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ABSTRACT

The 'China shock' operated in part through the housing market, and that is an important reason why the China shock was as big as it was. If housing prices had not responded at all to the China shock, then the total employment effect of the China shock would have been reduced by more than one-half. Housing prices in the United States did respond to the China shock, however, so the independent employment effect of the China shock is reduced by about 20–30%, with that remainder reflecting exogenous changes in housing prices.

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1 Introduction

In an influential study, Autor, Dorn, and Hanson (2013, hereafter ADH) show that rising import competition from China has been an important contributor to the recent decline in the employment rate of working age population in the United States. Exploiting variation in exposure to Chinese import across local labor markets (commuting zones) over 1990-2007, they find that Chinese import exposure caused a large reduction in manufacturing employment: a $1,000 per worker increase in import exposure over a decade reduces manufacturing employment per working-age population by 0.596 percentage points (their Table 3, column 6), explaining about 44 percent of the actual decline in manufacturing employment from 1990 through 2007. Furthermore, the negative employment shock by Chinese imports goes beyond manufacturing and exists for nonmanufacturing workers. To be more specific, import exposure to Chinese imports caused a substantial employment decline in *both* manufacturing and nonmanufacturing sectors for workers without college education; while for workers with college education, import exposure caused substantial job loss in manufacturing sectors but a statistically insignificant increase in employment in nonmanufacturing sectors (their Table 5, Panel B).

Such results, accompanied with findings in other studies such as Pierce and Schott (2015) and Acemoglu et al. (2016), have important policy implications and challenge the benign view towards globalization. Meanwhile, studies on Europe, mainly Germany, show that the estimates of the effect of 'China shock' have been moderate. Dauth et al. (2014) analyze the effect of the rise of 'the East' (China and Eastern Europe) in the period 1988-2008 on German local labor markets. Using an empirical approach similar to ADH, they find that a ten-year increase of €1,000 per worker in import exposure reduces manufacturing employment per working-age population by 0.19 percentage points (their Table 1, column 5). Taking into account that their analysis is conducted in 2005 euro instead of the 2007 dollar in ADH, this coefficient can be converted to around -0.14 and compared to -0.60 in ADH. Furthermore, they find that the negative impact of import competition is more than offset by a positive effect of export expansion.[1] Badinger

[1] In the aggregate, they estimate 0.44 million job gains in Germany over the period 1988-2008 that would not exist without the trade integration with China and the Eastern Europe. Feenstra, Ma and Xu (2019) examine the job creating effect of export expansion for the United States.

and Reuter (2017), who analyze the employment effect of trade for 1146 regions in 17 Western European countries over 1991-2011, also report a small average coefficient of -0.14 for import exposure.[2]

In this paper, we investigate one reason for the strong impact of the 'China shock' on US labor market, as compared to Germany and other countries of Western Europe, that is the housing market in the United States. We find that the employment effect of the China shock was *magnified* through the housing market. If housing prices had not responded to the China shock at all, then the total employment effect of import exposure from China would have been reduced by more than half. Controlling the possible endogenous response of housing prices, the impact of China shock on total employment is still reduced by 20–30%.

These results are obtained because during the same period when the United States faces increasing import competition from China, its domestic economy also experiences a national housing boom that starts from the late 1990s and varies across regions. While manufacturing workers faced import competition, nonmanufacturing sectors – in particular the construction sector and the financial services sector experienced a demand boom.[3] If the China shock influenced the housing market, then omitting any variables for housing demand would mean that the estimated effect of import exposure should be interpreted as a reduced form rather than a structural coefficient. This reduced form coefficient would be overstated, however, if commuting zones that experienced larger increases in import exposure also had smaller increases in housing prices, in part for *exogenous* reasons and without those variables included. Thus, to the extent that the housing boom and busts are endogenous to the China shock, then we are adding a structural interpretation for the magnitude of the shock.[4] But to the extent that some component of the housing boom and bust is correlated but not causal, then leaving it out will overstate the true magnitude of the shock.

Our empirical approach builds on that in ADH but augments it with a housing variable. To take into account the endogenous part of the housing, we employ two instrumental variables. We first

[2] The 17 countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.

[3] Similar idea has been elaborated in Charles et al.(2016a, 2016b), who argue that during 2000-2007 unemployment was 'masked' by the strong housing boom which promoted employment in the construction sector.

[4] Feler and Senses (2016) propose that housing prices respond endogenously to import exposure. They show that commuting zones more exposed to the China shock experienced larger reductions in housing values, business activity, and the provision of local public goods.

use the estimated structural break from high-frequency housing price changes as our instrument (Ferreira and Gyourko, 2011; Charles et al. 2016). This instrument relies on the emerging consensus that much of the variation in housing prices during the housing boom in the U.S. was from speculative activities and not from changes in fundamentals like income, productivity, or population. We therefore estimate for each local area a structural break in the evolution of housing prices and treat these 'sharp' breaks exogenous to fundamental shocks. We also use the land topology-based measure of housing supply elasticity introduced by Saiz (2010) as an alternative instrument. Saiz (2010) proposes that housing development is effectively constrained by geographic situation, such as the presence of steep slopes, wet lands, lakes and so on. Saiz constructs an exact measure of land availability and uses this measure to estimate the housing supply elasticity for local areas. The estimated supply elasticity is exogenous to housing demand shocks and used commonly in the literature as instrument for housing price changes, see for example, Mian and Sufi (2011, 2014).

With the housing instruments, we perform both standard two stage least square (TSLS) estimation and reduced form estimations. In the TSLS estimation, we find that the China shock does operate partly through the housing market. This can be seen from the first stage regression of housing price changes on either of the housing instruments – structural break or supply elasticity, and the ADH China shock instrument. [5] Both coefficients are significant. Therefore, the China shock affects U.S. employment through at least two channels: one is the direct effect on employment through import competition, the other is the indirect effect through the magnification of housing market. Controlling housing prices, the direct effect of import exposure on U.S. total employment would reduce by more than half. To isolate the endogenous response of housing market, we also construct a predicted housing price change calculated using only the housing instrument term from the first stage regression, and use it as a control variable in the second stage regression. We also perform a pure reduced form regression – replacing the endogenous variables with instruments directly in the main regression. Either way shows that, after controlling the endogenous response of housing price to import exposure, the exogenous variation in housing price changes can still reduce the impact of the China shock on total employment by about 20–30%.

[5] ADH instruments the U.S. import exposure with the import exposure of other eight developed countries to isolate the supply-driven component of imports. We follow this in our estimation.

Given the fact that imports from China started to accelerate after 2001 when China gained accession into the WTO, and at the same time U.S. national housing market experienced a boom and busts cycle mainly in the 2000s, we also explore looking at an alternative sample over both the housing boom and busts periods: 2000-2007 and 2007-2011. We find that the magnification effect of housing market is confirmed during these two periods. During 2000-2011, the China shock still has a negative effect on U.S. manufacturing employment. However, it also has a significantly positive effect on non-manufacturing employment, even without controlling housing. This offsets the negative effect on manufacturing employment and makes the effect on total employment positive. Controlling housing reduces both the negative and positive effects (in absolute value) of the China shock. Therefore, the fact that domestic housing market creating jobs during boom and destructing jobs during busts cannot be neglected when estimating the effect of an outside shock, such as the China shock. Otherwise, the effect of the China shock would be overstated.

The rest of the paper is structured as follows. Section 2 presents the empirical strategy and describes our instruments for housing. Section 3 shows the estimated role of housing in examining the employment effect of the China shock. Section 4 performs robustness checks, and section 5 concludes.

2 Empirical Strategy

2.1 Import Exposure and Housing

ADH (2013) point out that US regions (commuting zones) have different exposures to import competition from China due to their industry structure. Those regions that have larger shares of employment in industries that experienced larger growth of Chinese imports (at the national level) will suffer more from import competition from China. Their specification is:

$$\Delta L_{it} = \gamma_t + \beta_1 \Delta IPW_{it} + X_{it}\beta_2 + \delta_r + e_{it}, \tag{1}$$

where ΔL_{it} is the decadal change in the employment share of the working-age population in commuting zone i. In different specifications, we can distinguish ΔL_{it} by sectors (manufacturing vs. nonmanufacturing), or replace it with unemployment rate or the fraction of the population not in the labor force (NILF). ΔIPW_{it} is the change in import exposure, which is instrumented by China's exports to other high-income countries.[6] γ_t is a time dummy for each decadal period. The vector X_{it} contains a set of economic and demographic controls at the start of each decade.[7] In addition, δ_r augments the model with geographic dummies for the nine Census divisions to absorb region-specific trends.

During the same period when imports from China grew quickly, the US also experienced large changes in housing price. Importantly, such changes in housing price also vary across regions. For example, Charles, Hurst, and Notowidigdo (2016b) argue that during 2000-2006 when there was large and persistent decline in manufacturing employment, the housing boom simultaneously increased employment in construction. Thus, the housing boom 'masks' the adverse labor market effects of the manufacturing decline. In addition, the housing boom may also affect employment through the collateral channel, whereby firms that own real estate increase their investment in response to rising real estate prices (Chaney, Sraer, and Thesmar, 2012). So, if commuting zones that experienced larger changes in import exposure also had smaller increases in housing prices, then omitting any variable for housing demand means that the estimated effect of import exposure should be interpreted as a reduced form rather than a structural coefficient. This reduced form coefficient would be overstated, however, if the change in housing prices are in part *exogenous* and suitable instrumental variables are not used. To explore whether this occurs, we augment ADH's original specification in equation (1) by including housing price change as an additional variable:

$$\Delta L_{it} = \gamma_t + \beta_1 \Delta IPW_{it} + \beta_2 \Delta HPI_{it} + X_{it}\beta_3 + \delta_r + e_{it}, \tag{2}$$

where ΔHPI_{it} is the change in housing price at the commuting zone level.

