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MAGNIFICATION OF THE ‘CHINA SHOCK’ THROUGH THE U.S. HOUSING MARKET

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ABSTRACT

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Abstract

The ‘China shock’ operated in part through the housing market, which is one reason why its impact was so large in the United States. We add housing to a multi-region monopolistic competition model, with individuals choosing whether and where to work. Controlling for housing reduces the negative coefficient of import exposure on manufacturing employment by 20-25%, with a significant indirect magnification through the housing market. Combining manufacturing and construction employment, the indirect effect of the China shock through the housing market explains one-fifth as much of the variance in employment as the direct effect of import exposure, with further employment impacts through independent fluctuations in the housing market.

Keywords: China Trade Shock, Employment, Housing Market
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1 Introduction

In an influential study, Autor, Dorn, and Hanson (2013, hereafter ADH) show that rising import competition from China (i.e., the 'China shock') 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 reduced manufacturing employment per working-age population by 0.60 percentage points (their Table 3, column 6). Furthermore, the negative employment shock by Chinese imports goes beyond manufacturing and exists for nonmanufacturing workers (their Table 5).

Such results, accompanied with findings in other studies such as Acemoglu et al. (2016, hereafter AADHP) and Pierce and Schott (2016), have important policy implications and challenge the benign view towards globalization. Meanwhile, studies on other countries, mainly Germany, show that the estimates of the effect of the 'China shock' have been more 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 euro 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, comparing 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]

In this paper, we investigate one reason for the strong impact of the 'China shock' on U.S. labor market, and that is the *magnification* effect of the U.S. housing market. Our analysis is motivated by the fact that during the same period when the U.S. faced increasing import competition from China, its domestic economy also experienced a substantial national boom and bust in the housing market that varied largely across regions. Commuting zones that experienced larger increases in import exposure also had smaller increases in housing prices (see Appendix, Figure A.1). Thus, to the extent that the housing boom and bust is endogenous to the China shock, then that shock will have both a *direct* impact on employment through import competition and an *indirect* impact through the housing market. Our goal is to measure both the direct and indirect impacts on manufacturing employment, as well as the impact of the China shock and fluctuations in the housing market on non-manufacturing employment, especially the construction sector.

To achieve these goals, we start with a model of monopolistic competition that expands on ADH (2013, Appendix). Our first change to that model is to add a housing sector. But to allow the price

[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.

of housing to respond endogenously to regional demand, we also need to go further. In their model, ADH rely on the external trade imbalance of each region to influence regional demand. Because there is no data on the external trade imbalance of regions as small as commuting zones (CZ), they treat these changes as exogenous in their model and construct an empirical counterpart for it. Specifically, ADH measure changes to a CZ trade imbalance by considering the changes to the overall U.S. trade imbalance with China, with the primary focus on products imported from China. ADH then attribute changes in the overall import from China to the CZ level based on the share of employment of each industry in the CZ that competes with products imported from China: this is the "shift-share" analysis.

This modeling approach does not work when we want to make demand in a region fully endogenous, however, so as to determine both local employment and housing prices. So in addition to adding a housing sector, we make two other changes to the ADH model: workers can choose in which region to reside and whether to work or not; and payroll taxes are collected in each region by the national government, which funds unemployment benefits in each region. We are able to solve for the net transfers (transfers minus taxes) made to each region, based on the *national* trade balance and based on the tax and transfer rates in each region. Because the net transfers equal the difference between expenditure and income in each region, then the trade balance is directly linked to employment, in both the monopolistic competition sector (i.e. manufacturing) and in services (for example, housing construction). Furthermore, it turns out that the estimating equation for employment is very similar to that used in ADH (2013) or in AADHP (2016), except with the addition of a housing variable, so that we can directly compare our results with those specifications.

In our empirical analysis, we employ instrumental variables (IV) to account for the possible endogeneity of housing. We first use the land topology-based measure of housing supply elasticity introduced by Saiz (2010). Housing development in each region is effectively constrained by its geographic situation, such as the presence of steep slopes, wet lands, lakes and so on. Using satellite-based geographic data on land use and slope maps, Saiz (2010) constructs a measure of exogenous land availability and uses this measure to estimate the housing supply elasticity for local areas. This estimated supply elasticity is closely related to the changes in local housing prices. The areas with more elastic housing supply are expected to experience smaller housing price changes with respect to demand shocks. Therefore, even if the China shock is the only shock in the economy, by considering the housing variable instrumented by the Saiz elasticity, we are able to capture the heterogeneity in how local areas with different housing supply elasticity magnify the shock's impact on employment.

