) the manufacturing shocks themselves had larger non-employment effects for older workers, which is primarily what accounts for the differences in the share explained across the age groups. One striking fact to note in this table is that despite our estimates suggesting similar amount of "masking" across demographic groups, there was much larger non-employment growth among younger workers between 2000 and 2007. During this time period, non-employment surged by 2.9 percentage points. What factors drove such a large number of men out of the labor market – precisely during the years when the housing boom was "masking" non-employment growth across almost all demographic groups – is an important question for future research.

We conclude with several important caveats with these counterfactual exercises. It is always difficult to apply "local" 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 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.[26]

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

[26]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.

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 was one of the causes of the housing/construction boom. Our results suggest such a channel is implausible. We find across local labor markets that declines in manufacturing put downward pressure on house prices, so any nationwide effect linking manufacturing busts to housing booms would have to overwhelm these local effects.

Next, the fact that we are focusing on housing prices may be causing us to underestimate some of the effect of the national housing boom on employment. As alluded to above, changes in housing demand that do not show up in housing prices will be missed by our analysis. Put another way, even though places like Las Vegas (which had a large housing boom) had larger increases in construction activity than places like Charlotte (which had no housing boom), places like Charlotte still saw some increase in construction employment over this time period relative to their long run trend. If this increase would not have occured in the absence of the housing boom, then this likely causes us to understate the effect of the housing boom on the national labor market.

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 steady 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 that none of national decline in manufacturing employment between 2007-2011 is due to same economic forces behind the 2000-2007 decline (Appendix Table A10), we compute 15% of non-employment growth between 2007-2011 and 32% during 2000-2011 as ultimately traceable to longer run shifts in manufacturing industry (as compared to 35% and 48%).

With these various caveats in mind, our conclusion from these counterfactuals is that a significant share of non-employment growth during the 2007-2011 period represents "structural non-employment."

9 Housing Booms and College Enrollment

We conclude by investigating the extent to which individuals alter human capital investments in response to housing shocks. As discussed in the Introduction, this exercise is motivated by the time series evidence in Figure 2, which shows that the share of me and women age 18-29 having attended any college begins to lag trend precisely when housing prices start to increase nationally in 1997. Moreover, the lagging continually widens until the housing bust begins, when the series for each gender begins to quickly revert back to trend. In 2007, we compute that the share of men who have attended any college lags trend by 2.2 percentage points, and for women the share lags by 3.4 percentage points.

We investigate whether the same pattern in the time series holds within local labor markets; specifically, we ask whether local housing booms affect enrollment at local colleges and universities. To do this, we use data from the IPEDS survey between 2000 and 2007. These data contain information on enrollments for the vast majority of colleges and universities in the U.S., including many community colleges, junior colleges, and technical colleges. The enrollment data are broken down by age, gender, full-time/part-time, and "status" of student (e.g., undergraduate, graduate, etc.). We aggregate the data by state, and we construct as our primary outcome of interest the total *first-time*, full-year, undergraduate enrollment over the entire 2000-2007 period. We include both full-time and part-time enrollment together in all specifications.[27]

Using these local enrollment data, we estimate the same OLS and IV models as above using log total college enrollment as the dependent variable, and we report the results in Table 12. The left panel reports results for total enrollments across community colleges, junior colleges, and technical colleges. Columns (1) and (2) report OLS and IV results for total enrollment (men and women together), while columns (3) through (6) report results for men and women separately. Across columns (1) through (6), the results suggest that local housing booms cause sharp declines in undergraduate enrollment, with similar magnitudes across genders. Columns (7) through (12) report analogous results using total undergraduate enrollments across all colleges and universities; the estimates are somewhat smaller in magnitude, though still economically significant. In particular, the results in column (7) suggest that a one standard deviation housing shock reduces total undergraduate enrollment over the 2000-2007 period by 7.6%. In Appendix Table A11, we report estimates for total graduate student enrollment, and we find no economically or statistically significant estimates in any of the specifications. We interpret the lack of responsiveness for graduate student enrollment as evidence that our housing boom estimates for undergraduate students are not primarily driven by omitted variables or unobserved trends, but rather represent a genuine effect of the housing boom on individuals' decisions to enroll in any college at all.[28]

[27] We focus on first-time, full-year enrollment following recent work of Lovenheim (2011) and also because we expected this to be the most responsive margin. Though our unit of analysis continues to be the metropolitan area, we collapse the enrollment data to the state level in recognition of the fact that the relevant geographic market for college enrollment decisions may be broader than the local labor market. For example, when we look at all colleges and universities, we want to make sure to be able to capture changes in enrollment at flagship state colleges and universities that may not be located in the same metropolitan area.

[28] In recent work, Lovenheim (2011) uses micro-level data to estimate the effect of housing wealth on college enrollment. He

To summarize, we conclude that housing booms sharply reduced college enrollment, especially among students considering community colleges, junior colleges, and technical colleges. Moreover, when we apply our local estimates nationally as in the counterfactual analyses above, we can account for a fairly large fraction of the "trend breaks" highlighted in Figure 2. In particular, our estimates can account for about 64% of the "gap" in 2007 (relative to trend) for men and 37% for women.[29] However, we suggest caution in interpreting these results for two reasons: first, our statistical is somewhat more limited for the enrollment outcomes as compared to the labor market outcomes. Second, as with the non-employment counterfactuals discussed in Section 5, there are a variety of concerns about extrapolating our local estimates to the national setting that should be kept in mind. Nevertheless, we see these results as a first step and hope that they stimulate future work on estimating the effects of housing booms and housing busts on college enrollment.

10 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 35 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

finds that increases in housing wealth raise college enrollment, with the largest effects concentrated among poorer households. Our aggregate-level results are not necessarily inconsistent with these results. In particular, our results do not rule out that – at an individual level – increases in home equity raise college enrollment. However, our results suggest that the first-order aggregate effect of housing booms is that they reduce college enrollment due to the fact that housing demand shocks raise labor demand for individuals on the margin of college enrollment; our estimates suggest that (in the aggregate) this effect overwhelms the liquidity constraint channel that Loveneim (2011) emphasizes. In Lovenheim (2011), these aggregate effects are "differenced out" by design, since the micro-level estimates include MSA fixed effects in all specifications.

[29] The counterfactual analysis for this exercise is substantially more involved than for employment, since the college enrollment estimates are proportional effects relative to (initial) enrollment levels, while the projections are for the share of population that have attended any college. Additionally, the CPS time series focuses on ages 18-29, but the IPEDS data do not report separate first-time, first-year enrollment by age categories. We therefore take the following steps to convert our empirical estimates (which are percentage changes in total first-time enrollment across 2000-2007 relative to initial year 2000 enrollment levels) into a percentage point change in the share of population with any college (in 2007):

1. First, we assume that the proportional effects are the same across the age distribution, so that we can shrink our estimates by the age 18-29 share of total (nationwide) enrollment (across all ages). This share is 0.788 for men and 0.722 for women.
2. Next, we multiply this result by the share of age 18-29 population currently enrollment as undergrads (0.171 for men and 0.198 for women).
3. Finally, we multiply this result by total first-time enrollment across 2000-2007 as a share of total (initial) enrollment in 2000 (1.27 for both men and women).

These steps convert our preferred total college enrollment estimates for men and women (columns (9) and (11) of Table 12, respectively) into predicted changes of 1.43 percentage points for men and 1.30 percentage points for women. Dividing these by the "gaps" computed from Figure 2 gives the percentages reported in the main text.

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 non-college men, but we find nontrivial effects of the manufacturing decline and the extent to which the housing boom masked those effects for both non-college 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 many of 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.[30] 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 non-college workers was to induce a higher level of skill acquisition. As we have shown, the housing boom actually interrupted that process. Places that saw a large housing boom saw a larger decline in college enrollments, particularly for community colleges, junior colleges, and technical colleges. As housing prices fell between 2007 and 2011, the propensity to accumulate at least one year of college education reversed course again and started increasing. A natural next question is to see whether the housing boom permanently lowered human capital levels of the cohort of young individuals who would have accumulated human capital absent the boom. If so, part of the natural response to persistent declines in demand for low skilled workers may be delayed.

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 non-college individuals. As those hiring subsidies and infrastructure investments expire, the labor demand for non-college 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 non-employed 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 leave the labor force as a result of the ongoing decline in the manufacturing sector.

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

References

Autor, David, David Dorn, and Gordon Hanson (2012). "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *MIT Working Paper.*

Autor, David, Frank Levy, and Richard Murnane (2003). "The Skill Content Of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118(4): 1279-1333.

Bartik, Timothy (1991). "Who Benefits From State and Local Economic Development Policies", W.E. Upjohn Institute for Employment Research: Kalamazoo, Mich.

Blanchard, Olivier and Lawrence F. Katz (1992). "Regional Evolutions," *Brookings Papers on Economic Activity*, 23(1): 1-76

Borjas, George (2003). "The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market," *Quarterly Journal of Economics.*

Bound, John and Harry J. Holzer (1993). "Industrial Shifts, Skills Levels, and the Labor Market for White and Black Males," *The Review of Economics and Statistics*, 75(3): 387-96.

Clark, Sandra Luckett, John Iceland, Thomas Palumbo, Kirby Posey, and Mai Weismantle (2003). "Comparing Employment, Income, and Poverty: Census 2000 and the Current Population Survey." Report for the Housing and Household Economic Statistics Division of the U.S. Census.

Chinco, Alex and Chris Mayer (2012). "Distant Speculators and Asset Bubbles in Housing Markets", Columbia University Working Paper.

Davidoff, Tom (2012). "Supply Elasticity and the Housing Cycle of the 2000s", *Real Estate Economics*, forthcoming.

Guerrieri, Veronica, Daniel Hartley, and Erik Hurst (2012). "Endogenous Gentrification and Housing Price Dynamics", University of Chicago Working Paper.

Leamer, Ed (2007). "Housing and the Business Cycle", Housing, Housing Finance, and Monetary Policy Symposium Sponsored by the Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming.

Luttmer, Erzo (2005). "Neighbors as Negatives: Relative Earnings and Well-Being", *Quarterly Journal of Economics*, 120(3), 963-1002.

Mian, Atif and Amir Sufi (2012). "What Explains High Unemployment? The Aggregate Demand Channel", University of Chicago Working Paper.

Mian, Atif and Amir Sufi (2011). "House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crises", *American Economic Review*, 101, 2132-56.

Notowidigdo, Matthew J. (2011). "The Incidence of Local Labor Demand Shocks", University of Chicago Working Paper.

Ruggles, Steven, Matthew Sobek, Trent Alexander, Catherine Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander (2004). *Integrated Public Use Microdata Series.* Minneapolis, MN: Minnesota Population Center.

Sahin, Aysegul, Joseph Song, Giorgio Topa, and Giovanni Violante (2012). "Mismatch Unemployment", New York University Working Paper.

Saiz, Albert (2010). "The Geographic Determinants of Housing Supply", *Quarterly Journal of Economics*, 125(3), 1253-96.

Appendix A: Data Appendix

This section gives more detail on the data sources used in this paper.

Constructing Manufacturing Instrument in Census and ACS

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:

$$\Delta D_k^M = \sum_{g=1}^{G} \varphi_{k,g,2000} \left(\upsilon_{-k,g,2007} - \upsilon_{-k,g,2000} \right)$$

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

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.).[31] 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.

IPEDS Data

We use IPEDS data between 2000 and 2007. Our primary enrollment measure is the total statewide first-time, first-year enrollment (full-time + part-time) at all colleges and universities in the sample over the years 2000 through 2007.