Figure 1 plots the correlation between changes in local import exposure from China and changes in the local housing price index, for the pooled period 1990-2007, and for 1990-2000 and 2000-

[6] The measurement of ΔIPW_{it} by ADH (2013, p. 2128) uses the change in US imports from China in each industry, weighted by initial commuting zone employment relative to total US employment in each industry, and summed over industries. The idea for the instrument is that China's exports to other high-income countries are correlated with the US imports from China due to productivity improvements in China or falling trade costs within the same sector. ADH (2013) uses the China's total exports to eight countries: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. The change in these exports by industry are weighted by decade-old commuting zone employment relative to total US employment in each industry, and summed over industries, to obtain the instrument.

[7] These control variables include: the percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, and the average offshorability index of occupations.

2007 separately.[8] There is an obvious negative correlation between the two variables of interest, which appears to be much stronger in the 2000-2007 period: regions that experienced larger import shocks also experienced smaller increases in housing prices.

[Figure 1 here]

One concern about controlling the effect of housing market is that the change in local housing price may be partly the result of import exposure. Feler and Senses (2016), for example, argue that commuting zones more exposed to the ADH China shock experienced larger reductiond in housing values, business activity, and the provision of local public goods. In this case, estimating equation (2) without controlling for endogeneity would lead to biased estimate of import exposure as well. Other factors can lead to endogeneity too, for example: unobserved local conditions may affect employment and housing price simultaneously; and local job opportunities can also reversely affect housing prices. To deal with these endogeneity issues, we employ instrumental variables for housing prices. The aim is to isolate exogenous variations in housing prices that are not related to import competition as well as other demand or supply shocks.

2.2 Housing Instruments

We first instrument housing price changes using the estimated structural break from rapid changes in housing prices that occurred in the local area (Ferreira and Gyourko, 2011; Charles et al. 2016b). The idea is that underlying fundamentals for housing demand (such as productivity, income, or population) do not change abruptly and are smoothly incorporated into prices when they do change. So the sharp breaks from the trend would reflect variations due to exogenous speculative activities or other housing-specific forces, for example, the irrational exuberance documented in Shiller (2009), Mayer (2011), Chinco and Mayer (2014), the introduction of market products like interest-only mortgages in Barlevy and Fisher (2010) and so on.

More specifically, following Charles et al. (2016b), we estimate for each local area an OLS regression with a structural break, and search for the break date that maximizes the R^2 of the

[8] The annual housing data at US county level can be downloaded from the Federal Housing Finance Agency website: https://www.fhfa.gov/DataTools/Downloads/pages/house-price-index.aspx. After aggregating and matching counties to commuting zones, we have housing price information for 522 commuting zones in 1990-2007, as compared to the 722 commuting zones in ADH (2013). The excluded commuting zones are mainly rural regions without housing price information.

regression:

$$lnP_{it} = \omega_i + \tau_i t + \lambda_i(t - t_i^*)D_{it} + \epsilon_{it}, \tag{3}$$

where lnP_{it} is the log value of quarterly housing price index for each area i in year-quarter t, and ω_i is a constant. D_{it} is a dummy variable which equals 1 for periods after the date of structural break t_i^*, and 0 otherwise. Thus τ_i is the linear time trend before the structural break, while λ_i captures the size of the structural break. [9]

Our estimation is run for each metropolitan statistical area (MSA) for which the quarterly housing price series is available. We estimate separately over the periods 1990-2000 and 2000-2007, and use the annualized size of the structural break λ_i as the instrument for the decadal changes in housing prices. [10] Figure 2 illustrates how structural breaks are found and estimated for some MSAs as an example. The left panel shows the example over the first period and the right panel shows the result over the second period. The first row shows areas that experienced smooth evolution of prices, suggesting close to zero structural break. The second row shows areas that experienced 'sharp' price increase at some point, suggesting a positive structural break. Similarly, the last shows a negative structural break found over the sample period. On average, most areas experienced housing booms after 2000 and they had a relatively slowdown before that, so the correlation between the estimated structural break λ_i and housing price growth is negative for the first period and positive for the second period. Figure 3 first row plots the correlation. In our regression analysis later, we therefore construct our structural break instrument by taking the value of -λ_i over 1990-2000 and the value of λ_i over 2000-2007 to avoid cancellation of the correlations due to opposite signs.[11]

[Figure 2 here]

An alternative instrument we use is the land topology-based measure of housing supply elasticity introduced by Saiz (2010). Saiz (2010) proposes that housing development is effectively

[9] To estimate structural break, we use the high-frequency quarterly housing data, which is available at the metropolitan statistical area (MSA) level. We have 350 MSAs that have the quarterly price information on both periods.

[10] We use the quarterly price series to do the estimation. For the first period, we restrict the break date to be between 1991Q1 to 2000Q4. For the second period instrument, we restrict the break date to be between 2001Q1 and 2005Q4. We restrict the break to be before 2006 since housing booms had already started to burst in 2006 for some MSAs. Extending the search of the break date to 2006Q4, however, leads to qualitatively similar results.

[11] We also try interact λ_i with the period dummies to instrument separately for the housing price changes over the two periods. The results are qualitatively similar.

constrained by its geographic situation, such as the presence of steep slopes, wet lands, lakes and so on. Use satellite-based geographic data on land use and slope maps, Saiz constructs a precise measure of exogenous land availability and uses this measure to estimate the housing supply elasticity for local areas. The estimated supply elasticity is exogenous to housing demand shocks and closely related to housing price changes. The more elastic housing supply areas are expected to experience less housing price changes with respect to demand shocks. We confirm this relationship in our data. Saiz's supply elasticity ranges from 0 to 12 and is increasing in elasticity. Figure 3 second row plots housing price growth over the two periods against the inverse of Saiz elasticity measure at the MSA level. [12] There is a clear correlation between the two variables, and it is even significant in the second period, when most areas experienced housing booms. In the first period, when most areas experienced a slow down, the relationship is negative and less obvious. Similarly, in our regression analysis, we construct our supply elasticity instrument by taking the value of negative elasticity over 1990-2000 and the value of elasticity itself over 2000-2007.

[Figure 3 here]

3 The Role of Housing

3.1 The Sample

In this section, we examine the effect of housing in the employment effect of import exposure. We estimate equation (2) using the housing instrument discussed in the previous section. Following ADH, we run the estimation over periods 1990-2000 and 2000-2007. Table 1 provides summary statistics of key variables of interest in the ADH sample and our sample. ADH covers 722 commuting zones over two periods. We need quarterly housing price data to construct the structural break instrument. We first estimate the structural breaks at MSA level and then match the 350 MSAs with commuting zones. This reduces the sample to 291 commuting zones. To use the Saiz's supply elasticity as the instrument for housing, we match the 262 elasticity at MSA/NECMA level provided by Saiz (2010) with commuting zones, which leads to a sample of 250 commuting zones. The sample with the structural break housing instrument accounts for 90 percent of the U.S. pop-

[12] We have 262 MSAs that have elasticity information on both periods.

ulation. The sample with the supply elasticity housing instrument accounts for 85 percent of the U.S. population. Table 1 shows that they both closely resemble the original, complete sample in the statistics of key variables.

[Table 1 here]

3.2 Two Stage Least Square Estimation

We estimate equation (2) using two stage least square estimation (TSLS) with housing instrumented by the estimated structural break and supply elasticity respectively. Table 2 reports the results with the structural break instrument. For ease of comparison, Panel I reproduces ADH's results with 722 commuting zones over two decadal periods. Panel II then uses the matched sample with structural break housing data. The dependent variables, as indicated in the top of each column, are the manufacturing employment-to-population rate (column 1), nonmanufacturing employment-to-population rate (column 2), total employment-to-population rate (column 3), unemployment rate (column 4), and not-in-the-labor-force rate (NILF, column 5). By the definition of the population shares and the property of linear regressions, we know that the coefficents for each column satisfy the relationship $col1 + col2 = col3 = -(col4 + col5)$.

[Table 2 here]

Panel II confirms the results of ADH: import exposure substantially reduces the manufacturing employment rate while it has a negative but insignificant effect on the nonmanufacturing employment rate, resulting in rising unemployment and NILF. In fact, the effect of China import exposure is even stronger for the reduced sample of commuting zones: a $1,000 per worker increase in a CZ's import exposure reduces its manufacturing employment to population rate by 0.705 percentage points, and its nonmanufacturing employment rate by 0.218 percentage points (though not significant), resulting in a total drop in the employment rate of 0.923 percentage points. Further decomposing the effect by workers' education levels confirms what ADH find: a $1,000 import exposure from China reduces the noncollege employment rate by a highly significant 1.31 percentage points, consisting of 0.686 percentage points drop in manufacturing and 0.624 percentage points drop in nonmanufacturing sector, respectively. College employment in manufacturing also experienced a significant drop of 0.704 percentage points, while in nonmanufacturing it increases by 0.202 percentage points, with the net negative effect on employment rate at a highly significantly 0.502 percentage points.