We estimate the impact of the China shock and housing market fluctuations on manufacturing employment, and then go beyond manufacturing and look at the distinct effects on non-manufacturing employment, including the construction sector and FIRE (finance, insurance and real estate). We also examine whether the results differ by the education level of workers. For each employment group, we start with the same case as in ADH (2013) by ignoring housing. We then introduce the housing variable into the estimation. Before considering housing, the estimated impact of the China shock measures the ‘overall’ effect of the change in import exposure on local labor market. After introducing housing, the overall effect of import exposure comes from both the ‘direct effect’ of import competition and the ‘indirect effect’ operating through the housing market.

We find that controlling for housing reduces the negative coefficient of import exposure on U.S. manufacturing employment by 25%, but housing fluctuations play a significant role, suggesting that import exposure is transmitted in part through contracting housing values. For the construction sector, virtually *all* of the negative impact of import exposure comes through the indirect magnification of the housing market. Commuting zones more exposed to the China shock experienced larger reductions in housing value and therefore less employment in the construction sector, but also less employment in manufacturing due to a negative wealth effect from reduced housing value. When we combine manufacturing and construction employment and perform a variance analysis, we find that the ‘direct effect’ of import exposure explains 5.5% of the variation in employment, while the ‘indirect effect’ through the housing market accounts for 1.1% of the variation. Thus, the indirect magnification of the China shock through the housing market contributes one-fifth (1.1/5.5) as much to the variance in employment as does the direct effect of import exposure. We also find that the Saiz elasticity explains 11.1% of the variance in employment from its impact on the housing market itself, which is nearly twice as large as the impact of the China shock and appears to be independent of it.

The above results are obtained by closely following the long-difference strategy of ADH (2013), which involves pooling the differences computed over 1990 to 2000 and 2000 to 2007. Likewise, our theoretical model is intended to capture differences across steady-state equilibria. It can be expected, however, that there are some higher-frequency changes within regions that impact both employment and the dynamics of the housing market. Empirically, there is growing consensus that much of the variation in housing prices during the housing boom and bust in the U.S. was from credit expansion, low interest rates, and investor speculative activities, rather than from changes in fundamentals like income, productivity, or population (Mayer, 2011; Sinari, 2012). These higher-frequency dynamics are a source of variation in housing prices that would be distinct from the secular trends captured by the China shock variable and instrument as constructed following ADH (2013). It is possible that the high-frequency movement in housing prices might be correlated with some unmeasured, high-frequency aspects of the China shock.[2] To capture this extra variation, we introduce a second housing instrument: the estimated structural break from rapid changes in housing prices that occurred in the local area (Ferreira and Gyourko, 2011; Charles et al., 2018). The idea is that underlying fundamentals for housing demand do not change abruptly and are likely incorporated into prices smoothly when they do change. So the ‘sharp’ breaks in the evolution of housing prices would reflect variation that is distinct from the secular trends over decades.

By adding this second instrument to a just-identified system, we are not affecting the consistency

[2]We are not able to able to test for this correlation, however, and so we remain agnostic as to the underlying forces behind the high-frequency movement in housing prices.

of our estimates but improving their efficiency. Consistent with these expectations, we find that the point estimates of the China shock and housing market fluctuations on employment, by sector or by educational level, are not changed by much: now the negative coefficient of import exposure on U.S. manufacturing employment, for example, is reduced by 20% rather than 25%. The total direct plus indirect impacts of the ADH instrument for the China shock still explains 6.6% of the variation in manufacturing plus construction employment. The Saiz elasticity instrument alone explains less of the variation in employment than before (3.9% rather than 11.1%), but the structural break instrument itself explains 16.5% of that variation, so that taken together the two housing IV explain some 20% of the variation in manufacturing plus construction employment.

Our paper adds to the literature on the impact of the boom and bust in the housing sector on U.S. employment. Mian and Sufi (2014) show that the negative wealth effect linked to the collapse in house prices reduced household spending, which had a negative impact on employment. Charles et al., (2016, 2018) document that the decline in manufacturing was 'masked' by positive employment effects from housing boom and 'unmasked' when housing market collapsed. We connect this strand of literature to the 'China shock' literature by introducing housing to the ADH framework and emphasizing the importance of housing in *magnifying* the effect of import exposure. This serves as one possible explanation for why the 'China shock' has had a stronger impact on the U.S. labor market than on the German labor market. Hoffmann and Lemieux (2016) also document the surprisingly different labor market performance of the U.S., Canada and Germany during and after the Great Recession, and propose that differences in magnitude of the boom and bust in the construction sector is an important factor behind the different labor market performance of the three countries.