[31] 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.

Table 1
Summary Statistics

	N	Mean	Standard Dev.	Min	Percentiles 25th	50th	75th	Max
Housing market variables (% change over indicated time period)								
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 Non-employment 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 Workers 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
Land Availability (% Land Area Unavailable for Development) [Housing Boom Instrument]	235	0.298	0.213	0.005	0.104	0.258	0.405	0.860

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

Quality of Manufacturing Shock and Housing Shock Proxies

Dependent variable:	Change in Share of Non-College Men Employed in Manufacturing, 2000-2007		Change in Share of Non-College Men Employed in Construction, 2000-2007	
Specification:	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Predicted Change in Share of Non-College Men Employed in Manufacturing [Manufacturing Bust Proxy]	1.125	1.025		
	(0.072)	(0.071)		
	[0.000]	[0.000]		
Change in Housing Prices [Housing Boom Proxy]			0.033	0.026
			(0.005)	(0.007)
			[0.000]	[0.000]
Housing price effect (1σ)			**0.010**	**0.008**
Manufacturing effect (1σ)	**0.015**	**0.014**		
N	235	235	235	235
R^2	0.481	0.532	0.432	0.481
Include baseline controls		y		y

Notes: This table reports OLS regression results. The control variables in columns (2) and (4) are 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 3
First Stage for Changes in Housing Prices Using Land Availability Instrument

Dependent variable:	Change in House Prices, 2000-2007			Change in House Prices, 2007-2010		Change in Share of Non-College Men Employed in Manufacturing,	
Specification:	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Land Availability (% Land Area Unavailable for Development) [Housing Boom Instrument]	1.000	0.768	0.739	-0.664	-0.551	0.009	0.004
	(0.132)	(0.224)	(0.195)	(0.146)	(0.228)	(0.005)	(0.005)
	[0.000]	[0.001]	[0.000]	[0.000]	[0.020]	[0.101]	[0.371]
Predicted Change in Share of Non-College Men Employed in Manufacturing [Manufacturing Bust]			9.679			1.090	1.020
			(2.587)			(0.082)	(0.075)
			[0.001]			[0.000]	[0.000]
Housing instrument effect (1σ)	**0.213**	**0.163**	**0.157**	**-0.141**	**-0.117**	**0.002**	**0.001**
Manufacturing effect (1σ)			**0.131**			**0.015**	**0.014**
First-stage F-statistic	57.345	11.793	14.290	20.689	5.818		
N	235	235	235	235	235	235	235
R^2	0.346	0.484	0.556	0.239	0.358	0.492	0.534
Include baseline controls		y	y		y		y

Notes: This table reports OLS results of equation (6). The control variables in columns (2), (3), (5), and (7) 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 4

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	-0.035	0.059	0.048	0.024	0.027	0.001	0.006
[Housing Boom]	(0.011)	(0.015)	(0.010)	(0.013)	(0.006)	(0.011)	(0.004)	(0.007)
	[0.002]	[0.016]	[0.000]	[0.000]	[0.000]	[0.010]	[0.889]	[0.438]
Predicted Change in Share of	-0.724	-0.694	1.545	1.504	0.450	0.427	1.025	1.020
Non-College Men Empl. in Manuf.	(0.245)	(0.220)	(0.369)	(0.304)	(0.178)	(0.157)	(0.074)	(0.080)
[Manufacturing Bust]	[0.005]	[0.003]	[0.000]	[0.000]	[0.016]	[0.010]	[0.000]	[0.000]
Housing price effect (1σ)	**-0.011**	**-0.011**	**0.018**	**0.015**	**0.007**	**0.008**	**0.000**	**0.002**
Manufacturing effect (1σ)	**-0.010**	**-0.009**	**0.021**	**0.020**	**0.006**	**0.006**	**0.014**	**0.014**
First stage F-statistic		14.290		14.290		14.290		14.290
N	235	235	235	235	235	235	235	235
R^2	0.741	0.740	0.444	0.439	0.492	0.489	0.532	0.526
Include baseline controls	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y

Notes: This table reports results of estimating equations (5) and (6) 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 5
Robustness to Alternative Specifications

Dependent variable:	Change in Nonemployment Rate of Non-College Men, 2000-2007						
Specification:	OLS	IV	OLS	IV	IV	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Housing Prices	-0.034	-0.035	-0.034	-0.036	-0.033	-0.039	-0.031
[Housing Boom]	(0.011)	(0.015)	(0.009)	(0.014)	(0.011)	(0.018)	(0.011)
	[0.002]	[0.016]	[0.000]	[0.009]	[0.004]	[0.028]	[0.006]
Predicted Change in Share of	-0.724	-0.694	-0.608	-0.581	-0.694	-0.726	-0.809
Non-College Men Employed in Manuf.	(0.245)	(0.220)	(0.207)	(0.186)	(0.211)	(0.222)	(0.253)
[Manufacturing Bust]	[0.005]	[0.003]	[0.005]	[0.003]	[0.002]	[0.002]	[0.003]
Housing price effect (1σ)	**-0.011**	**-0.011**	**-0.011**	**-0.011**	**-0.010**	**-0.012**	**-0.010**
Manufacturing effect (1σ)	**-0.010**	**-0.009**	**-0.008**	**-0.008**	**-0.009**	**-0.010**	**-0.011**
First stage F-statistic		14.290		5.848	18.076	24.289	
Overidentification test statistic, $\chi^2(1)$					3.157		
[p-value]					[0.532]		
N	235	235	235	235	235	235	235
R^2	0.741	0.740	0.750	0.750	0.741	0.739	0.745
Include baseline controls	y	y	y	y	y	y	y
Instrument with land availability		y		y			
Census region FEs (4 regions)			y	y			
Instrument with constitutent land availability measures (K = 5)					y		
Instrument with (housing supply elasticity)$^{-1}$						y	
Control for (housing supply elast.)$^{-1}$ and (housing supply elast.)$^{-1}$×Manufacturing Bust							y

Notes: This table reports results of estimating equations (5) and (6) 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 6
Nonemployment Effects for Other Gender×Skill Groups

Dependent variable:	Change in Nonemployment Rate, 2000-2007									
Sample:	Non-College Men		College Men		Non-College Women		College Women		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	-0.035	-0.010	-0.020	-0.022	-0.025	-0.007	-0.001	-0.027	-0.027
[Housing Boom]	(0.011)	(0.015)	(0.005)	(0.009)	(0.005)	(0.006)	(0.005)	(0.012)	(0.005)	(0.007)
	[0.002]	[0.016]	[0.055]	[0.029]	[0.000]	[0.000]	[0.135]	[0.917]	[0.000]	[0.000]
Predicted Change in Share of	-0.724	-0.694	-0.330	-0.313	-0.515	-0.494	-0.196	-0.195		
Non-College Men Empl. in Manuf.	(0.245)	(0.220)	(0.104)	(0.091)	(0.157)	(0.147)	(0.124)	(0.123)		
[Manufacturing Bust]	[0.005]	[0.003]	[0.003]	[0.001]	[0.002]	[0.002]	[0.121]	[0.122]		
Predicted Change in Share of									-0.687	-0.697
Population Employed in Manuf.									(0.165)	(0.140)
[Manufacturing Bust]									[0.000]	[0.000]
Housing price effect (1σ)	**-0.011**	**-0.011**	**-0.003**	**-0.006**	**-0.007**	**-0.008**	**-0.002**	**0.000**	**-0.008**	**-0.009**
Manufacturing effect (1σ)	**-0.010**	**-0.009**	**-0.004**	**-0.004**	**-0.007**	**-0.007**	**-0.003**	**-0.003**	**-0.007**	**-0.007**
First stage F-statistic		14.290		14.290		14.290		14.290		14.446
N	235	235	235	235	235	235	235	235	235	235
R^2	0.741	0.740	0.207	0.175	0.686	0.685	0.114	0.104	0.796	0.796
Include baseline controls	y	y	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y		y

Notes: This table reports results analogous to columns (1) and (2) in Table 4 for alternative demographic groups. See 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.

Table 7
Wages Effects for Other Gender×Skill Groups

Dependent variable:	Change in Average Wages, 2000-2007									
Sample:	Non-College Men		College Men		Non-College Women		College Women		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	0.014	0.037	0.032	0.024	-0.001	0.045	0.047
[Housing Boom]	(0.010)	(0.013)	(0.015)	(0.031)	(0.008)	(0.015)	(0.013)	(0.024)	(0.010)	(0.017)
	[0.000]	[0.000]	[0.110]	[0.636]	[0.000]	[0.028]	[0.061]	[0.974]	[0.000]	[0.004]
Predicted Change in Share of	1.545	1.504	0.303	0.291	0.860	0.833	0.503	0.503		
Non-College Men Empl. in Manuf.	(0.369)	(0.304)	(0.450)	(0.393)	(0.251)	(0.211)	(0.279)	(0.254)		
[Manufacturing Bust]	[0.000]	[0.000]	[0.504]	[0.463]	[0.001]	[0.000]	[0.078]	[0.054]		
Predicted Change in Share of									1.051	1.068
Population Employed in Manuf.									(0.335)	(0.303)
[Manufacturing Bust]									[0.003]	[0.001]
Housing price effect (1σ)	**0.018**	**0.015**	**0.008**	**0.005**	**0.012**	**0.010**	**0.008**	**0.000**	**0.014**	**0.015**
Manufacturing effect (1σ)	**0.021**	**0.020**	**0.004**	**0.004**	**0.012**	**0.011**	**0.007**	**0.007**	**0.011**	**0.011**
First stage F-statistic		14.290		14.290		14.290		14.290		14.446
N	235	235	235	235	235	235	235	235	235	235
R^2	0.444	0.439	0.088	0.082	0.486	0.485	0.153	0.120	0.455	0.455
Include baseline controls	y	y	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y		y

Notes: This table reports results analogous to columns (1) and (2) in Table 4 for alternative demographic groups. See 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.

Table 8
Differences by Age Group for Non-College Men

Dependent variable:	Change in Nonemployment Rate, 2000-2007						Change in Construction Employment Share, 2000-2007					
Sample:	[Baseline sample] Age 21-55		Age 21-35		Age 36-55		[Baseline sample] Age 21-55		Age 21-35		Age 36-55	
Specification:	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Change in Housing Prices	-0.034	-0.035	-0.034	-0.033	-0.034	-0.036	0.024	0.027	0.033	0.033	0.017	0.023
[Housing Boom]	(0.011)	(0.015)	(0.014)	(0.020)	(0.009)	(0.012)	(0.006)	(0.011)	(0.009)	(0.016)	(0.004)	(0.008)
	[0.002]	[0.016]	[0.020]	[0.098]	[0.000]	[0.003]	[0.000]	[0.010]	[0.001]	[0.046]	[0.000]	[0.002]
Predicted Change in Share of	-0.724	-0.694	-0.476	-0.457	-0.909	-0.868	0.450	0.427	0.424	0.406	0.360	0.333
Non-College Men Empl. in Manuf.	(0.245)	(0.220)	(0.213)	(0.190)	(0.266)	(0.246)	(0.178)	(0.157)	(0.188)	(0.165)	(0.154)	(0.139)
[Manufacturing Bust]	[0.005]	[0.003]	[0.031]	[0.020]	[0.001]	[0.001]	[0.016]	[0.010]	[0.030]	[0.018]	[0.024]	[0.021]
Housing price effect (1σ)	**-0.011**	**-0.011**	**-0.011**	**-0.010**	**-0.011**	**-0.011**	**0.007**	**0.008**	**0.010**	**0.010**	**0.005**	**0.007**
Manufacturing effect (1σ)	**-0.010**	**-0.009**	**-0.009**	**-0.008**	**-0.010**	**-0.010**	**0.006**	**0.006**	**0.008**	**0.007**	**0.004**	**0.004**
First stage F-statistic		14.290		14.239		14.353		14.290		14.239		14.353
N	235	235	235	235	235	235	235	235	235	235	235	235
R^2	0.741	0.740	0.623	0.623	0.731	0.731	0.492	0.489	0.358	0.358	0.408	0.396
Include baseline controls	y	y	y	y	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y		y		y

Notes: This table reports results analogous to columns (1) and (2) in Table 4 for alternative demographic groups. See 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.