The effect of import exposure, however, is mitigated if we include housing price change, instrumented by the estimated structural break. This is shown in panel III. First, the effects on manufacturing employment rate (column 1), total employment rate (column 3), unemployment (column 4) and NILF (column 5) are all reduced by different magnitudes. The last three rows of the table show the percentage reduction in the estimated coefficients. For example, a \$1,000 increase in Chinese imports per worker reduces manufacturing employment by 0.705 percentage points and total employment by 0.923 percentage points in Panel II. But when we include housing price changes, the effect drops to 0.595 percentage points for manufacturing employment (i.e., a 16% drop) and 0.430 percentage points for total employment (i.e., a 53% drop) in Panel III. The reduction for NILF is even bigger at a 63% drop and the reduction for unemployment is 32%. The same is true when we distinguish college and non-college education level. Second, in a number of cases, the effect of import exposure on total employment and NILF loses statistical significances in Panel III. Thirdly, in all cases, local housing booms promote employment in both manufacturing and nonmanufacturing strongly and significantly, and reduce unemployment and the share of NILF.

The result on nonmanufacturing employment is even striking. Some conclusions by ADH no longer arise. In particular, ADH find that import exposure reduces the no-college employment rate, at similar magnitudes in both the manufacturing and nonmanufacturing sectors. Including the changes in housing demand, however, makes the impact of import exposure on no-college employment in the nonmanufacturing sector close to zero (87% drop) and becomes insignificant, indicating the importance of correcting for the 'masking' effect of the housing boom. As for college workers, ADH (2013) find that import exposure reduced their employment rate substantially in manufacturing, but had only a modest and insignificant effect in the nonmanufacturing sector. In contrast, we find that the detrimental effect on college workers in manufacturing is still there, but that the effect on those in nonmanufacturing turns *positive and significant* after including housing price changes. The effects on manufacturing and nonmanufacturing offset each other, resulting in a small and insignificant impact of import exposure on total employment for college workers.

Tables 3 reports the estimation results with housing instrumented by Saiz's supply elasticity. The findings in table 2 are confirmed and even strengthened here: including housing reduces the effect of import exposure on manufacturing employment, total employment, unemployment and NILF by 23-26%, 65-79%, 20-47% and 76-79%; the negative effect of import exposure on non-manufacturing employment for both college and no-college workers disappears and it increases the nonmanufacturing employment for college workers significantly.

[Table 3 here]

Table 4 goes further to report the estimation results with housing instrumented by both the structural break and the supply elasticity. The findings are consistent. When we have two instruments for housing and one instrument for import shock, we are over-identified. The table also reports the p-value of Hansen J statistic. It is large in most of the regressions, implying the validity of instrument exogeneity.

[Table 4 here]

Including housing variable reduces the 'direct' effect of the China shock. The China shock, however, may also transmit partly through the housing market. This can be seen from the first stage results reported in Table 5. The coefficient on the import exposure instrument is also significant for the housing price regression, which means that the China shock also operates through the housing market. Therefore, the China shock affects U.S. labor market through at least two channels. One is the 'direct' effect on employment through import competition, the other is the 'indirect' effect through the magnification of the housing market, as we examine next.

[Table 5 here]

3.3 Reduced Form Estimation

The next experiment we do is to shut down the endogenous response of the housing variable to the China shock. To achieve this, we construct a *predicted* housing price growth calculated using only the housing instrument term from the first stage regression in Tables 2, 3 or 4. More specifically, we run a first stage regression

$$\Delta HPI_{it} = \gamma_t + \alpha_1 \Delta IPW_{it} + \alpha_2 IV_{it} + \delta_r + e_{it}, \tag{4}$$

as we did above, but now we use only the fitted value of $\alpha_2 IV_{it}$ as the housing variable in the second stage regression. In this way, the constructed housing price growth is no longer responsive to import exposure. The results are reported in Tables 6, 7 and 8, with predicted housing calculated using different instruments.

Table 6 reports the results when predicted housing is calculated using the structural break instrument. Comparing with the results in Table 2 Panel II and III, we find that, shutting down the endogenous responses of housing to the China shock does mitigate the reduction in the effect of China shock. However, the patterns are still obvious: the effect on total employment of the China shock is still reduces by 22-30% after controlling the pure exogenous effect of housing; the effect on nonmanufacturing employment for college workers still turns to be positive and statistically significant.

[Table 6 here]

Table 7 and 8 go further to report the results when predicted housing is calculated using the supply elasticity or both instruments. The results are qualitatively similar, with the effect even strengthened when both instruments are included.

[Table 7 and Table 8 here]

We also perform a simple reduced-form regression to control the pure exogenous effect of housing. Table 9 reports the results. We directly replace the endogenous variables in the main regression with the corresponding instrumental variables. To have a direct comparison, in Panel I, we first consider no housing and replace the endogenous US imports from China with its instrument, i,e., other eight countries' imports from China, and see what the estimated effect of the China shock would be. Then in Panel II, we consider housing and replaces it using both structural break and supply elasticity instruments. We find that controlling housing can still reduce the employment effects of the China shock. Now the effect on manufacturing employment, total employment, unemployment, NILF is reduced by 6-11%, 33-38%, 22-31%, and 37-41%. The effect on nonmanufacturing employment for college workers still turns positive and is statistically significant.

[Table 9 here]

3.4 Quantifying the Results

We can apply the observed import growth from China to quantify the economic magnitude of import exposure on manufacturing, nonmanufacturing and total employment. According to ADH (2013), Chinese import exposure rose by $1,140 per worker between 1990 and 2000 and by an additional $1,839 per worker between 2000 and 2007. Using their estimated coefficients based on a sample of 722 commuting zones (Table 2, Panel I), they find a net reduction in US manufacturing employment of 1.53 million workers for the full period 1990-2007. Applying the same calculation to nonmanufacturing employment implies another 0.46 million job loss, or 1.99 million lost jobs in total, as can be seen from Panel I in table 10.

We perform a similar calculation, but using the coefficients that we re-estimated. To have a direct measure of the effect of housing, we compare the predicted employment changes between the estimates of controlling and not controlling housing based on the same sample (the matched sample). Table 10 Panel II is based on the estimated coefficients reported in Table 4 Panel I, which consists a sample of 249 commuting zones that have information on both housing structural break and supply elasticity during 1990-2007. The estimates are even stronger than the ADH estimates, which therefore implies a net reduction of 1.88 million workers in manufacturing, a reduction of 0.478 million workers and 2.36 million workers in total. Controlling for housing price changes, however, changed the results. Panel III shows that although Chinese import exposure caused a reduction in manufacturing employment by 1.61 million workers, it also caused an *increase* in nonmanufacturing employment by 0.49 millions. Thus the net reduction in total U.S. employment due to rising Chinese import exposure was about 1.13 million workers, or less than one-half of that implied by the estimates without controlling housing. This striking contrast comes mainly from the different response from the nonmanufacturing sector. In particular, rising Chinese import exposure led to a reduction in noncollege nonmanufacturing jobs (0.07 millions), whereas it increased employment for college nonmanufacturing workers by 0.65 millions.

Panel IV performs the calculation based on estimates that shut down the endogenous responses of housing to import shock. Controlling the indirect effects magnified by the housing market, we still find that Chinese import exposure caused an *increase* in nonmanufacturing employment by 0.06 millions, and the net reduction in total employment was 1.65 millions, still about 30% less than that implied by the estimates without controlling housing. Again, this comes mainly from the *increase* of employment in nonmanufacturing sectors for college workers.

[Table 10 here]

4 Robustness Check

4.1 Effects on Wages

In Table 11, we consider the impact of import exposure on average weekly wage of U.S. workers. Similar to the employment regressions, we first replicate the results of ADH (2013, Table 6), while Panel II uses the matched sample of 249 commuting zones with information on both structural break and supply elasticity (similar to our Table 4).[13] Both panels show a significant negative effect of import exposure on the average wages of workers within commuting zones . Such negative effects mainly show up for non-manufacturing workers, while the effect on manufacturing workers' wages is positive but not significant. The same pattern holds when we separately look at college and noncollege workers. But when we control housing price in panels III and IV, the depressing effects of import exposure on total wage and non-manufacturing wages are reduced substantially. Panel III controls housing using the TSLS estimation with structural break and elasticity as the instruments. In this panel, the estimated effect of import exposure on total wages decreases by more than half (69%), and become insignificant. The same is true for college workers. For noncollege workers, the effect on wages become even positive, though not significant. Panel IV controls housing using the reduced-form estimation which shuts down the endogenous response of housing to instruments. Again, the estimated effect of import exposure on wages is reduced (by 39%).

[Table 11 here]

[13] We only report the results with two instruments. Results from using each instrument separately are similar and are available upon request.

4.2 Housing Boom and Bust

In the previous section, we follow ADH and stack the differences for the two periods (i.e. 1990-2000 and 2000-2007). Imports from China started to accelerate after 2001, when China gained accession into the WTO. Before 2001, the share of US imports from China increased by about 0.5 percentage point annually, while after 2001 that share grew by 1.2 percentage points per year. Import penetration by China (i.e. imports from China as a share of total US expenditure) increased by 0.14 percentage points per year before 2001 and then by 0.38 percentage points after 2001. At the same time, the U.S. national housing boom and busts lasted mainly from the late 1990s to the late 2000s. Figure 4 shows the U.S. national housing price index from 1990 to 2015. It shows a housing boom starting from the late 1990s and then bust around 2006 till 2011. Therefore, in this section, we explore looking at an alternative sample that stacks the housing boom and bust periods: 2000-2007 and 2007-2011.