The rest of the paper is structured as follows. Section 2 presents our regional model with monopolistic competition. Section 3 discusses the empirical strategy and data. Section 4 presents our estimation results as well as a variance decomposition analysis, and section 5 concludes.

2 The Model

As mentioned in the Introduction, we introduce three new features into the monopolistic competition model of ADH (2013, Appendix): a housing sector; workers can choose in which region to reside and whether to work or not; and payroll taxes that are collected in each region by the national government to fund unemployment benefits in each region. To ease our exposition, we make several simplifying assumptions. First, we model a single manufacturing sector producing a differentiated good, which means that all regions compete equally with imports of that differentiated good. In other words, we ignore in the model that some regions compete more directly with imports from China based on their industry structure (of course, this feature is introduced into the empirical specification). Second, we treat the housing sector as the only non-traded sector in each region, though we are confident that other nontraded services could be included with little effect on our results. Third, we assume the landowners rent housing to other individuals and to themselves. This means that workers and those not in the labor force do not experience any capital gains or losses on housing when moving between regions. For simplicity, we assume that landowners themselves do not move. In this section, we outline the key equations of the model that motivate the estimating equation we use for regional employment, and the full model is described in the Appendix.

Model Outline

There are $i = 1, ..., N$ regions, the first $N-1$ of which are located in the home country, while the final region N is the foreign country. Each region produces a traded differentiated good using only labor and also imports varieties from every other region. We let L_{mi} denote manufacturing employment, L_{hi} denote employment in housing construction, and L_{ni} denote the residents of region i who are not in the labor force, with total residents (not including landowners) in each home region of $L_{mi}+L_{hi}+L_{ni}$. The total endowment of home population that is mobile between regions is therefore[3]

$$\bar{L} = \sum_{i=1}^{N-1} \left(L_{mi} + L_{hi} + L_{ni}\right). \tag{1}$$

Housing is a nontraded good produced with labor and land. In a steady-state with H_i housing units and a fraction δ of these depreciating each period, then δH_i new houses are built with the production function $\delta H_i = f_i(L_{hi}, \delta T_i)$, where T_i denotes the fixed endowment of land in region i with δT_i becoming available through depreciation. The land coming available is valued at the price of p_{Ti} per acre and we denote the wage rate by w_i. We suppose that the rental price of housing r_{hi} reflects the depreciation rate times the construction cost per housing unit, which equal $c_i(w_i, p_{Ti})$ where c_i is the unit-cost function dual to f_i. That is, the rental price of housing is $r_{hi} = \delta c_i(w_i, p_{Ti})$.[4] Multiplying by H_i we find that $r_{hi}H_i = (\delta H_i)c_i(w_i, p_{Ti})$, so that in the steady-state, the rental value of the entire housing stock equals the construction costs of new housing. We will make the simplifying assumption that $f_i(.)$ and $c_i(.)$ are Cobb-Douglas, so that the share of labor in construction costs, $\theta_{Li} \equiv w_i L_{hi}/(r_{hi}H_i)$, is constant in each region. It follows that the steady-state labor used in construction, $L_{hi} = \theta_{Li} r_{hi} H_i / w_i$, takes on a particularly simple form when log-differenced:

$$\Delta \ln L_{hi} = \Delta \ln \left(\frac{r_{hi}H_i}{w_i}\right). \tag{2}$$

Utility of residents (including landowners) in region i is a CES function over consumption of the differentiated varieties in the manufacturing industry, produced locally and imported from other

[3] We are not allowing for migration from the rest of the world, though that could be incorporated into the model.

[4] If we define the rental price of an acre of land by $r_{Ti} \equiv \delta p_{Ti}$, then we can alternatively express the rental price of housing as $r_{hi} = c_i(\delta w_i, r_{Ti})$, depending on the amortized labor costs in construction plus the rental price of land per housing unit.

regions and the rest of the world, and then Cobb-Douglas over the manufacturing industry (with share α) and housing (with share $1-\alpha$). Let P_i denote the CES price index of the manufacturing good in region i, reflecting locally produced and imported varieties, where the latter depend on the transport costs to reach each region. There is an *ad valorem* payroll tax of t, paid to the national government, to fund the unemployment benefits to those not in the labor force. Workers in region i earn the net of tax wage $(1-t)w_i$ so their indirect utility is $V_i = (1-t)w_i/(P_i^\alpha r_{hi}^{1-\alpha})$. Residents of region i who are not in the labor force receive unemployment benefits of $u_i < (1-t)w_i$ so their indirect utility is $V_{ni} = u_i/(P_i^\alpha r_{hi}^{1-\alpha})$.