Table 9

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

	Dependent Variable: Change in Non-employment Rate for Non-College Men for…									
	2000-2007		2007-2010		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	-0.035			-0.001	0.009				
[Housing Boom]	(0.011)	(0.015)			(0.019)	(0.024)				
	[0.002]	[0.016]			[0.965]	[0.702]				
Change in Housing Prices, 2007-2010			-0.056	-0.057			-0.036	-0.013		
[Housing Bust]			(0.008)	(0.013)			(0.011)	(0.032)		
			[0.000]	[0.000]			[0.002]	[0.690]		
Change in Housing Prices, 2000-2010									-0.091	0.034
[Housing Boom-Bust Cycle]									(0.025)	(0.100)
									[0.001]	[0.733]
<u>Predicted</u> Change in Share of Non-College Men	-0.724	-0.694	-0.406	-0.455	-0.653	-0.659	-0.653	-0.659	-0.653	-0.659
Employed in Manufacturing	(0.245)	(0.220)	(0.297)	(0.265)	(0.299)	(0.292)	(0.270)	(0.282)	(0.248)	(0.362)
[Manufacturing Bust]	[0.005]	[0.003]	[0.178]	[0.093]	[0.034]	[0.029]	[0.020]	[0.024]	[0.012]	[0.076]
Housing price effect (1σ)	**-0.011**	**-0.011**	**-0.016**	**-0.017**	**0.000**	**0.003**	**-0.010**	**-0.004**	**-0.013**	**0.005**
Manufacturing effect (1σ)	**-0.010**	**-0.009**	**-0.006**	**-0.007**	**-0.018**	**-0.018**	**-0.018**	**-0.018**	**-0.018**	**-0.018**
First stage F-statistic		14.290		6.175		12.598		6.221		8.018
R^2	0.741	0.740	0.425	0.425	0.595	0.591	0.628	0.614	0.680	0.519
Include baseline controls	y	y	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y		y

<u>Notes:</u> N=235 in all columns. This table reports results analogous to columns (1) and (2) in Table 4 for alternative demographic groups. See Table 4 for more details. In all columns, the manufacturing bust instrument is measured across the years in the columns (i.e., in columns (3) and (4) the predicted change is formed for the 2007-2010 time period). Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Table 10

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	0.033	-0.013	0.002	92.6%
2007-2011	0.086	0.016	0.013	0.057	33.6%
2000-2011	0.108	0.049	0.000	0.059	45.6%

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	0.027	-0.010	0.002	90.5%
2007-2011	0.066	0.013	0.010	0.043	35.2%
2000-2011	0.085	0.040	0.000	0.045	47.6%

Notes: This table reports counterfactual estimates of predicted changes in aggregate non-employment. In Panel A, the coefficient estimates from column (2) in Table 4 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.

Table 11

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

[Separate Counterfactuals for Non-College Men by Age Group]

Panel A: Accounting for National Trends of Non-College Men **[Age 21-35]**

	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	0.029	0.025	-0.012	0.017	43.0%
2007-2011	0.105	0.011	0.012	0.082	**22.1%**
2000-2011	0.134	0.036	0.000	0.098	26.6%

Panel B: Accounting for National Trends of Non-College Men **[Age 36-55]**

	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	0.017	0.037	-0.013	-0.007	141.2%
2007-2011	0.071	0.020	0.013	0.038	**46.9%**
2000-2011	0.088	0.057	0.000	0.031	65.1%

Notes: This table reports counterfactual estimates of predicted changes in aggregate non-employment. In Panel A, the coefficient estimates from column (4) in Table 8 are used in calibration; in Panel B, the estimates from column (6) in Table 8 are used. Actual changes in non-employment, housing prices, and manufacturing employment are taken from the CPS.

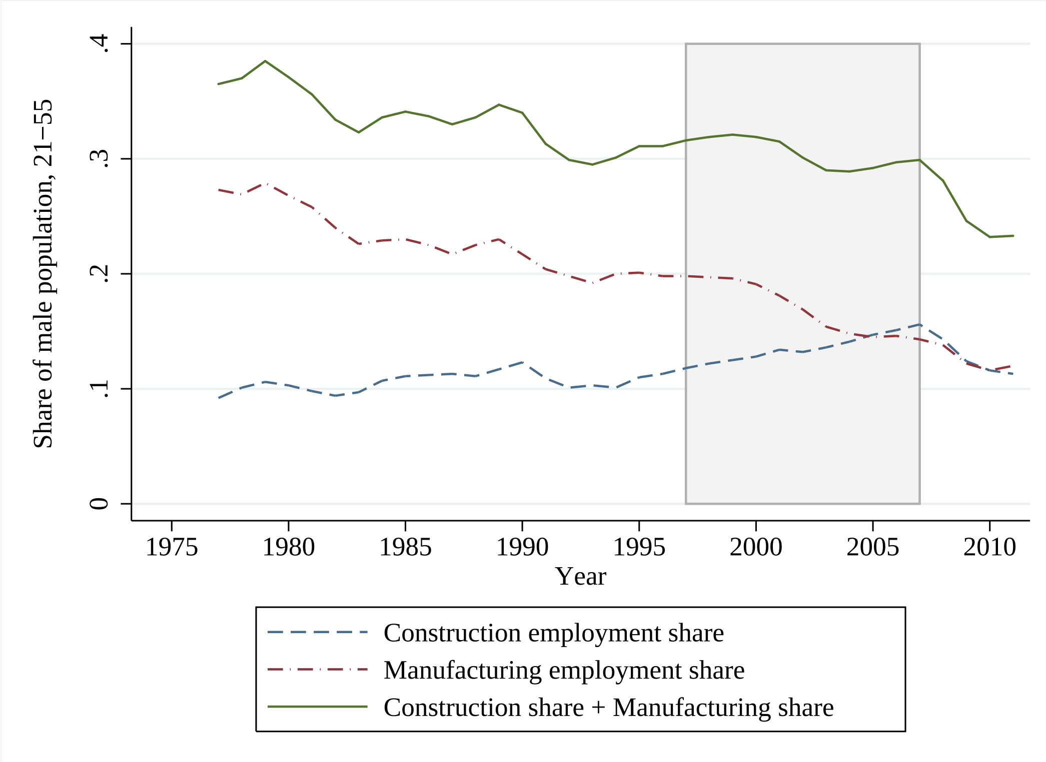
Table 12

Manufacturing Busts, Housing Booms, and College Enrollment

Dependent variable:	Log of Total First-Time Undergraduate Student Enrollment in State, 2000-2007											
Sample of Colleges and Universities:	Community Colleges, Junior Colleges, and Technical Colleges Only						All Colleges and Universities					
Gender Restrictions:	Men and Women		Men Only		Women Only		Men and Women		Men Only		Women Only	
Specification:	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Change in Housing Prices	-0.537	-0.545	-0.518	-0.559	-0.559	-0.541	-0.209	-0.280	-0.226	-0.304	-0.194	-0.261
[Housing Boom]	(0.161)	(0.313)	(0.169)	(0.325)	(0.158)	(0.310)	(0.088)	(0.187)	(0.090)	(0.192)	(0.088)	(0.185)
	[0.002]	[0.082]	[0.004]	[0.086]	[0.001]	[0.082]	[0.022]	[0.133]	[0.016]	[0.113]	[0.033]	[0.158]
<u>Predicted</u> Change in Share of	1.344	1.806	1.889	2.362	0.778	1.236	0.893	1.216	0.523	0.873	1.173	1.474
Non-College Men Empl. in Manuf.	(3.755)	(3.361)	(3.936)	(3.613)	(3.716)	(3.264)	(2.111)	(2.083)	(2.217)	(2.185)	(2.072)	(2.044)
[Manufacturing Bust]	[0.722]	[0.594]	[0.634]	[0.517]	[0.835]	[0.707]	[0.674]	[0.562]	[0.815]	[0.692]	[0.574]	[0.475]
Housing price effect (1σ)	**-0.168**	**-0.170**	**-0.162**	**-0.175**	**-0.175**	**-0.169**	**-0.065**	**-0.088**	**-0.071**	**-0.095**	**-0.061**	**-0.082**
Manufacturing effect (1σ)	**0.018**	**0.024**	**0.026**	**0.032**	**0.011**	**0.017**	**0.012**	**0.016**	**0.007**	**0.012**	**0.016**	**0.020**
First stage F-statistic		14.290		14.290		14.290		14.290		14.290		14.290
N	235	235	235	235	235	235	235	235	235	235	235	235
R^2	0.348	0.348	0.329	0.328	0.353	0.352	0.968	0.967	0.966	0.966	0.966	0.966
Include controls	y	y	y	y	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y		y		y

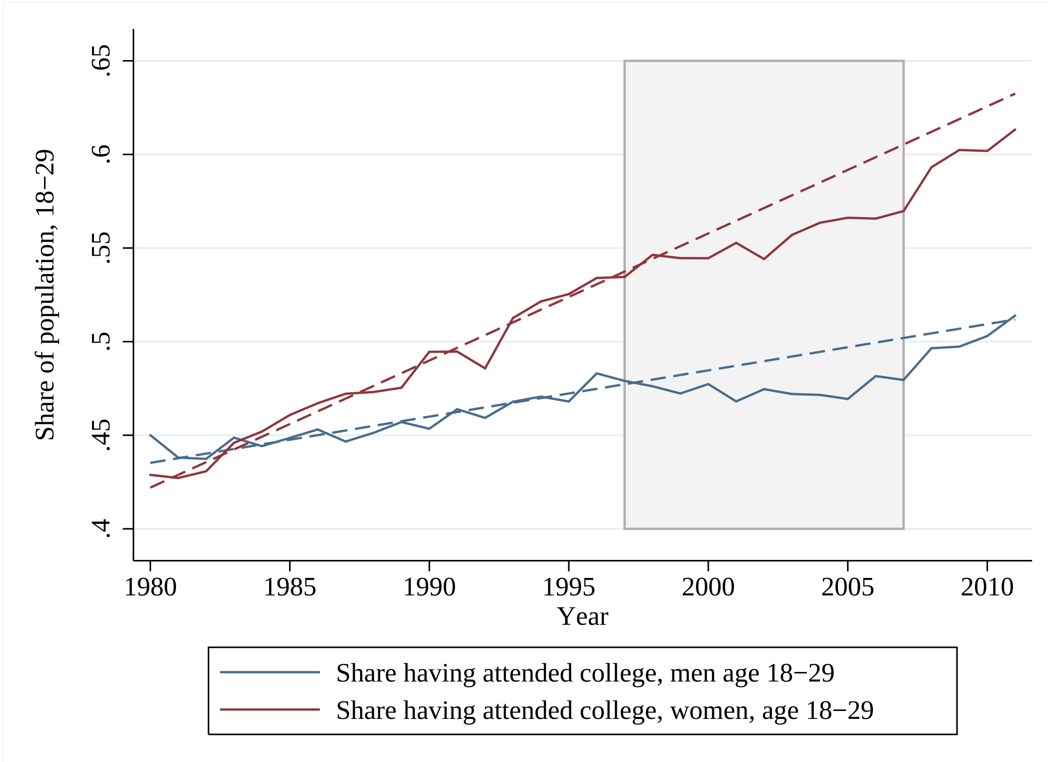
<u>Notes:</u> This table reports results analogous to columns (1) and (2) in Table 3 for alternative demographic groups. See Table 4 for more details. The dependent variable is the log of the total first-time, full-year, undergraduate student enrollment in the states across the years 2000-2007. The data come from the IPEDS survey of colleges and universities. In addition to the baseline controls, all columns include control for log of initial (year 2000) total undergraduate enrollment. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

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 non-institutionalized and age 21-55.