[Figure 4 here]

We follow closely ADH to construct the trade and employment data in 2011 and annualize the changes over two periods before stacking them. We construct two instruments, i.e., the structural break and supply elasticity, as in section 2.2. Table 11 reports the estimated results. Panel I considers the ADH regression without housing. We find that over the alternative period 2000-2011, some findings of ADH have already changed, even without controlling for housing. Panel I shows that the China shock still has a negative effect on U.S. manufacturing employment. However, it also has a significantly positive effect on non-manufacturing employment, which offsets the negative effect on manufacturing employment and makes the effect on total employment positive.

The same is true when we distinguish college and non-college education levels. Panels II and III go further to control for housing in the employment regression. We report the estimation results using two instruments.[14] Panel II performs TSLS estimation and Panel III performs reduced form estimation. Both show that controlling for housing reduces the estimated effect of the China shock on US employment. The reduction in the effect of import exposure is about 12-14% for manufacturing employment, 20-22% for nonmanufacturing employment, and 31-38% for total

[14]Results from using each instrument separately are similar and are available upon request.

employment, when performing TSLS estimation directly. When shutting down the endogenous responses of housing, the reduction in the effect on manufacturing, nonmanufacturing and total employment is still about 4-7%, 15-22%, and 26-49%. Therefore, the fact that the domestic housing market is creating jobs during booms and losing jobs during busts cannot be neglected when estimating the effect of outside China shock. Otherwise, estimates on the China shock would be overstated.

[Table 12 here]

4.3 Inference Correction to Shift-Share Instrument

One concern raised by the very recent literature is that usual inference to a shift-share (or ”Bartik”) instrument may substantially understate the true variability of the estimator. For example, Adao, Kolesar and Morales (2019, AKM hereafter) conduct a placebo exercise and find that hypothesis tests based on usual standard errors tend to over-reject the null of no effect, because regression residuals could be correlated across regions with similar sectoral shares, independently of their geographic location. They then derive a new inference method to take into account cross-region correlation and find that it would increase the standard error of the estimated impact of China shock in the ADH application.[15]

In Table 13, we apply the AKM method to our estimation. Since the AKM procedure is only designed to correct the standard error for the shift-share instrument, (i.e., the China shock instrument), we can only apply it to our case of the reduced form regression with housing as an additional control. To have a comparison, we start with the ADH regression without housing. Panel I uses the ADH sample of 722 commuting zones. Clustered SE are the usual standard error that clusters commuting zones in the same state. Hypothesis tests based on clustered SE are indicated along with the estimated coefficients. These can also be found in ADH Table 5 Panel B and our Table 2 Panel I. In contrast, the AKM SE are the standard errors calculated by applying AKM method. The results shows that the AKM standard errors (and therefore the corresponding confidence intervals) are much wider than the clustered standard errors. Although the significance of the estimated co-

[15] Similar arguments are discussed in Borusyak, Hull and Jaravel (2018), in which they propose a transformation of commuting zone regression to weighted sector regression.

efficient remains valid, the uncertainty regarding the magnitude of the estimated impact is greater than that implied by usual inference procedures.

Panel II of Table 13 does the same ADH regression, but uses a subsample of 249 commuting zones that have housing information. The estimation results and the clustered standard errors can also be found in our Table 4 Panel I. In this case, the AKM standard errors are substantially larger than the clustered standard errors, and the estimated effects of China shock on U.S. labor market outcomes are not statistically significant anymore. This might be related to the fact that the this subsample of 249 commuting zones are mainly metropolitan areas, for which the cross-region correlations of the regression residuals are much higher than those in the rural areas. Panel III uses the same sample as in Panel II, but adds the predicted housing variable as an additional control. Now, on the one hand, housing reduces the magnitude of the estimated impact of the China shock (see also our Table 8); on the other hand, AKM inference increases the standard errors substantially, such that all the estimated effects of the China shock are not significant.

[Table 13 here]

5 Conclusion

The rapid growth in imports from China has been found to be responsible for the great US employment sag by several studies (ADH, 2013, Acemoglu et al, 2016, Pierce and Schott, 2016). ADH (2013) show in their influential work that rising exposure to imports from China led to a reduction of about 1.5 million manufacturing jobs, with a further 0.5 million jobs lost outside the manufacturing sector or roughly 2 million lost jobs in total.

In this paper, we re-estimate the empirical results and propose one reason for the strong impact of the 'China shock' on U.S. labor market, which is the housing market in the United States. We find that the employment effect of the China shock operated in part through the housing market. If housing prices had not responded at all to the China shock, then the total employment effect of the China shock would have been reduced by more than one-half. Housing prices in the United States did respond to the China shock, however, so the independent employment effect of the China shock is reduced by about 30%, with that remainder reflecting exogenous changes in housing prices.

Differing results are also found across sectors and education levels. Noncollege workers in the manufacturing sector continue to experience a reduction in employment, but that reduction does not occur in the nonmanufacturing sector. For college workers, their employment in the nonmanufacturing sector even rises significantly with import exposure from China. This is a surprising finding because we have not calculated the employment gains due to increased US *exports* to China, but rather, we continue to work with the exposure to Chinese *imports* as proposed by ADH. Of course, for general equilibrium reasons, resources that are freed up due to import competition can be expected to be re-employed, with some lag, into export (or domestic) activities (see Feenstra, Ma and Xu, 2019). The data from ADH also suggest that some employment opportunities in the nonmanufacturing sector were created by the China shock, and exploring this topic is an important direction for further research.

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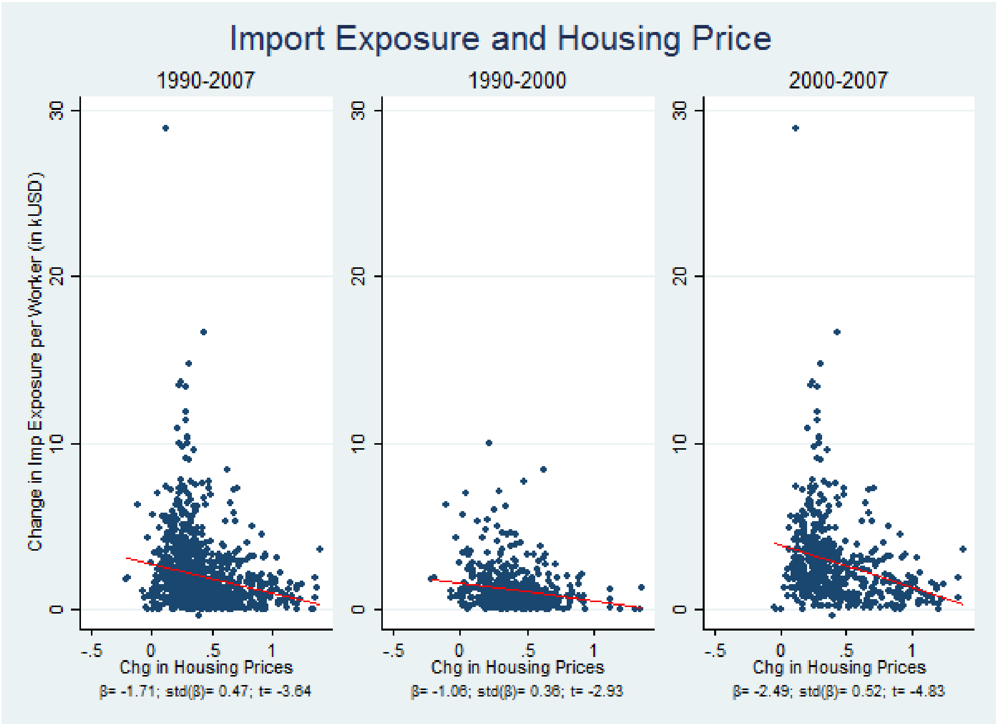
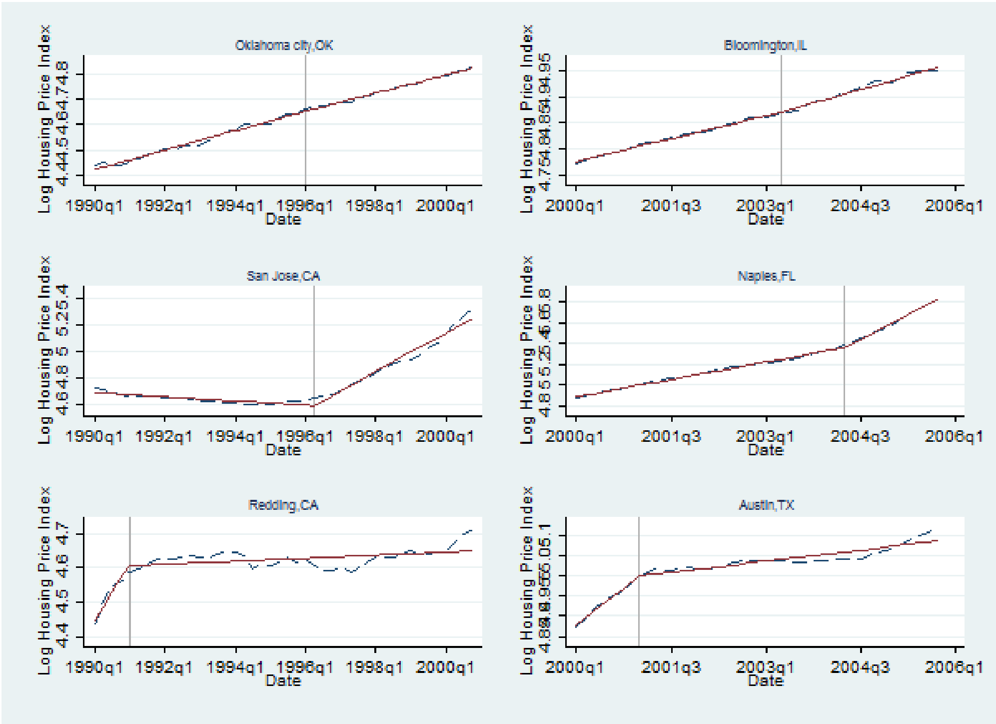
Figure 1: Correlation of import exposure and housing price changes



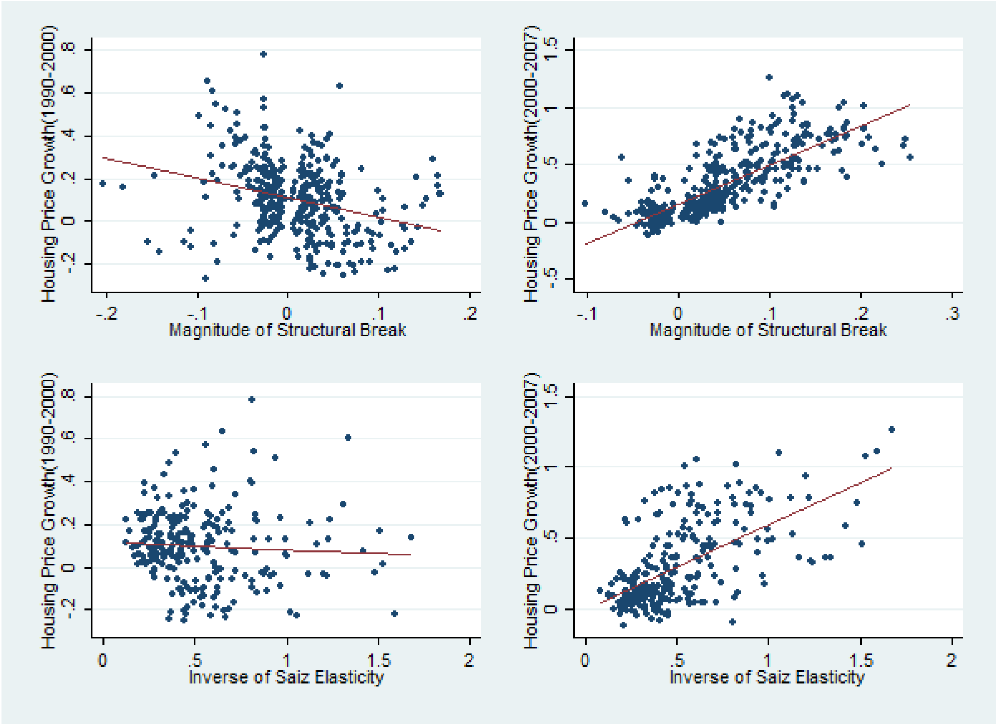
Note: This figure shows the correlation between changes in import exposure and changes in housing price index at the commuting zones.

Figure 2: Structural Breaks Across MSAs



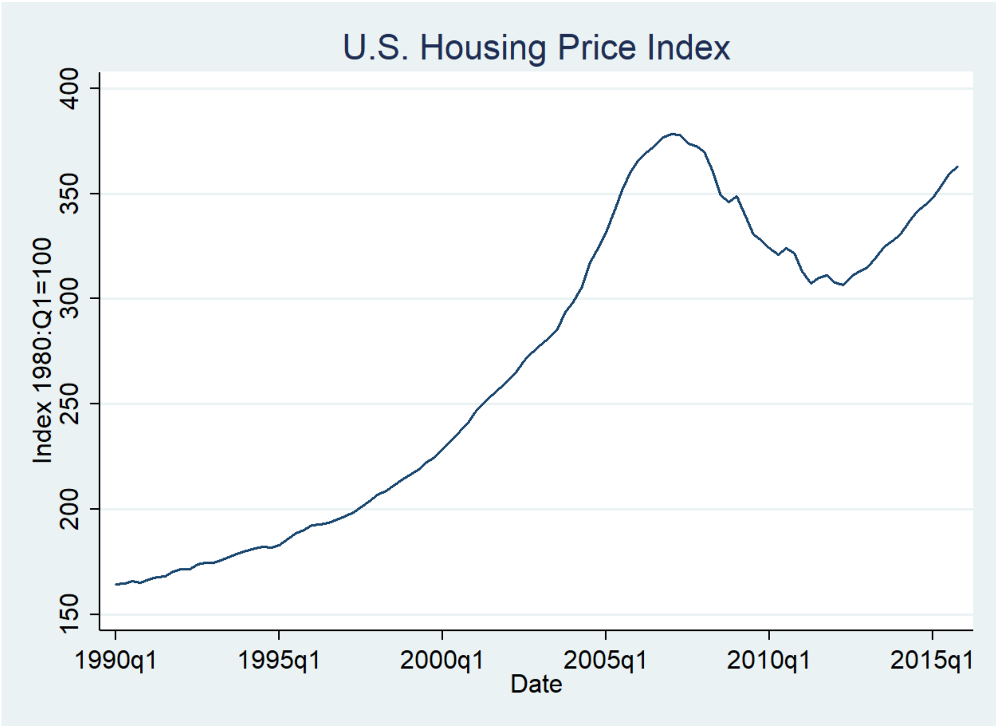
Note: This figure plots the quarterly housing price data for selective MSAs. The dashed line is the quarterly log housing price index. The solid red line is the estimated linear trend. The vertical grey line is the estimated break date that can maximize the R^2 of equation (3).

Figure 3: Correlation of housing price change and its IVs



Note: The first row of the figure plots the correlation between housing price change and the estimated structural break instrument. The second row plots the correlation between housing price change and the Saiz Elasticity instrument.

Figure 4: U.S. National Housing Price Index



Source: U.S. Federal Housing Finance Agency.

Table 1: Summary Statistics

Variable	Obs	Mean	Std.Dev
ADH Sample (722 CZ)			
Δ Imports from China/workers	1444	1.884	1.752
Δ manuf. employment/working-age pop	1444	-2.401	1.746
Δ non-manuf. employment/working-age pop	1444	2.496	2.819
Matched Sample with Structural Break IV data (291 CZ, Pop Share=90%)			
Δ Imports from China/workers	582	1.837	1.609
Δ manuf. employment/working-age pop	582	-2.460	1.601
Δ non-manuf. employment/working-age pop	582	2.448	2.819
Matched Sample with Supply Elasticity IV data (250 CZ, Pop Share=85%)			
Δ Imports from China/workers	500	1.835	1.597
Δ manuf. employment/working-age pop	500	-2.481	1.566
Δ non-manuf. employment/working-age pop	500	2.444	2.835

Note: ADH sample (N = 1,444 = 722 commuting zones $\times$ 2 time periods) is adopted from the data in ADH (2013). The matched sample includes commuting zones that have information on housing price and the corresponding instruments. We keep the sample balanced over two periods.

Table 2: Imports from China and US Employment: TSLS with Structural Break

Dependent variables: Changes in population shares by employment status

	(1) Mfg emp	(2) Non-mfg emp	(3) Total Emp	(4) Unemp	(5) NILF
Panel I: ADH Sample, 722 CZ					
All education levels					
(Δ imports from China) /worker	-0.596***	-0.178	-0.774***	0.221***	0.553***
	(0.099)	(0.137)	(0.176)	(0.058)	(0.150)
College education					
(Δ imports from China) /worker	-0.592***	0.168	-0.424***	0.119***	0.304***
	(0.125)	(0.122)	(0.123)	(0.039)	(0.113)
No college education					
(Δ imports from China) /worker	-0.581***	-0.531***	-1.112***	0.282***	0.831***
	(0.095)	(0.203)	(0.252)	(0.085)	(0.211)
Panel II: Matched Sample, 291 CZ					
All education levels					
(Δ imports from China) /worker	-0.705***	-0.218	-0.923***	0.278***	0.646***
	(0.103)	(0.215)	(0.252)	(0.073)	(0.227)
College education					
(Δ imports from China) /worker	-0.704***	0.202	-0.502***	0.173***	0.329**
	(0.147)	(0.169)	(0.176)	(0.048)	(0.159)
No college education					
(Δ imports from China) /worker	-0.686***	-0.624**	-1.310***	0.330***	0.979***
	(0.108)	(0.310)	(0.364)	(0.115)	(0.322)
Panel III: Matched Sample, controlling housing with Structural Break IV					
All education levels					
(Δ imports from China)/worker	-0.595***	0.165	-0.430	0.189***	0.241
	(0.093)	(0.257)	(0.272)	(0.073)	(0.259)
Δ housing price index	1.550***	5.403***	6.953***	-1.243**	-5.710***
	0.480)	(1.202)	(1.549)	(0.510)	(1.255)
College education					
(Δ imports from China)/worker	-0.595***	0.451***	-0.145	0.113**	0.032
	(0.143)	(0.174)	(0.170)	(0.051)	(0.155)
Δ housing price index	1.534***	3.504***	5.037***	-0.845**	-4.192***
	0.495)	(0.348)	(0.600)	(0.364)	(0.446)
No college education					
(Δ imports from China)/worker	-0.557***	-0.082	-0.640	0.208*	0.431
	(0.105)	(0.377)	(0.421)	(0.115)	(0.393)
Δ housing price index	1.815***	7.634***	9.449***	-1.720**	-7.729***
	(0.562)	(2.151)	(2.573)	(0.710)	(2.105)
Reduction in Estimated Import Coefficient Magnitude					
All education levels	16%	/	53%	32%	63%
College education	15%	/	71%	35%	90%
No College education	19%	87%	51%	37%	56%

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We match the 350 MSAs that have quarterly housing price information to the commuting zone level and obtain 321 commuting zones during 2000-2007 and 291 commuting zones during 1990-2000. We keep the sample balanced at 291 commuting zones over both periods. The housing price variable is instrumented by the estimated structural break illustrated in section 2.2. All regressions include the full vector of controls and weight in ADH, that is, a dummy for the 2000-2007 period, a set of census division dummies, and the start of period economic and demographic conditions, including percentage of employment in manufacturing, percentage of college-educated population, percentage of foreign-born population, percentage of employment among women, percentage of employment in routine occupations, and finally average offshorability index of occupations. All regressions are weighted by start of period commuting zone's share of national population.