Figure 2: Housing Booms and College Enrollment, 1980-2011



Notes: This figure reports the share of men and women (age 18-29) who have attended any college, computed using the March CPS. The dashed lines report linear predictions from Weighted Least Squares (WLS) regressions using data from 1980-1996. The WLS regressions use exponential weights.

Figure 3: Graphical Solutions of Sectoral Choice Model

Figure 3a: Initial Equilibrium

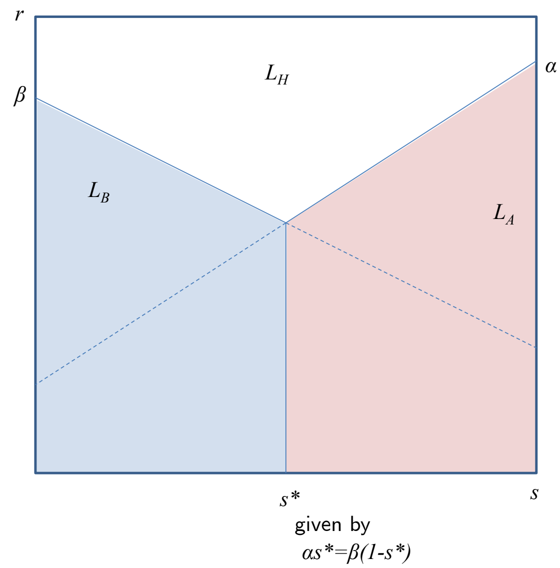


Figure 3b: Negative Shock to Sector A

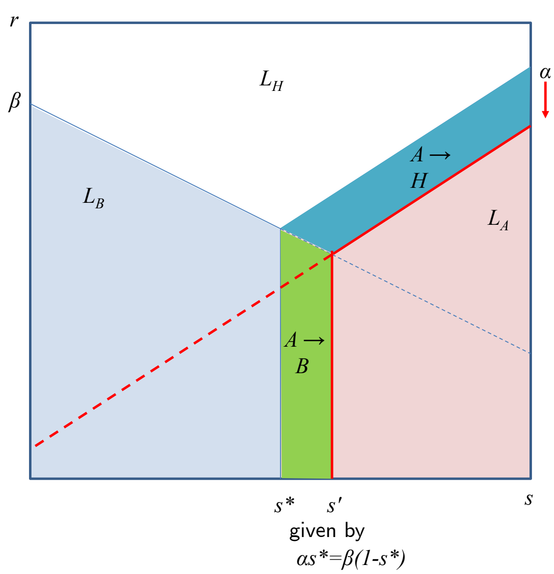
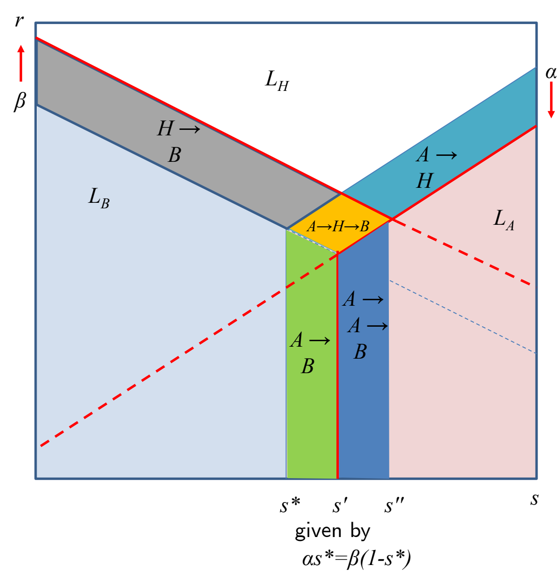
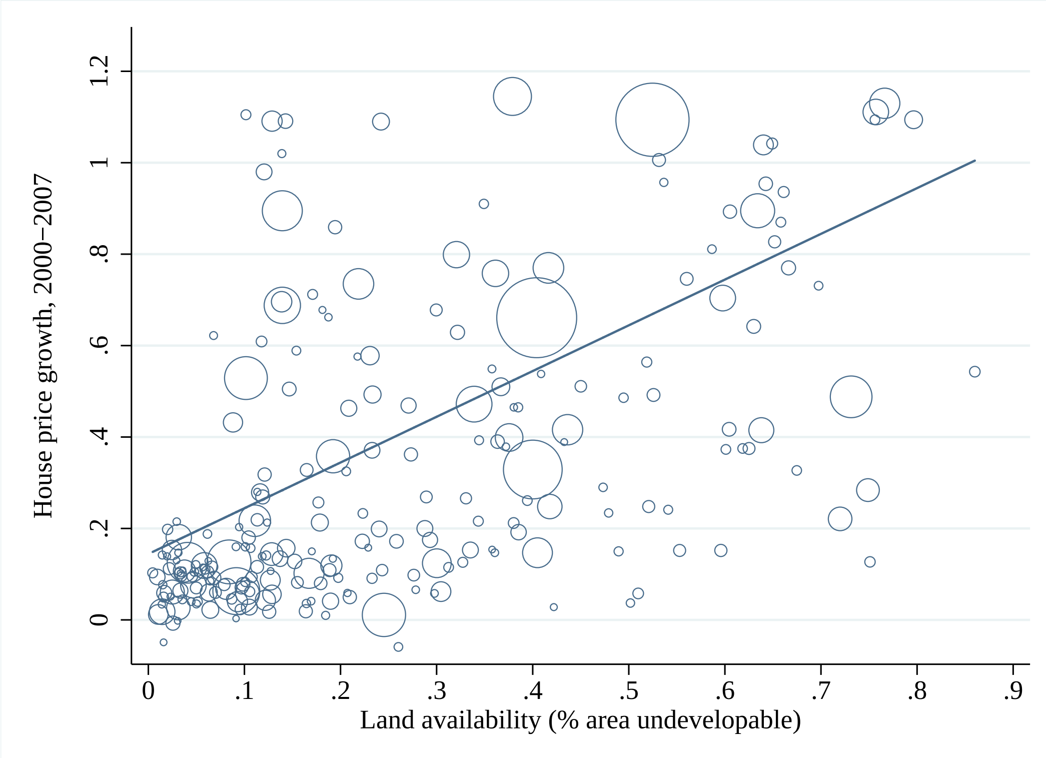


Figure 3c: Negative Shock to Sector A and "Offsetting" Positive Shock to Sector B



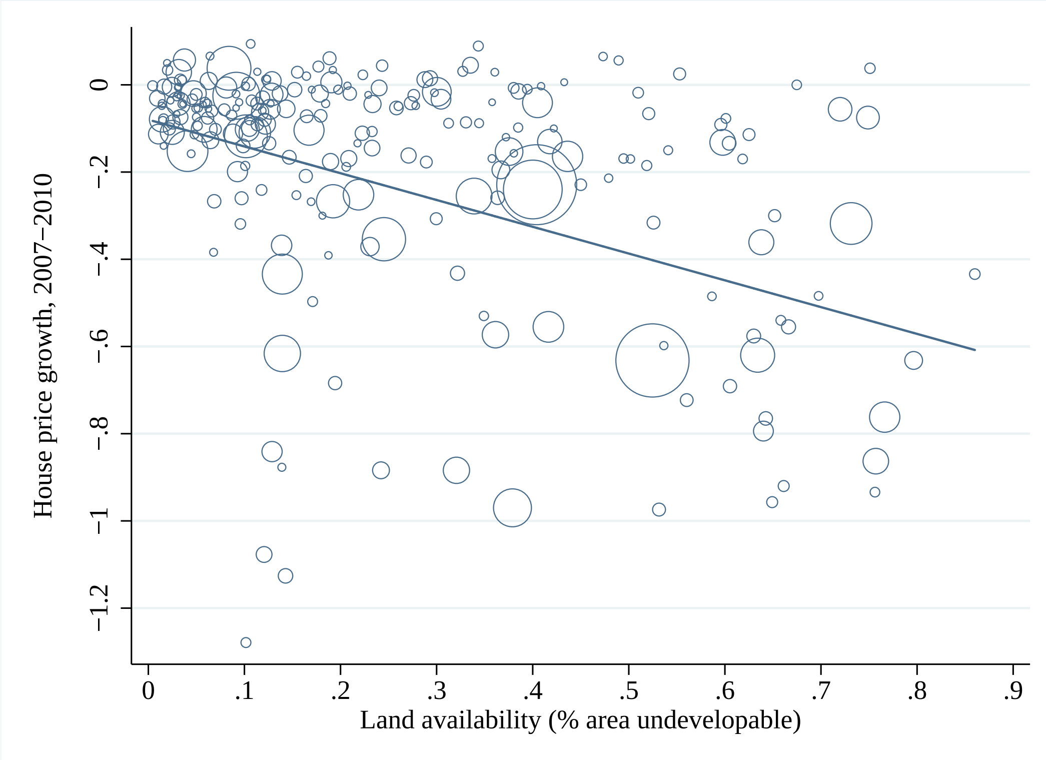
Notes: These figures show the graphic solutions of the model. In Figure 3a, we show the initial equilibrium, which shows the combination of s and r) parameters determine how workers self-select into sectors (or into non-employment, H). Figure 3b shows how the equilibrium responds to a negative shock to sector A; workers leave sector A for either sector B or enter non-employment (sector H), with the relative importance of these two channels depending on the mass of workers along each margin. Lastly, Figure 3c shows how the equilibrium responds an "offsetting" positive shock to sector B. In this case, some workers who would have entered non-employment in Figure 3b instead remain employed and enter sector B.