Table 3: Imports from China and US Employment: TSLS with Supply Elasticity

Dependent variables: Changes in population shares by employment status

	(1) Mfg emp	(2) Non-mfg emp	(3) Total Emp	(4) Unemp	(5) NILF
Panel I: Matched Sample, 250 CZ					
All education levels					
(Δ imports from China) /worker	-0.733***	-0.187	-0.919***	0.266***	0.653***
	(0.109)	(0.233)	(0.275)	(0.078)	(0.246)
College education					
(Δ imports from China) /worker	-0.744***	0.225	-0.519***	0.146***	0.373**
	(0.150)	(0.179)	(0.196)	(0.051)	(0.178)
No college education					
(Δ imports from China) /worker	-0.700***	-0.590*	-1.289***	0.335***	0.954***
	(0.119)	(0.335)	(0.389)	(0.120)	(0.340)
Panel II: Matched Sample, controlling housing with Supply Elasticity IV					
All education levels					
(Δ imports from China)/worker	-0.568***	0.245	-0.323	0.183**	0.140
	(0.098)	(0.264)	(0.286)	(0.073)	(0.283)
Δ housing price index	2.322***	6.090***	8.412***	-1.172**	-7.240***
	(0.575)	(1.331)	(1.683)	(0.565)	(1.395)
College education					
(Δ imports from China)/worker	-0.566***	0.457**	-0.109	0.117**	-0.008
	(0.147)	(0.189)	(0.182)	(0.054)	(0.178)
Δ housing price index	2.509***	3.271***	5.781***	-0.411	-5.369***
	(0.588)	(0.731)	(0.782)	(0.388)	(0.746)
No college education					
(Δ imports from China)/worker	-0.521***	0.111	-0.410	0.179	0.231
	(0.108)	(0.386)	(0.435)	(0.119)	(0.415)
Δ housing price index	2.524***	9.889***	12.413***	-2.201**	-10.211***
	(0.674)	(2.071)	(2.528)	(0.861)	(2.067)
Reduction in Estimated Import Coefficient Magnitude					
All education levels	23%	/	65%	31 %	79 %
College education	24%	/	79%	20 %	/
No College education	26%	/	68%	47 %	76 %

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We match the 262 MSAs that have information on Saiz's supply elasticity to the commuting zone level and obtain 250 commuting zones over 1990-2000 and 2000-2007. Thank Albert Saiz for providing the data. All regressions include the full vector of controls and weight in ADH.

Table 4: Imports from China and US Employment: TSLS with Both

Dependent variables: Changes in population shares by employment status

	(1) Mfg emp	(2) Non-mfg emp	(3) Total Emp	(4) Unemp	(5) NILF
Panel I: Matched Sample, 249 CZ					
All education levels					
(Δ imports from China)/worker	-0.733***	-0.186	-0.919***	0.266***	0.653***
	(0.109)	(0.233)	(0.275)	(0.078)	(0.247)
College education					
(Δ imports from China)/worker	-0.744***	0.225	-0.519***	0.146***	0.373**
	(0.150)	(0.179)	(0.196)	(0.051)	(0.178)
No college education					
(Δ imports from China)/worker	-0.699***	-0.588*	-1.288***	0.335***	0.953***
	(0.119)	(0.335)	(0.389)	(0.120)	(0.340)
Panel II: Matched Sample, controlling housing with both IVs					
All education levels					
(Δ imports from China)/worker	-0.628***	0.189	-0.439	0.175**	0.264
	(0.104)	(0.269)	(0.293)	(0.078)	(0.278)
Δ housing price index	1.662***	5.467***	7.129***	-1.255***	-5.873***
	(0.425)	(1.032)	(1.351)	(0.430)	(1.113)
Hansen J p-value	0.13	0.42	0.18	0.85	0.10
College education					
(Δ imports from China)/worker	-0.644***	0.469***	-0.175	0.085	0.091
	(0.149)	(0.178)	(0.190)	(0.053)	(0.178)
Δ housing price index	1.651***	3.399***	5.049***	-0.764***	-4.285***
	(0.435)	(0.361)	(0.526)	(0.296)	(0.414)
Hansen J p-value	0.09	0.79	0.23	0.25	0.07
No college education					
(Δ imports from China)/worker	-0.574***	-0.061	-0.635	0.210*	0.425
	(0.114)	(0.399)	(0.441)	(0.123) (0.408)	
Δ housing price index	1.937***	7.974***	9.911***	-1.860***	-8.050***
	(0.489)	(1.855)	(2.217)	0.606)	(1.844)
Hansen J p-value	0.22	0.10	0.07	0.56	0.06
Reduction in Estimated Import Coefficient Magnitude					
All education levels	14%	/	52%	34%	60%
College education	13%	/	66%	42%	76%
No College education	18%	90%	51%	37%	55%

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. In this table, we use both structural break and supply elasticity as instruments for housing price change, which leads to 249 commuting zones over 1990-2000 and 2000-2007. Hansen J p-values for over-identification test are also reported. All regressions include the full vector of controls and weight in ADH.

Table 5: First Stage Results for Different Instruments

	(1) (Δ imports from China)/worker	(2) Δ housing price index
Panel I: Table 2 Structural Break IV		
(Δ Other's imports from China) /worker	0.570***	-0.023**
	(0.096)	(0.010)
Structural break in housing price	-0.644	3.014**
	(1.196)	(0.225)
First Stage F Statistics	17.71	90.71
Kleibergen-Paap Wald F Statistics	16.03	
Stock-Yogo Critical Values: 10% Maximal IV size	7.03	
Stock-Yogo Critical Values: 15% Maximal IV size	4.58	
Stock-Yogo Critical Values: 20% Maximal IV size	3.95	
Panel II: Table 3 Elasticity IV		
(Δ Other's imports from China) /worker	0.567***	-0.027**
	(0.105)	(0.012)
Supply Elasticity	0.045	-0.124***
	(0.066)	(0.026)
First Stage F Statistics	16.11	14.37
Kleibergen-Paap Wald F Statistics	10.37	
Stock-Yogo Critical Values: 10% Maximal IV size	7.03	
Stock-Yogo Critical Values: 15% Maximal IV size	4.58	
Stock-Yogo Critical Values: 20% Maximal IV size	3.95	
Panel III: Table 4 Both IV		
(Δ Other's imports from China) /worker	0.568***	-0.018*
	(0.104)	(0.011)
Structural break in housing price	0.192	2.688***
	(1.004)	(0.246)
Supply Elasticity	0.050	-0.057***
	(0.066)	(0.015)
First Stage F Statistics	11.98	90.41
Kleibergen-Paap Wald F Statistics	9.983	
Stock-Yogo Critical Values: 10% Maximal IV size	13.43	
Stock-Yogo Critical Values: 15% Maximal IV size	8.18	
Stock-Yogo Critical Values: 20% Maximal IV size	6.40	
Stock-Yogo Critical Values: 25% Maximal IV size	5.45	

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the first-stage results for Tables2, 3 and 4. Individual F statistics and joint Kleibergen-Paap Wald F statistics are reported. Stock-Yogo critical values for different number of endogenous variables (n), number of instrumental variables (k) and desired maximal size (r) at 5% significance level are also reported.

Table 6: Imports from China and US Employment: Predicted Housing using Structural Break

	(1) Mfg emp	(2) Non-mfg emp	(3) Total Emp	(4) Unemp	(5) NILF
Matched Sample, 291 CZ					
All education levels					
Δ imports from China)/worker	-0.658***	-0.055	-0.713***	0.240***	0.473**
	(0.102)	(0.187)	(0.214)	(0.075)	(0.194)
Δ housing price Predicted	1.536***	5.356***	6.892***	-1.232**	-5.661***
	(0.542)	(1.277)	(1.712)	(0.538)	(1.366)
College education					
Δ imports from China)/worker	-0.658***	0.308**	-0.350**	0.147***	0.202
	(0.150)	(0.143)	(0.152)	(0.050)	(0.134)
Δ housing price Predicted	1.520***	3.473***	4.994***	-0.838**	-4.156***
	(0.559)	(0.393)	(0.799)	(0.387)	(0.578)
No college education					
(Δ imports from China)/worker	-0.631***	-0.393	-1.024***	0.278**	0.745***
	(0.100)	(0.278)	(0.313)	(0.114)	(0.283)
Δ housing price Predicted	1.799***	7.568***	9.367***	-1.705**	-7.662***
	(0.620)	(2.254)	(2.749)	(0.742)	(2.229)
Reduction in Estimated Import Coefficient Magnitude					
Comparing with Table 2 Panel II:					
All education levels	7%	75%	23%	14%	27%
College education	7%	/	30%	15%	39%
No College education	8%	37%	22%	16%	24%

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We run the same first-stage regression as in Table 2, but computed the predicted housing price change using ONLY the instrumental variable, i.e., the structural break term. The calculated predicted housing price change is then used as an additional control variable in the second-stage employment share regressions, together with all other controls in ADH.

Table 7: Imports from China and US Employment: Predicted Housing using Supply Elasticity

	(1) Mfg emp	(2) Non-mfg emp	(3) Total Emp	(4) Unemp	(5) NILF
Matched Sample, 250 CZ					
All education levels					
(Δ imports from China)/worker	-0.677***	-0.041	-0.718***	0.238***	0.480**
	(0.101)	(0.220)	(0.245)	(0.075)	(0.227)
Δ housing price Predicted	2.282***	5.986***	8.268***	-1.152*	-7.116***
	(0.778)	(2.126)	(2.767)	(0.633)	(2.354)
College education					
(Δ imports from China)/worker	-0.684***	0.303*	-0.380**	0.136***	0.244
	(0.143)	(0.180)	(0.179)	(0.052)	(0.161)
Δ housing price Predicted	2.466***	3.215***	5.681***	-0.404	-5.277***
	(0.826)	(1.102)	(1.621)	(0.429)	(1.386)
No college education					
(Δ imports from China)/worker	-0.639***	-0.354	-0.993***	0.283**	0.710**
	(0.113)	(0.304)	(0.350)	(0.115)	(0.321)
Δ housing price Predicted	2.480***	9.719***	12.200***	-2.164**	-10.036***
	(0.864)	(3.223)	(3.940)	(0.924)	(3.343)
Reduction in Estimated Import Coefficient Magnitude					
Comparing with Table 3 Panel I:					
All education levels	8%	78%	22%	11%	26%
College education	8%	/	27%	7%	35%
No College education	9%	40%	23%	16%	26%

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We run the same first-stage regression as in Table 3, but computed the predicted housing price change using ONLY the instrumental variable, i.e., the supply elasticity term. The calculated predicted housing price change is then used as an additional control variable in the second-stage employment share regressions, together with all other controls in ADH.

Table 8: Imports from China and US Employment: Predicted Housing using Both

	(1) Mfg emp	(2) Non-mfg emp	(3) Total Emp	(4) Unemp	(5) NILF
Matched Sample, 249 CZ					
All education levels					
(Δ imports from China)/worker	-0.668***	0.025	-0.643***	0.217***	0.426**
	(0.107)	(0.196)	(0.222)	(0.080)	(0.203)
Δ housing price Predicted	1.666***	5.454***	7.120***	-1.248***	-5.871***
	(0.477)	(1.190)	(1.578)	(0.456)	(1.292)
College education					
(Δ imports from China)/worker	-0.680***	0.357**	-0.324**	0.116**	0.207
	(0.152)	(0.151)	(0.164)	(0.054)	(0.145)
Δ housing price Predicted	1.658***	3.382***	5.040***	-0.755**	-4.284***
	(0.485)	(0.439)	(0.721)	(0.314)	(0.556)
No college education					
(Δ imports from China)/worker	-0.624***	-0.279	-0.903***	0.262**	0.641**
	(0.106)	(0.290)	(0.316)	(0.121)	(0.286)
Δ housing price Predicted	1.938***	7.972***	9.910***	-1.858***	-8.052***
	(0.545)	(2.055)	(2.489)	(0.638)	(2.063)
Reduction in Estimated Import Coefficient Magnitude					
Comparing with Table 4 Panel I:					
All education levels	9%	/	30%	18%	35%
College education	9%	/	38%	21%	45%
No College education	11%	53%	30%	22%	33%

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We run the same first-stage regression as in Table 4, but computed the predicted housing price change using ONLY the two instruments, i.e., the structural break and the supply elasticity terms. The calculated predicted housing price change is then used as an additional control variable in the second-stage employment share regressions, together with all other controls in ADH.

Table 9: Imports from China and US Employment: Reduced From Regression

	(1) Mfg emp	(2) Non-mfg emp	(3) Total Emp	(4) Unemp	(5) NILF
Panel I: Reduced Form without Housing					
All education levels					
Δ Other's imports from China)/worker	-0.405***	-0.125	-0.530***	0.159***	0.370***
	(0.047)	(0.120)	(0.114)	(0.034)	(0.115)
College education					
Δ Other's imports from China)/worker	-0.404***	0.116	-0.288***	0.099***	0.189**
	(0.059)	(0.099)	(0.090)	(0.029)	(0.083)
No college education					
Δ Other's imports from China)/worker	-0.393***	-0.358**	-0.751***	0.189***	0.562***
	(0.074)	(0.155)	(0.172)	(0.052)	(0.171)
Panel II: Reduced Form with Housing					
All education levels					
Δ Other's imports from China)/worker	-0.375***	0.018	-0.357***	0.124***	0.233**
	(0.051)	(0.115)	(0.100)	(0.039)	(0.105)
Structural break in housing price	2.865**	13.316***	16.181***	-3.504**	-12.677***
	(1.377)	(3.369)	(4.022)	(1.614)	(3.110)
Supply Elasticity	-0.242***	-0.412**	-0.654**	0.067	0.587
	(0.079)	(0.204)	(0.256)	(0.079)	(0.217)
College education					
Δ Other's imports from China)/worker	-0.381***	0.202**	-0.179**	0.068**	0.111
	(0.057)	(0.090)	(0.082)	(0.031)	(0.075)
Structural break in housing price	2.397	9.519***	11.916***	-2.804**	-9.111***
	(1.555)	(1.397)	(2.389)	(1.319)	(1.565)
Supply Elasticity	-0.277***	-0.146	-0.423**	-0.013	0.435***
	(0.099)	(0.122)	(0.169)	(0.056)	(0.150)
No college education					
Δ Other's imports from China)/worker	-0.351***	-0.146	-0.497***	0.147**	0.350**
	(0.076)	(0.154)	(0.150)	(0.057)	(0.157)
Structural break in housing price	3.769**	17.104***	20.872***	-4.174*	-16.699***
	(1.595)	(5.565)	(6.359)	(2.149)	(5.156)
Supply Elasticity	-0.243***	-0.795***	-1.038***	0.178	0.860***
	(0.080)	(0.288)	(0.342)	(0.119)	(0.282)
Reduction in Estimated Import Coefficient Magnitude					
All education levels	7 %	/	33%	22%	37%
College education	6 %	/	38%	31%	41%
No College education	11 %	59%	34%	22%	38%

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We perform reduced form regressions in this table. Panel I considers no housing and replaces the endogenous US imports from China with its instrument, i,e., other countries' imports from China. Panel II considers housing and replaces it using its two instruments, i.e., structural break and supply elasticity. All other variables included in the regressions are the same as before.

Table 10: Predicted Employment Changes (Millions workers, 1990-2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Education			College Education			No College Education	
	Manuf.	Non-manuf.	Total	Manuf.	Non-manuf.	Total	Manuf.	Non-manuf.	Total
Panel I: ADH Sample, 722 CZ									
Predicted Changes	-1.530	-0.457	-1.987	-0.820	0.233	-0.587	-0.687	-0.628	-1.315
Panel II: Matched Sample, 249 CZ									
Predicted Changes	-1.882	-0.478	-2.359	-1.030	0.311	-0.718	-0.827	-0.696	-1.524
Panel III: Matched Sample, with Break and Elasticity IVs									
Predicted Changes	-1.612	0.485	-1.127	-0.892	0.649	-0.242	-0.627	-0.072	-0.751
Panel IV: Matched Sample, Predicted Housing using Break and Elasticity									
Predicted Changes	-1.715	0.064	-1.651	-0.941	0.494	-0.449	-0.738	-0.330	-1.068

Note: This table reports the predicted employment changes (millions of workers) based on the corresponding estimates from ADH sample (Table 2 panel I), the matched sample with information on both housing structural break and supply elasticity (Table 4 Panel I), the matched sample controlling housing using TSLS estimation with both IVs (Table 4 Panel II), and the matched sample controlling housing using reduced form estimation with housing predicted by both IVs (Table 8). A negative sign means a decrease of employment whereas a positive sign means an increase of employment. The details of calculation are explained in the Appendix.