Figure 4: Land Availability and House Price Growth, 2000-2007



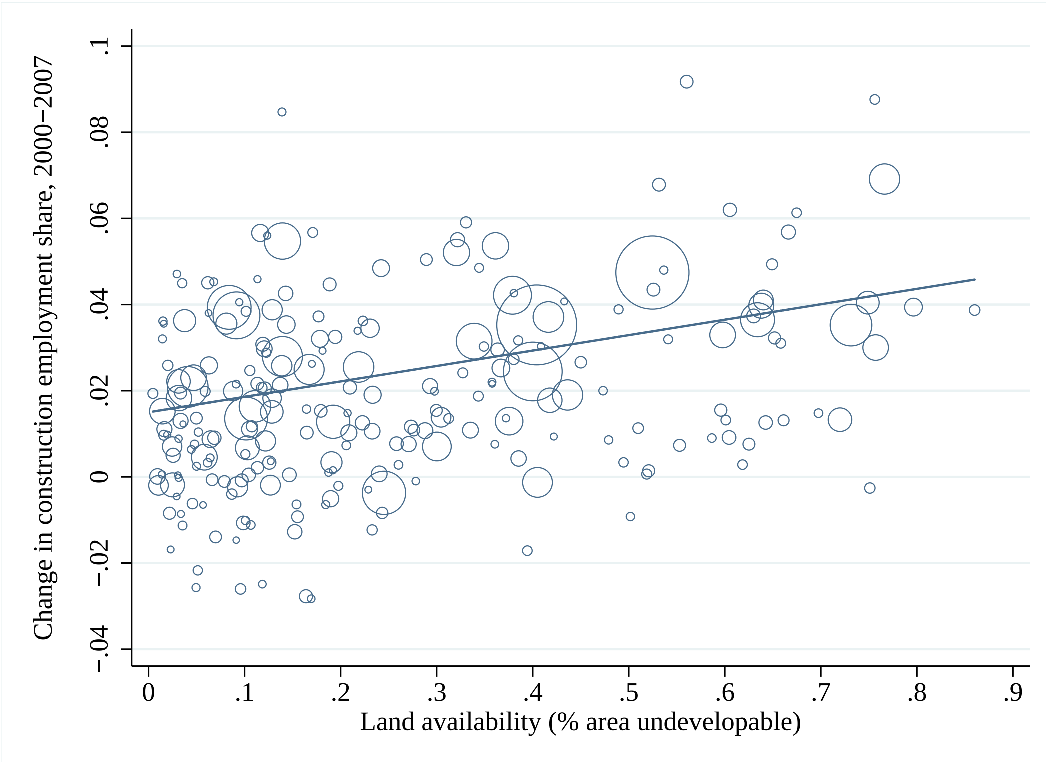
Notes: This figure reports the correlation across cities between 2000-2007 house price growth and the measure of land availability from Saiz (2010). Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 21-55 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Figure 5: Land Availability and House Price Growth, 2007-2011



Notes: This figure reports the correlation across cities between 2007-2011 house price growth and the measure of land availability 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 21-55 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Figure 6: Land Availability and Construction Employment, 2000-20007

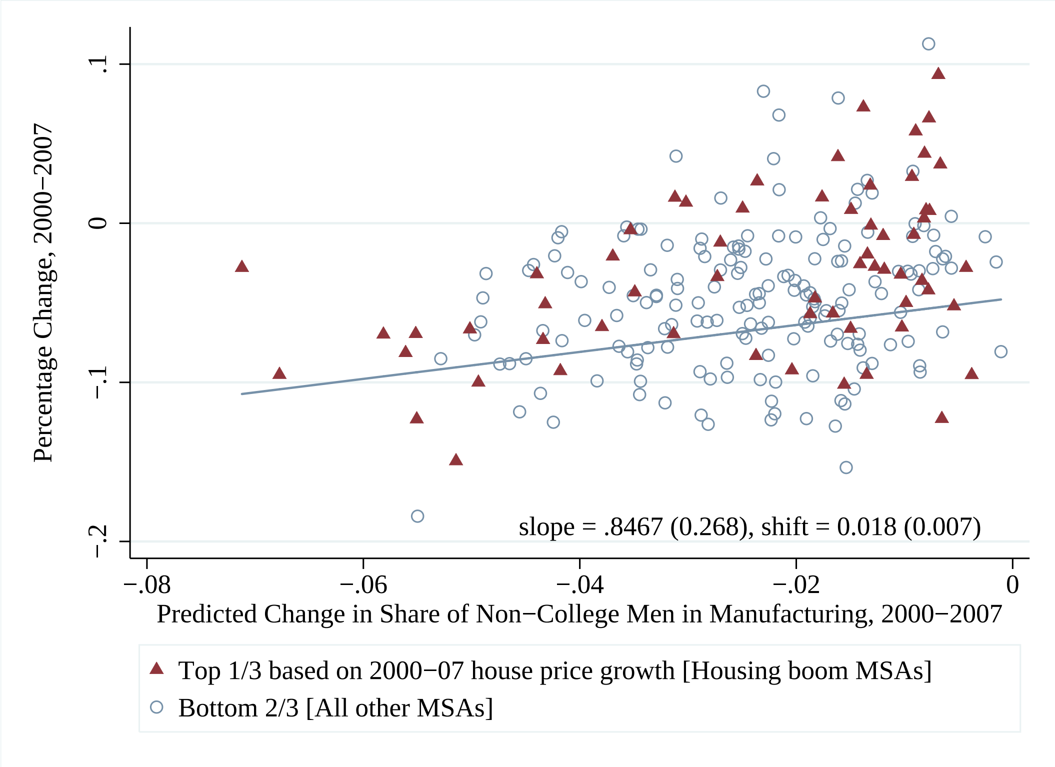


Notes: This figure reports correlation across cities between the 2000-2007 change in share of population of non-college men employed in construction and the measure of land availability from Saiz (2010). Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 21-55 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Figure 7: Change in Non-Employment Rate of Non-College Men, 2000-2007

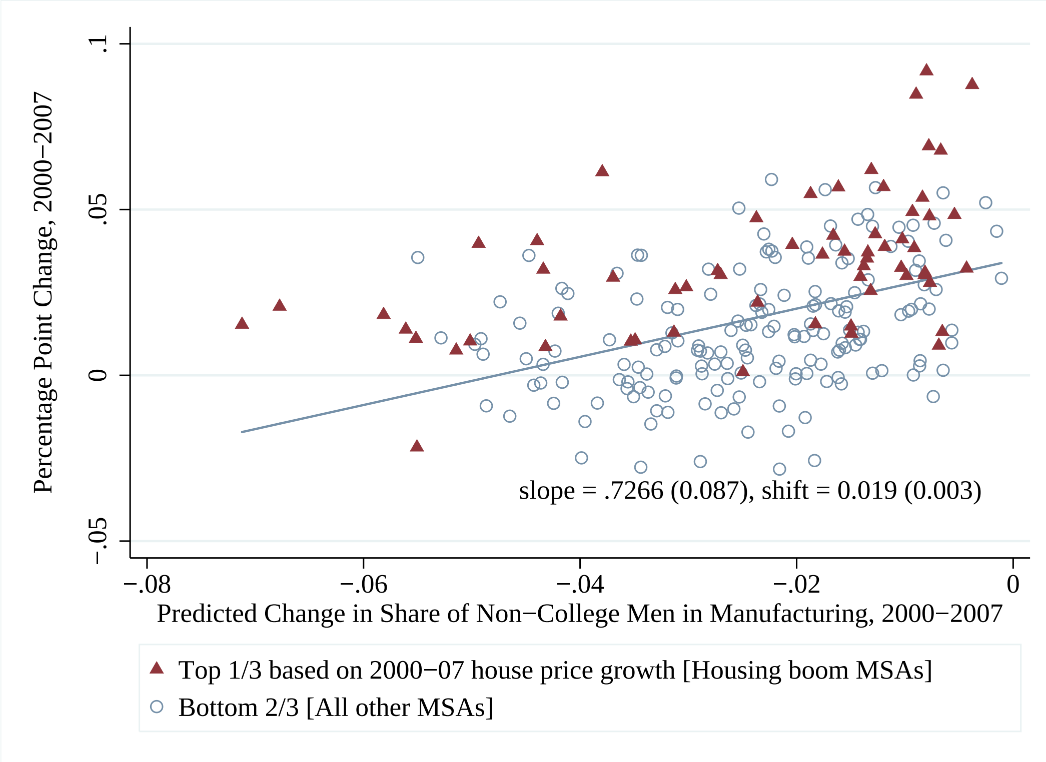
Notes: This figure reports the correlation across cities between shocks to local manufacturing industries and the change in the non-employment rate of non-college men (age 21-55) between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and 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 8: Change in Average Wage of Non-College Men, 2000-2007



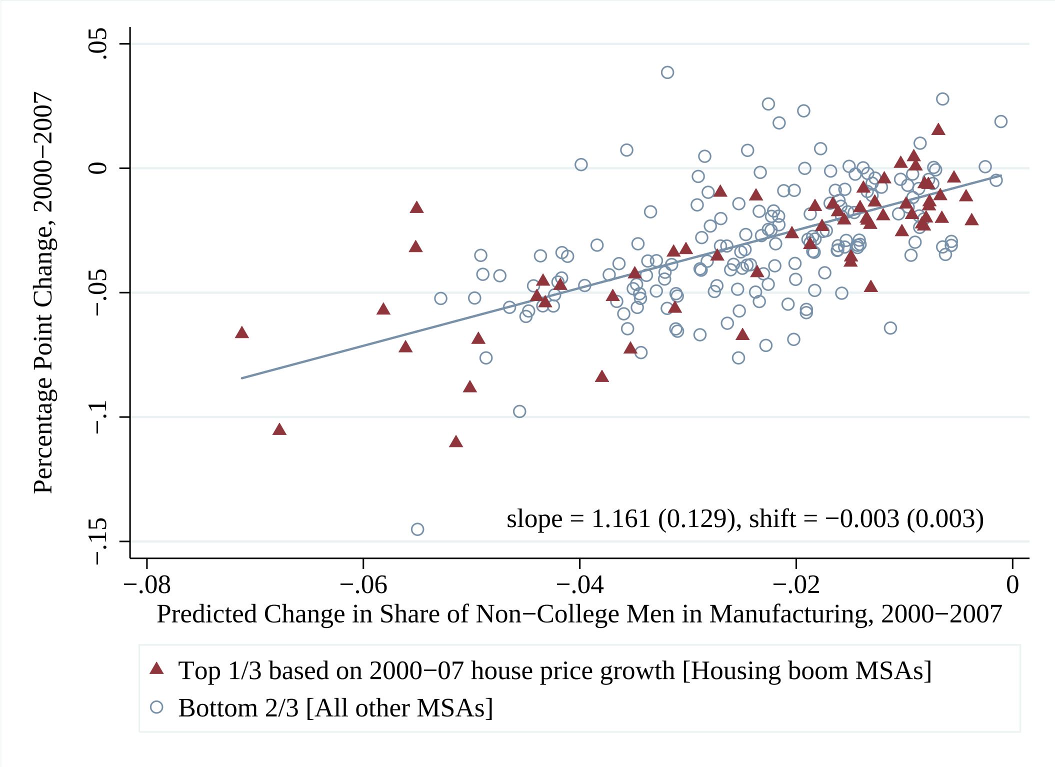
Notes: This figure reports the correlation across cities between local manufacturing shock and the change in the average wage of non-college men (age 21-55) between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 Census and the 2005-2007 ACS, and 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 9: 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 21-55) 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 10: Change in Share of Population Employed in Manufacturing, Non-College Men, 2000-2007

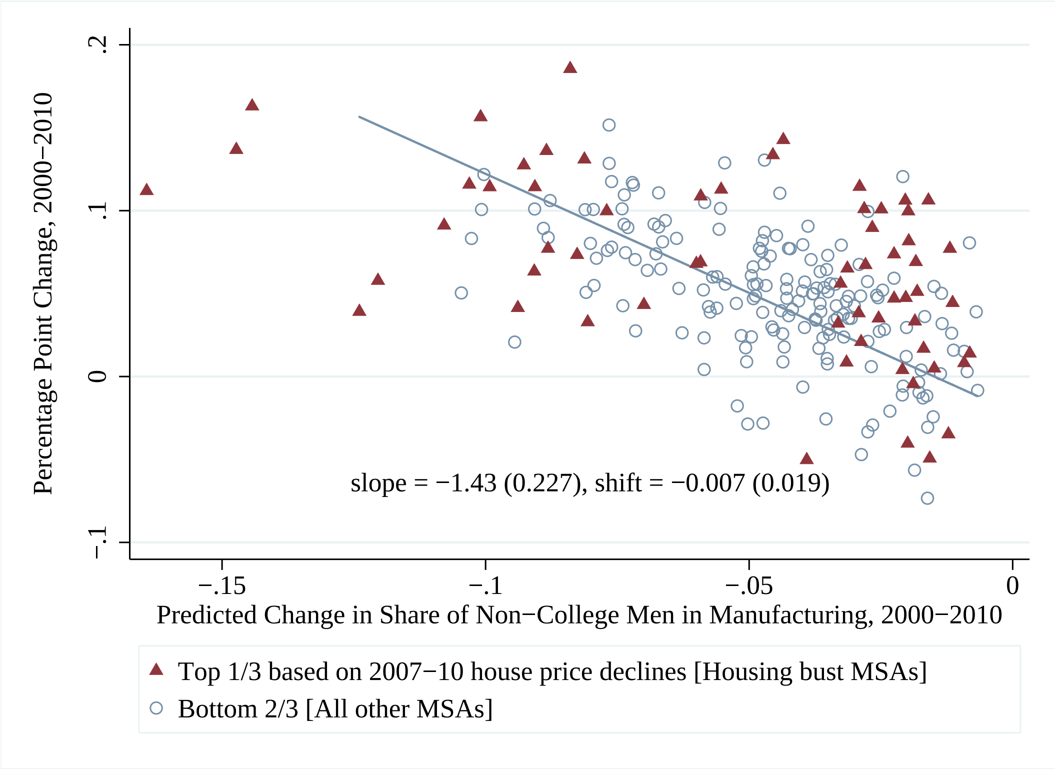


Notes: This figure reports the correlation across cities between local manufacturing shock and the change in the share of the non-college male population employed in manufacturing (age 21-55) between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991) using data from the 2000 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 11: 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 12: 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 Table A1
Robustness to Alternative Specifications
[Replace Non-employment with Average Wage in Table 4]

Dependent variable:	Change in Average Wage of Non-College Men, 2000-2007						
Specification:	OLS	IV	OLS	IV	IV	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Housing Prices	0.059	0.048	0.063	0.052	0.048	0.048	0.065
[Housing Boom]	(0.010)	(0.013)	(0.016)	(0.023)	(0.014)	(0.011)	(0.013)
	[0.000]	[0.000]	[0.000]	[0.023]	[0.000]	[0.000]	[0.000]
Predicted Change in Share of	1.545	1.504	1.369	1.330	1.503	1.548	1.456
Non-College Men Employed in Manuf.	(0.369)	(0.304)	(0.351)	(0.278)	(0.295)	(0.306)	(0.363)
[Manufacturing Bust]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Housing price effect (1σ)	**0.018**	**0.015**	**0.020**	**0.016**	**0.015**	**0.015**	**0.020**
Manufacturing effect (1σ)	**0.021**	**0.020**	**0.019**	**0.018**	**0.020**	**0.021**	**0.020**
First stage F-statistic		14.290		5.848	18.076	24.289	
Overidentification test statistic, $\chi^2(1)$					3.074		
[p-value]					[0.546]		
N	235	235	235	235	235	235	235
R^2	0.444	0.439	0.461	0.458	0.439	0.439	0.453
Include baseline controls	y	y	y	y	y	y	y
Instrument with land availability		y		y			
Census region FEs (4 regions)			y	y			
Instrument with constitutent land availability measures (K = 5)					y		
Instrument with (housing supply elasticity)$^{-1}$						y	
Control for (housing supply elast.)$^{-1}$ and (housing supply elast.)$^{-1}$×Manufacturing Bust							y

Notes: This table reports results of estimating equations (5) and (6) 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.

Appendix Table A2

Robustness to Alternative Specifications

[Replace Non-employment with Construction Employment Share in Table 4]

Dependent variable:	Change in Construction Employment of Non-College Men, 2000-2007						
Specification:	OLS	IV	OLS	IV	IV	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Housing Prices	0.024	0.027	0.021	0.026	0.025	0.023	0.024
[Housing Boom]	(0.006)	(0.011)	(0.006)	(0.011)	(0.007)	(0.010)	(0.006)
	[0.000]	[0.010]	[0.001]	[0.016]	[0.000]	[0.026]	[0.000]
Predicted Change in Share of	0.450	0.427	0.303	0.284	0.427	0.451	0.490
Non-College Men Employed in Manuf.	(0.178)	(0.157)	(0.142)	(0.126)	(0.153)	(0.163)	(0.185)
[Manufacturing Bust]	[0.016]	[0.010]	[0.038]	[0.029]	[0.008]	[0.008]	[0.011]
Housing price effect (1σ)	**0.007**	**0.008**	**0.006**	**0.008**	**0.008**	**0.007**	**0.008**
Manufacturing effect (1σ)	**0.006**	**0.006**	**0.004**	**0.004**	**0.006**	**0.006**	**0.007**
First stage F-statistic		14.290		5.848	18.076	24.289	
Overidentification test statistic, $\chi^2(1)$					3.903		
[p-value]					[0.419]		
N	235	235	235	235	235	235	235
R^2	0.492	0.489	0.543	0.537	0.491	0.491	0.496
Include baseline controls	y	y	y	y	y	y	y
Instrument with land availability		y		y			
Census region FEs (4 regions)			y	y			
Instrument with constitutent land availability measures (K = 5)					y		
Instrument with (housing supply elasticity)$^{-1}$						y	
Control for (housing supply elast.)$^{-1}$ and (housing supply elast.)$^{-1}$×Manufacturing Bust							y

Notes: This table reports results of estimating equations (5) and (6) 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.

Appendix Table A3

Robustness to Alternative Specifications

[Replace Non-employment with Manufacturing Employment Share in Table 4]

Dependent variable:	Change in Manufacturing Employment of Non-College Men, 2000-2007						
Specification:	OLS	IV	OLS	IV	IV	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Housing Prices	0.001	0.006	-0.001	0.004	0.003	0.007	-0.003
[Housing Boom]	(0.004)	(0.007)	(0.004)	(0.009)	(0.005)	(0.008)	(0.005)
	[0.889]	[0.438]	[0.719]	[0.668]	[0.581]	[0.397]	[0.605]
<u>Predicted</u> Change in Share of	1.025	1.020	1.024	1.021	1.022	1.025	1.004
Non-College Men Employed in Manuf.	(0.074)	(0.080)	(0.054)	(0.062)	(0.074)	(0.083)	(0.089)
[Manufacturing Bust]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Housing price effect (1σ)	**0.000**	**0.002**	**0.000**	**0.001**	**0.001**	**0.002**	**-0.001**
Manufacturing effect (1σ)	**0.014**	**0.014**	**0.014**	**0.014**	**0.014**	**0.014**	**0.014**
First stage F-statistic		14.290		5.848	18.076	24.289	
Overidentification test statistic, $\chi^2(1)$					3.652		
[p-value]					[0.455]		
N	235	235	235	235	235	235	235
R^2	0.532	0.526	0.563	0.557	0.531	0.523	0.538
Include baseline controls	y	y	y	y	y	y	y
Instrument with land availability		y		y			
Census region FEs (4 regions)			y	y			
Instrument with constitutent land availability measures (K = 5)					y		
Instrument with (housing supply elasticity)$^{-1}$						y	
Control for (housing supply elast.)$^{-1}$ and (housing supply elast.)$^{-1}$×Manufacturing Bust							y

<u>Notes:</u> This table reports results of estimating equations (5) and (6) 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.

Appendix Table A4
Robustness to Alternative Specifications
[Replace Non-employment with Population in Table 4]

Dependent variable:	Change in Population of Non-College Men, 2000-2007						
Specification:	OLS	IV	OLS	IV	IV	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in Housing Prices	0.004	-0.188	-0.020	-0.296	-0.042	-0.188	0.112
[Housing Boom]	(0.045)	(0.072)	(0.033)	(0.192)	(0.055)	(0.053)	(0.042)
	[0.935]	[0.009]	[0.549]	[0.124]	[0.446]	[0.000]	[0.011]
Predicted Change in Share of	2.395	2.555	1.752	1.970	2.432	2.383	2.179
Non-College Men Employed in Manuf.	(0.704)	(1.230)	(0.747)	(1.308)	(0.759)	(1.250)	(0.926)
[Manufacturing Bust]	[0.001]	[0.044]	[0.024]	[0.139]	[0.003]	[0.063]	[0.023]
Housing price effect (1σ)	**0.001**	**-0.059**	**-0.006**	**-0.092**	**-0.013**	**-0.059**	**0.035**
Manufacturing effect (1σ)	**0.032**	**0.035**	**0.024**	**0.027**	**0.033**	**0.032**	**0.029**
First stage F-statistic		14.290		5.848	18.076	24.289	
Overidentification test statistic, $\chi^2(1)$					6.792		
[p-value]					[0.147]		
N	235	235	235	235	235	235	235
R^2	0.149	-0.236	0.300	-0.314	0.127	-0.234	0.371
Include baseline controls	y	y	y	y	y	y	y
Instrument with land availability		y		y			
Census region FEs (4 regions)			y	y			
Instrument with constitutent land availability measures (K = 5)					y		
Instrument with (housing supply elasticity)$^{-1}$						y	
Control for (housing supply elast.)$^{-1}$ and (housing supply elast.)$^{-1}$×Manufacturing Bust							y

Notes: This table reports results of estimating equations (5) and (6) 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.

Appendix Table A5

Differences by Age Group for Non-College Men

[Replace with Averages Wages and Manufacturing Employment in Table 7]

Dependent variable:	Change in Average Wages, 2000-2007						Change in Manufacturing Employment Share, 2000-2007					
Sample:	[Baseline sample] Age 21-55		Age 21-35		Age 36-55		[Baseline sample] Age 21-55		Age 21-35		Age 36-55	
Specification:	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Change in Housing Prices	0.059	0.048	0.066	0.058	0.056	0.030	0.001	0.006	-0.003	0.002	0.004	0.007
[Housing Boom]	(0.010)	(0.013)	(0.015)	(0.022)	(0.013)	(0.013)	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)	(0.009)
	[0.000]	[0.000]	[0.000]	[0.007]	[0.000]	[0.018]	[0.889]	[0.438]	[0.547]	[0.776]	[0.380]	[0.427]
Predicted Change in Share of	1.545	1.504	1.466	1.434	1.821	1.786	1.025	1.020	1.042	1.041	0.979	0.971
Non-College Men Empl. in Manuf.	(0.369)	(0.304)	(0.375)	(0.306)	(0.358)	(0.316)	(0.074)	(0.080)	(0.076)	(0.076)	(0.152)	(0.149)
[Manufacturing Bust]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Housing price effect (1σ)	**0.018**	**0.015**	**0.021**	**0.018**	**0.018**	**0.009**	**0.000**	**0.002**	**-0.001**	**0.001**	**0.001**	**0.002**
Manufacturing effect (1σ)	**0.021**	**0.020**	**0.027**	**0.026**	**0.021**	**0.021**	**0.014**	**0.014**	**0.019**	**0.019**	**0.011**	**0.011**
First stage F-statistic		14.290		14.239		14.353		14.290		14.239		14.353
N	235	235	235	235	235	235	235	235	235	235	235	235
R^2	0.444	0.439	0.443	0.441	0.445	0.420	0.532	0.526	0.479	0.476	0.379	0.378
Include baseline controls	y	y	y	y	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y		y		y

Notes: This table reports results analogous to columns (1) through (2) in Table 4 for alternative age groups. See 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 A6
Manufacturing Busts, Housing Booms, and Declining Employment Non-College Men
[Replace ALL Non-College Men with NATIVE-BORN Non-College Men in Table 3]