Table 11: Imports from China and U.S. Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Education			College Education			No College Education	
	Manuf.	Non-manuf.	Total	Manuf.	Non-manuf.	Total	Manuf.	Non-manuf.	Total
Panel I: ADH Sample, 722 CZ									
(Δ imports from China)/worker	0.151	-0.761***	-0.759***	0.458	-0.743**	-0.757**	-0.101	-0.822***	-0.814***
	(0.482)	(0.261)	(0.253)	(0.340)	(0.297)	(0.308)	(0.369)	(0.246)	(0.236)
Panel II: Matched Sample, 249 CZ									
(Δ imports from China)/worker	0.077	-0.932**	-0.947**	0.560	-1.117**	-1.116**	-0.243	-0.648	-0.734*
	(0.734)	(0.418)	(0.394)	(0.475)	(0.451)	(0.450)	(0.581)	(0.430)	(0.412)
Panel III: Matched Sample, with Break and Elasticity IVs									
(Δ imports from China)/worker	0.566	-0.233	-0.289	0.814*	-0.508	-0.550	0.578	0.386	0.258
	(0.773)	(0.341)	(0.362)	(0.468)	(0.407)	(0.439)	(0.664)	(0.432)	(0.435)
Δ housing price index	9.008***	9.735***	9.432***	5.200***	8.543***	8.136***	12.714***	14.518***	14.172***
	(1.570)	(1.145)	(1.188)	(1.399)	(1.337)	(1.415)	(1.894)	(1.301)	(1.382)
Reduction in Coefficient	/	75%	69%	/	55%	51%	/	/	/
Panel IV: Matched Sample, Predicted Housing using Break and Elasticity									
(Δ imports from China)/worker	0.430	-0.556*	-0.582*	0.765*	-0.788**	-0.801**	0.251	-0.087	-0.186
	(0.672)	(0.306)	(0.314)	(0.432)	(0.366)	(0.391)	(0.507)	(0.300)	(0.301)
Δ housing price Predicted	9.098***	9.685***	9.401***	5.277***	8.503***	8.110***	12.728***	14.451***	14.121***
	(1.688)	(1.290)	(1.355)	(1.368)	(1.400)	(1.474)	(2.277)	(1.708)	(1.825)
Reduction in Coefficient	/	40%	39%	/	29%	28%	/	87%	75%

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We perform the same regression as in the employment regressions but with the dependent variable being the average weekly wages for U.S. workers. Panel I uses the ADH 722 commuting zones. Panel II uses the matched sample with information on structural break and supply elasticity, which leads to 249 commuting zones. Panel III uses the same sample as in panel II and controls housing using TSLS estimation. Panel IV uses the reduced-form estimation. All other variables included in the regressions are the same as before.

Table 12: Housing Boom and Bust (2000-2011)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Education			College Education			No College Education		
	Manuf.	Non-manuf.	Total	Manuf.	Non-manuf.	Total	Manuf.	Non-manuf.	Total
Panel I: Boom and Bust Sample, 2000-2011									
(Δ imports from China)/worker	-0.473***	0.757**	0.283	-0.349**	0.609**	0.260	-0.503**	0.812	0.309
	(0.168)	(0.370)	(0.436)	(0.167)	(0.275)	(0.289)	(0.225)	(0.517)	(0.585)
Panel II: Boom and Bust Sample, with Break and Elasticity IVs									
(Δ imports from China)/worker	-0.415**	0.609**	0.195	-0.299	0.477**	0.177	-0.443	0.635	0.192
	(0.210)	(0.252)	(0.359)	(0.194)	(0.206)	(0.245)	(0.276)	(0.395)	(0.456)
Δ housing price index	-0.739	4.011***	3.271***	-0.770*	2.994***	2.224***	-0.763	5.966***	5.203***
	(0.570)	(0.736)	(0.843)	(0.427)	(0.604)	(0.699)	(0.951)	(1.230)	(1.207)
Reduction in Coefficient	12%	20%	31%	14%	22%	32%	12%	22%	38%
Panel III: Boom and Bust Sample, Predicted Housing using Break and Elasticity									
(Δ imports from China)/worker	-0.452**	0.635*	0.183	-0.326*	0.519**	0.192	-0.481**	0.630	0.149
	(0.177)	(0.334)	(0.417)	(0.173)	(0.256)	(0.277)	(0.238)	(0.475)	(0.554)
Δ housing price Predicted	-0.710	4.024***	3.314***	-0.751**	2.982***	2.231**	-0.733	6.028***	5.295***
	(0.503)	(0.967)	(1.117)	(0.374)	(0.869)	(0.929)	(0.885)	(1.266)	(1.460)
Reduction in Coefficient	4%	16%	35%	7%	15%	26%	4%	22%	49%

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We perform similar analysis as before but on alternative sample periods. This sample covers two stacked periods 2000-2007 (housing boom) and 2007-2011 (housing bust). Each period is annualized. Panel I considers no housing. Panel II performs TSLS estimation with structural break and elasticity as instruments. Panel III performs reduced-form estimation using structural break and elasticity to construct predicted housing. All other variables included in the regressions are the same as before.

Table 13: AKM Inference Method (Adao, Kolesar abd Morales, 2019)

	(1)	(2)	(3)	(4)	(5)
	Mfg emp	Non-mfg emp	Total Emp	Unemp	NILF
Panel I: ADH Sample, 722 CZ					
(Δ imports from China) /worker	-0.596***	-0.178	-0.774***	0.221***	0.553***
Cluster SE	(0.099)	(0.137)	(0.176)	(0.058)	(0.150)
AKM SE	(0.126)	(0.184)	(0.240)	(0.068)	(0.208)
Panel II: Matched Sample, 249 CZ					
(Δ imports from China) /worker	-0.733***	-0.186	-0.919***	0.266***	0.653***
Cluster SE	(0.109)	(0.233)	(0.275)	(0.078)	(0.247)
AKM SE	(0.607)	(1.208)	(1.549)	(0.562)	(1.196)
Panel III: Matched Sample, with Predicted Housing using both IVs					
(Δ imports from China)/worker	-0.668***	0.025	-0.643***	0.217***	0.426**
Cluster SE	(0.107)	(0.196)	(0.222)	(0.080)	(0.203)
AKM SE	(0.480)	(0.850)	(1.028)	(0.463)	(0.751)

Note: AKM SE is the standard error calculated using the inference method proposed by Adao, Kolesar abd Morales(2019). Cluster SE is the standard error that clusters of CZs in the same state. Reported * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ are based on the cluster SE. Panel I uses the ADH sample with 722 CZs without controlling housing (see also Table 2 Panel I). Panel II and III use a matched sample with 249 CZs that have information on both housing structural break and supply elasticity. Panel II performs the estimation without controlling housing (see also Table 4 Panel I). Panel III controls housing by using the predicted housing variable constructed with both structural break and supply elasticity (see also Table 8). All regressions include the full vector of controls and weight in ADH. For simplicity, we only report the results for all education levels in this table.

Appendix

I. Calculating employment changes due to import exposure

Using the CensusACS data, ADH calculate that the US mainland population was 157.6, 178.7, and 194.3 million adults ages 16 through 64 in 1990, 2000 and 2007 respectively. Therefore, they find a supply-shock driven net reduction in US manufacturing employment of approximately 1.53 million workers:

- $[0.5\times(157.6+178.7)\times1.14+0.5\times(178.7+194.3)\times1.84]\times(-0.00596\times0.48)=-1.53$

Note that 0.00596 is the coefficient from the ADH benchmark regression on manufacturing employment share, while 0.48 is the proportion of the variation in rising Chinese import exposure that can be attributed to the supply-driven components (see ADH, 2013, p. 2140 for details). We adopt this 0.48 proportion in our quantitative exercise.

Based on these numbers and our re-estimated coefficients, we can calculate our predicted employment changes. For example, using our coefficients reported in Table 4 Panel II, which is estimated over a sample of 249 commuting zones that have information on both housing structural break and supply elasticity over 1990-2007, we have the following calculation:

- $[0.5\times(157.6+178.7)\times1.14+0.5\times(178.7+194.3)\times1.84]\times(-0.00628\times0.48)= -1.612$

We do not have detailed information on employment by education (i.e., employment for college workers versus noncollege workers), so we use available information from ADH to back out this number:

- First, the working-age population by commuting zone can be extracted from Acemoglu et al (2016).[16] Using the share of a CZ's population with a college education, available from ADH in the years 1990 and 2000, we can estimate for each commuting zone the working-age population with or without a college education in 1990 and 2000.[17]

- Using the percentage change of working-age population with a college education from 2000 to 2007, we can calculate the working-age population with college education in 2007.

- Aggregating the commuting zone level working-age population by education to the national level, we obtain the shares of college-educated workers for 1990, 2000, and 2007 as 48.2%, 53.6%, and 57.3% respectively.

- Applying these shares to the total working-age population reported in ADH (2013, note 31), we obtain total working-age population with college education as 75.9, 95.8, and 111.3 million in 1990, 2000, and 2007 respectively. Similarly, for noncollege workers the numbers are 81.7, 82.9, and 83.0 million in 1990, 2000, and 2007 respectively.

Based on these numbers and our re-estimated coefficients, we can calculate the predicted employment changes for college and noncollege workers separately. For example, using our coefficients reported in Table 4 Panel II, our calculations are as follows:

[16] Note that the national working age population aggregated from this data is 163, 186, and 201 million, in 1990, 2000, and 2007 respectively, which is slightly higher than ADH's number in their note 31.

[17] Since we use the population share of college-educated person, we may underestimate the actual share of college-educated workers relative to total *working-age* population.

a. $[0.5\times(75.9+95.8)\times1.14+0.5\times(95.8+111.3)\times1.84]\times(-0.00644\times0.48)=-0.892$ million for college, manufacturing jobs;

b. $[0.5\times(75.9+95.8)\times1.14+0.5\times(95.8+111.3)\times1.84]\times(0.00469\times0.48)=0.649$ million for college, nonmanufacturing jobs;

c. $[0.5\times(81.7+82.9)\times1.14+0.5\times(82.9+83.0)\times1.84]\times(-0.00574\times0.48)=-0.679$ million for noncollege, manufacturing jobs;

d. $[0.5\times(81.7+82.9)\times1.14+0.5\times(82.9+83.0)\times1.84]\times(-0.00061\times0.48)=-0.072$ million for noncollege, nonmanufacturing jobs.