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	-0.011	-0.017	0.061	0.048	0.020	0.032	-0.002	0.005
[Housing Boom]	(0.006)	(0.010)	(0.010)	(0.011)	(0.003)	(0.007)	(0.003)	(0.006)
	[0.068]	[0.089]	[0.000]	[0.000]	[0.000]	[0.000]	[0.450]	[0.400]
Predicted Change in Share of	-0.842	-0.828	1.761	1.721	0.187	0.160	1.099	1.095
Non-College Men Empl. in Manuf.	(0.141)	(0.139)	(0.327)	(0.252)	(0.112)	(0.122)	(0.057)	(0.061)
[Manufacturing Bust]	[0.000]	[0.000]	[0.000]	[0.000]	[0.103]	[0.196]	[0.000]	[0.000]
Housing price effect (1σ)	**-0.004**	**-0.005**	**0.019**	**0.015**	**0.006**	**0.010**	**-0.001**	**0.001**
Manufacturing effect (1σ)	**-0.011**	**-0.011**	**0.024**	**0.023**	**0.003**	**0.002**	**0.015**	**0.015**
First stage F-statistic		14.290		14.290		14.290		14.290
N	235	235	235	235	235	235	235	235
R^2	0.479	0.473	0.457	0.448	0.256	0.181	0.547	0.535
Include baseline controls	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y

Notes: This table reports results of estimating equations (5) and (6) by either OLS or IV, as indicated. 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 A7
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	-0.751	-0.173	0.391	-0.155	-0.116	-0.220	-0.207
[Housing Boom]	(0.161)	(0.335)	(0.341)	(0.593)	(0.112)	(0.208)	(0.114)	(0.214)
	[0.001]	[0.025]	[0.615]	[0.510]	[0.173]	[0.578]	[0.059]	[0.334]
Predicted Change in Share of	-12.297	-11.661	-10.948	-11.279	-1.319	-1.221	-2.463	-2.288
Non-College Men Empl. in Manuf.	(4.033)	(4.003)	(4.888)	(5.784)	(1.988)	(1.759)	(2.120)	(1.906)
[Manufacturing Bust]	[0.004]	[0.006]	[0.030]	[0.058]	[0.511]	[0.491]	[0.252]	[0.236]
Housing price effect (1σ)	**-0.184**	**-0.235**	**-0.054**	**0.122**	**-0.049**	**-0.036**	**-0.069**	**-0.065**
Manufacturing effect (1σ)	**-0.166**	**-0.158**	**-0.148**	**-0.153**	**-0.018**	**-0.017**	**-0.033**	**-0.031**
First stage F-statistic		14.290		14.290		14.290		14.290
N	235	235	235	235	235	235	235	235
R^2	0.398	0.388	0.135	0.045	0.088	0.085	0.159	0.159
Include baseline controls	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y

Notes: This table replicates analysis in Table 4 for alternative dependent variables. 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 A8

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

[Replace Non-employment with Unemployment in Table 7]

	Dependent Variable: Change in Share of Non-College Men Not in the Labor Force for…									
	2000-2007		2007-2010		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	-0.015	-0.011			0.015	0.031				
[Housing Boom]	(0.004)	(0.006)			(0.012)	(0.015)				
	[0.002]	[0.059]			[0.233]	[0.045]				
Change in Housing Prices, 2007-2010			-0.049	-0.055			-0.045	-0.042		
[Housing Bust]			(0.006)	(0.010)			(0.009)	(0.016)		
			[0.000]	[0.000]			[0.000]	[0.007]		
Change in Housing Prices, 2000-2010									-0.064	0.114
[Housing Boom-Bust Cycle]									(0.013)	(0.102)
									[0.000]	[0.265]
Predicted Change in Share of Non-College Men	-0.319	-0.310	-0.241	-0.288	-0.314	-0.334	-0.314	-0.334	-0.314	-0.334
Employed in Manufacturing	(0.134)	(0.116)	(0.240)	(0.218)	(0.211)	(0.201)	(0.176)	(0.164)	(0.189)	(0.403)
[Manufacturing Bust]	[0.022]	[0.011]	[0.321]	[0.194]	[0.145]	[0.103]	[0.081]	[0.047]	[0.105]	[0.411]
Housing price effect (1σ)	**-0.005**	**-0.003**	**-0.014**	**-0.016**	**0.005**	**0.010**	**-0.013**	**-0.012**	**-0.009**	**0.017**
Manufacturing effect (1σ)	**-0.004**	**-0.004**	**-0.004**	**-0.004**	**-0.009**	**-0.009**	**-0.009**	**-0.009**	**-0.009**	**-0.009**
First stage F-statistic		14.290		6.175		12.598		6.221		8.018
R^2	0.475	0.468	0.474	0.468	0.233	0.201	0.413	0.413	0.377	-0.957
Include baseline controls	y	y	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y		y

Notes: N=235 in all columns. This table reports alternative specifications baesd on columns (1) and (2) of Table 4, which are reproduced in columns (1) and (2) of this table. In all columns, the manufacturing bust instrument is measured across the years in the columns (i.e., in columns (3) and (4) the predicted change is formed for the 2007-2010 time period). 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 A9

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

[Replace Non-employment with Non-participation in Table 7]

	Dependent Variable: Change in Share of Non-College Men Not in the Labor Force for…									
	2000-2007		2007-2010		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	-0.019	-0.024			-0.016	-0.022				
[Housing Boom]	(0.008)	(0.015)			(0.008)	(0.016)				
	[0.015]	[0.097]			[0.059]	[0.175]				
Change in Housing Prices, 2007-2010			-0.007	-0.002			0.009	0.030		
[Housing Bust]			(0.003)	(0.008)			(0.007)	(0.023)		
			[0.045]	[0.766]			[0.213]	[0.205]		
Change in Housing Prices, 2000-2010									-0.027	-0.080
[Housing Boom-Bust Cycle]									(0.016)	(0.061)
									[0.092]	[0.190]
<u>Predicted</u> Change in Share of Non-College Men	-0.405	-0.384	-0.166	-0.168	-0.340	-0.325	-0.340	-0.325	-0.340	-0.325
Employed in Manufacturing	(0.170)	(0.156)	(0.093)	(0.099)	(0.128)	(0.126)	(0.138)	(0.158)	(0.124)	(0.181)
[Manufacturing Bust]	[0.021]	[0.018]	[0.084]	[0.098]	[0.011]	[0.014]	[0.018]	[0.046]	[0.009]	[0.080]
Housing price effect (1σ)	**-0.006**	**-0.008**	**-0.002**	**-0.001**	**-0.005**	**-0.007**	**0.003**	**0.009**	**-0.004**	**-0.012**
Manufacturing effect (1σ)	**-0.005**	**-0.005**	**-0.002**	**-0.003**	**-0.010**	**-0.009**	**-0.010**	**-0.009**	**-0.010**	**-0.009**
First stage F-statistic		14.290		6.175		12.598		6.221		8.018
R^2	0.706	0.704	0.119	0.111	0.695	0.693	0.683	0.662	0.694	0.637
Include baseline controls	y	y	y	y	y	y	y	y	y	y
Instrument with land availability		y		y		y		y		y

<u>Notes:</u> N=235 in all columns. This table reports alternative specifications baesd on columns (1) and (2) of Table 4, which are reproduced in columns (1) and (2) of this table. In all columns, the manufacturing bust instrument is measured across the years in the columns (i.e., in columns (3) and (4) the predicted change is formed for the 2007-2010 time period). 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 A10

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

[Alternative Counterfactual Assuming No Manufacturing Shock during 2007-2011]

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	0.033	-0.013	0.002	92.6%
2007-2011	0.086	**0.000**	0.013	0.073	**15.1%**
2000-2011	0.108	**0.033**	0.000	0.075	**30.8%**

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	0.027	-0.010	0.002	90.5%
2007-2011	0.066	**0.000**	0.010	0.056	**15.1%**
2000-2011	0.085	**0.027**	0.000	0.058	**32.0%**

Notes: This table reports counterfactual estimates of predicted changes in aggregate non-employment. Unlike Table 10, in this calibartion the actual changes in manufacturing employment between 2007-2010 is replaced with 0; i.e., this calibration assumes that none of the decline in manufacturing employment between 2007-2010 represents longer run trends.

Appendix Table A11

Manufacturing Busts, Housing Booms, and College Enrollment

[Replace Undergraduate Students with Graduate Students in Table 10]

Dependent variable:	Log of Total First-Time **GRADUATE STUDENT** Enrollment in State,					
Sample of Colleges and Universities:	All Colleges and Universities					
Gender Restrictions:	Men and Women		Men Only		Women Only	
Specification:	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Housing Prices	-0.127	0.003	-0.170	-0.045	-0.080	0.048
[Housing Boom]	(0.132)	(0.252)	(0.135)	(0.260)	(0.133)	(0.249)
	[0.341]	[0.992]	[0.216]	[0.863]	[0.549]	[0.848]
Predicted Change in Share of	-0.221	-0.223	0.091	0.129	-0.600	-0.641
Non-College Men Empl. in Manuf.	(3.467)	(3.074)	(3.489)	(3.072)	(3.689)	(3.335)
[Manufacturing Bust]	[0.950]	[0.943]	[0.979]	[0.967]	[0.871]	[0.848]
Housing price effect (1σ)	**-0.040**	**0.001**	**-0.053**	**-0.014**	**-0.025**	**0.015**
Manufacturing effect (1σ)	**-0.003**	**-0.003**	**0.001**	**0.002**	**-0.008**	**-0.009**
First stage F-statistic		14.316		14.316		14.316
N	233	233	233	233	233	233
R^2	0.117	0.099	0.135	0.121	0.089	0.072
Include baseline controls	y	y	y	y	y	y
Instrument with land availability		y		y		y

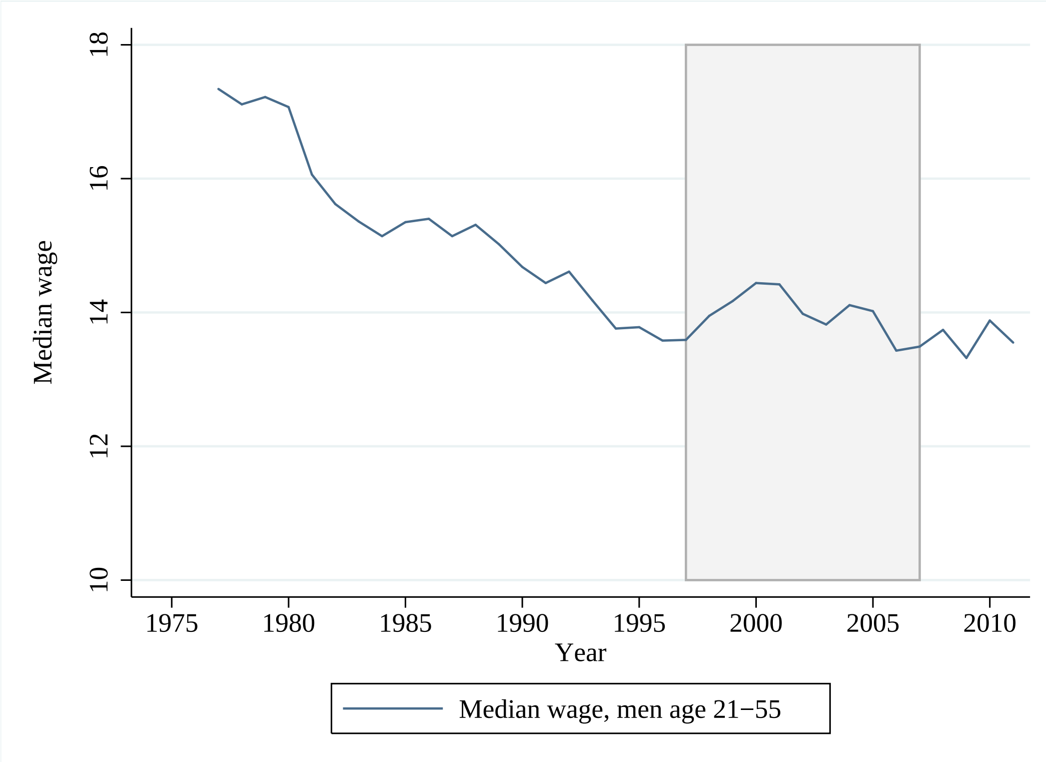
Notes: This table reports results analogous to columns (1) and (2) in Table 4 for alternative demographic groups. See Table 4 for more details. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each state, are in parentheses and p-values are in brackets.

Appendix Table A12
Manufacturing Busts, Housing Booms, and Declining Employment of Non-College Men
[Investigation of Interaction Effects]

Dependent variable:	Change in Non-employment 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	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Change in Housing Prices	-0.038	0.061	0.023	0.002
[Housing Boom]	(0.012)	(0.010)	(0.006)	(0.005)
	[0.004]	[0.000]	[0.001]	[0.671]
Predicted Change in Share of	-0.250	0.843	0.223	0.968
Non-College Men Empl. in Manuf.	(0.207)	(0.355)	(0.164)	(0.099)
[Partial Effect of Manufacturing]	[0.232]	[0.022]	[0.181]	[0.000]
Change in Housing Prices ×	**0.760**	**-0.565**	**0.156**	**-0.330**
Predicted Change in Share of	**(0.940)**	**(1.033)**	**(0.468)**	**(0.333)**
Non-Coll. Men Empl. in Manuf.	**[0.423]**	**[0.587]**	**[0.741]**	**[0.327]**
Predicted Change in Share of	-0.646	1.487	0.466	0.991
Non-College Men Empl. in Manuf.	(0.242)	(0.437)	(0.191)	(0.077)
[Total Effect of Manufacturing]	[0.011]	[0.001]	[0.019]	[0.000]
Housing price effect (1σ)	**-0.012**	**0.019**	**0.007**	**0.001**
Manufacturing effect (1σ)	**-0.009**	**0.020**	**0.006**	**0.013**
N	235	235	235	235
R^2	0.744	0.446	0.492	0.535
Include baseline controls	y	y	y	y

Notes: This table reports results of estimating equations (5) and (6) by either OLS or IV, as indicated. 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.

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

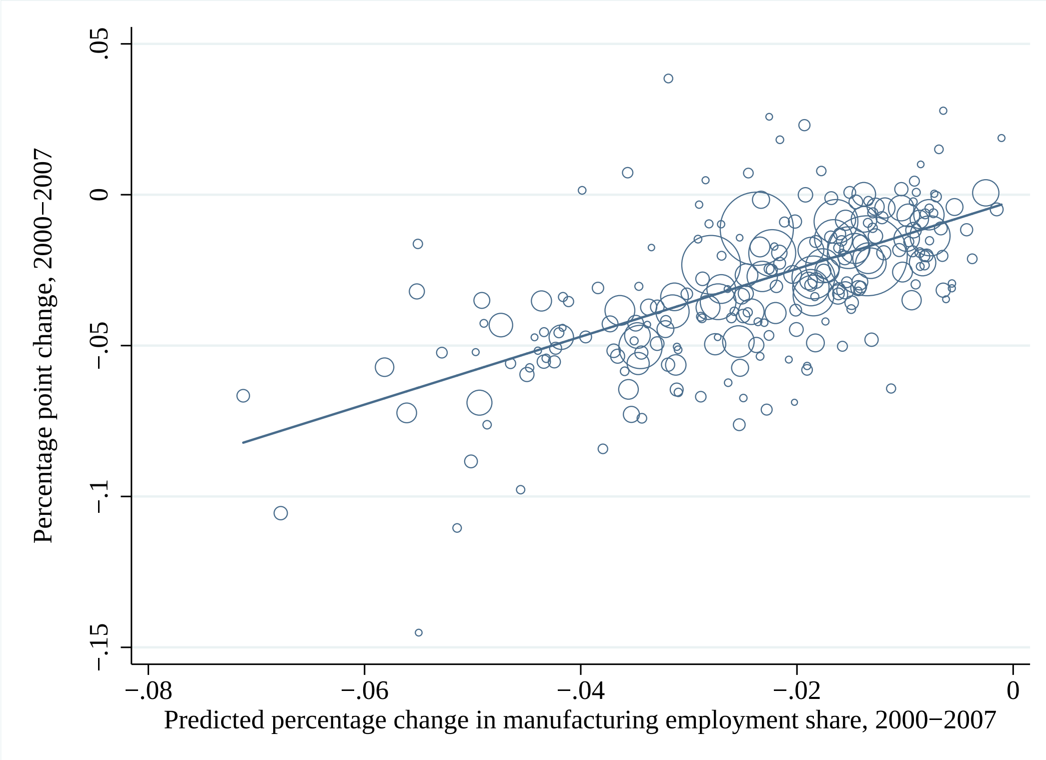


Notes: This figure uses data from the March CPS. The sample includes all men without a college degree that are noninstitutionalized and age 21-55.

Appendix Figure 2: 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 21-55 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Appendix Figure 3: Manufacturing Shocks and Manufacturing Employment, Non-College Men, 2000-2007

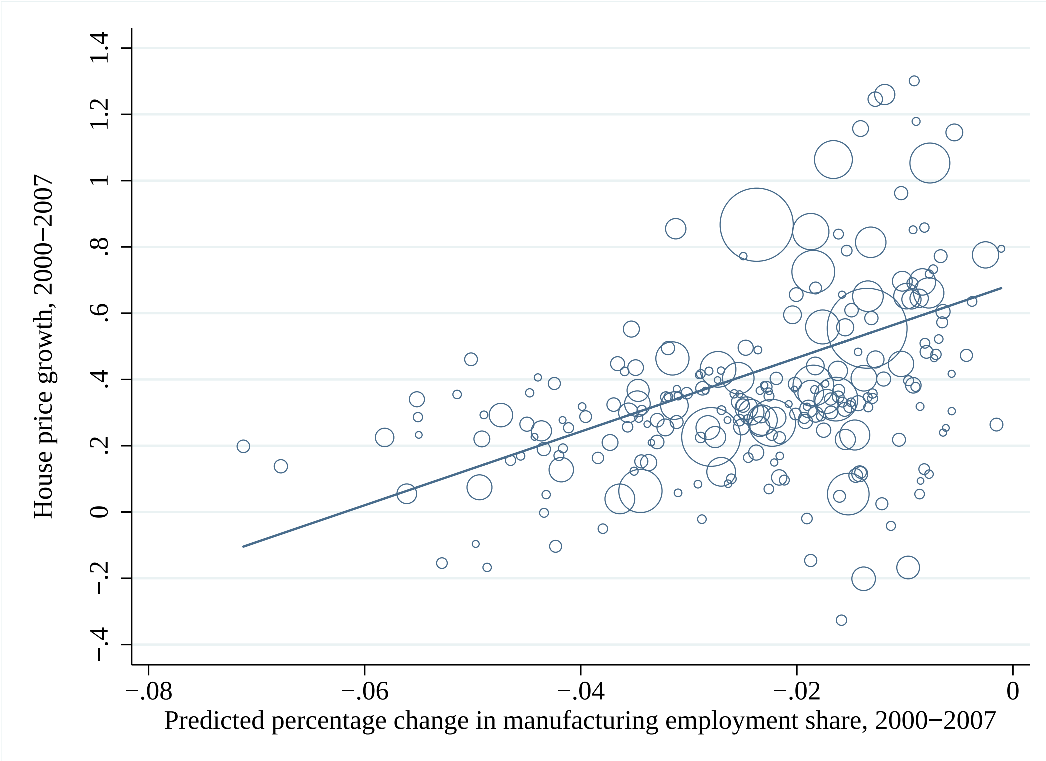


Notes: This figure reports the correlation across cities between shocks to local manufacturing industries and changes in manufacturing employment between 2000 and 2007. The manufacturing shock is constructed following Bartik (1991); see Appendix for details. The change in manufacturing employment is 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 21-55 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Appendix Figure 4: Construction Employment and Housing Price Growth, 2000-20007

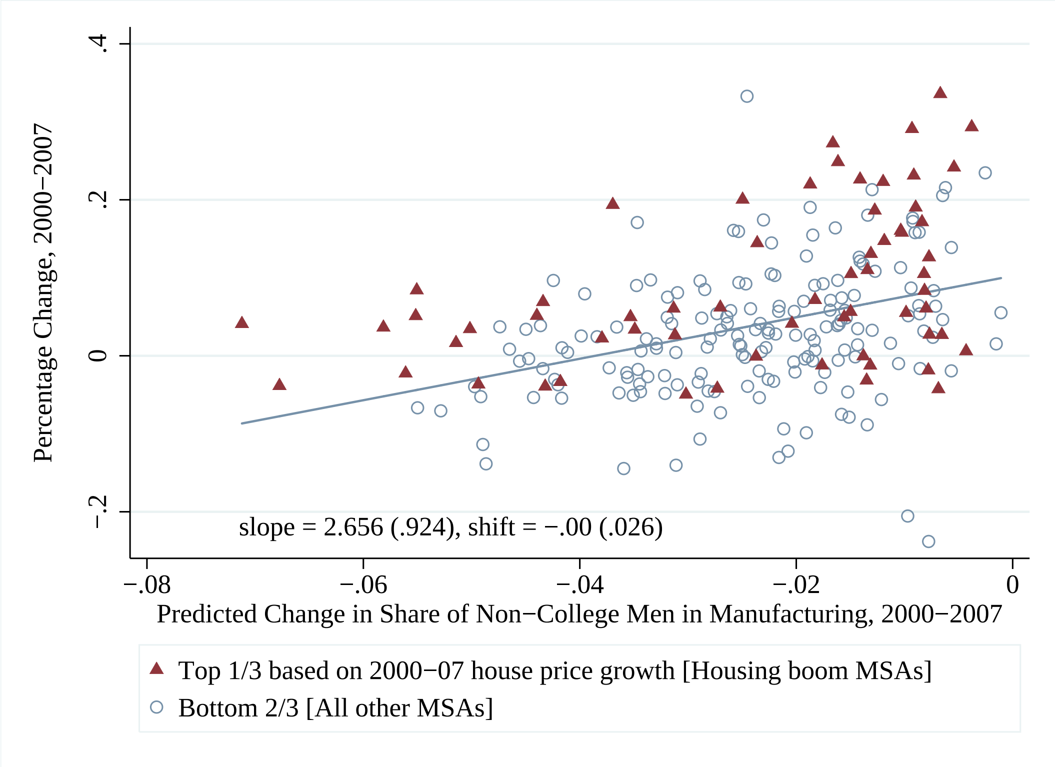
Notes: This figure reports correlation across cities between the 2000-2007 change in share of population of non-college men employed in construction and the change in housing prices over the same time period. Each circle represents a metropolitan area, and the size of the circle is proportional to the number of non-college men age 21-55 in the metropolitan area as computed in the 2000 Census. The solid line represents the weighted OLS regression line.

Appendix Figure 5: 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 21-55 in the metropolitan area as computed in the 2000 Census. The measure of land availability 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.

Appendix Figure 6: Change 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 21-55) 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.