As already mentioned, land is owned locally by residents who do not work and do not move between regions, and who earn the rents $r_{Ti}T_i$ on their land.[5] Other home residents make a choice of which region to live and simultaneously the decision of whether to work there or not, as we shall describe below. There are no savings in the static model, so regional expenditure consists of labor earnings net of taxes, $(1-t)w_i(L_{hi}+L_{mi})$, plus total transfers of unemployment benefits, u_iL_{ni}, plus land earnings $r_{Ti}T_i$:

$$E_i = (1-t)w_i(L_{hi}+L_{mi}) + u_iL_{ni} + r_{Ti}T_i. \tag{3}$$

Notice that *income earned* in region i does not include the tax or transfers, so it is

$$I_i = w_i(L_{hi}+L_{mi}) + r_{Ti}T_i. \tag{4}$$

The balance of trade for region i reflects the gap between earned income and expenditure,

$$B_i = I_i - E_i = tw_i(L_{hi}+L_{mi}) - u_iL_{ni}. \tag{5}$$

Mobility between Regions

To model the decision of mobile residents on where to reside, we add a further stochastic portion to utility, and suppose that a worker ω in region i receives the utility

$$\tilde{V}_i(\omega) = a_i(\omega)V_i,$$

where $a_i(\omega)$ denotes the amenity value of living in region i, which is the realization of a random variable for worker ω. We follow Redding (2016) in assuming that amenities a_i for each worker ω in region i are independently drawn from the Fréchet distribution

$$G_i(a) = e^{-A_i a^{-\eta}},$$

[5]As in note 4, we define $r_{Ti} \equiv \delta p_{Ti}$ as the rental price of land in the steady-state. Then $r_{hi} = c_i(\delta w_i, r_{Ti})$, so that a portion of the housing rents collected by landowners goes to pay for new construction, with the remainder as the land rents.

where the scale parameter $A_i > 0$ determines the average amenities for each region and the shape parameter $\eta > 0$ controls the dispersion of amenities across workers. We likewise allow a non-worker ω' in region i to receive the stochastic utility

$$\tilde{V}_{ni}(\omega') = a_i(\omega')V_{ni}.$$

Note that each individual receives *independent* draws of amenities values from each region and also independent draws $a_i(\omega)$ and $a_i(\omega')$ when deciding whether to be in the labor force in region i or not.[6]

With this framework as shown by Redding (2016), the probability that a mobile individual from anywhere in the country chooses to work in region j reflects the indirect utility V_j raised to the Fréchet parameter η, and multiplied by the scale parameter A_j making regions with higher average amenities more attractive:[7]

$$\lambda_j = \frac{A_j[(1-t)w_j/(P_j^{\alpha}p_{hj}^{1-\alpha})]^{\eta}}{\sum_{i=1}^{N-1} A_i[u_i/(P_i^{\alpha}r_{hi}^{1-\alpha})]^{\eta} + A_i[(1-t)w_i/(P_i^{\alpha}r_{hi}^{1-\alpha})]^{\eta}}, \quad j = 1, ..., N-1. \tag{6}$$

The probability that they withdraw from the labor force but reside in region j is similarly obtained with the indirect utility V_{jn},

$$\lambda_{nj} = \frac{A_j[u_j/(P_j^{\alpha}p_{hj}^{1-\alpha})]^{\eta}}{\sum_{i=1}^{N-1} A_i[u_i/(P_i^{\alpha}r_{hi}^{1-\alpha})]^{\eta} + A_i[(1-t)w_i/(P_i^{\alpha}r_{hi}^{1-\alpha})]^{\eta}} = \rho_j^{\eta}\lambda_j, \text{ with } \rho_j \equiv \frac{u_j}{(1-t)w_j}, \tag{7}$$

where the term $\rho_j < 1$ reflects the extent to which unemployment benefits replace after-tax wage earnings in region j. By construction, $\sum_{j=1}^{N-1} \lambda_j + \lambda_{jn} = 1$.

Using (6) and (7), the mass of workers in region j equals $L_{hj} + L_{mj} = \lambda_j \overline{L}$, and those not in labor force equal $L_{nj} = \lambda_{nj}\overline{L} = \rho_j^{\eta}\lambda_j\overline{L}$. It follows that the total population in each region (not including landowners) is endogenously determined as

$$L_{hi} + L_{mi} + L_{ni} = (\lambda_i + \lambda_{ni})\overline{L} = (1 + \rho_i^{\eta})\lambda_i\overline{L}. \tag{8}$$

Notice that with these conditions and ρ_j in (7), the balance of trade (5) in each region becomes

$$B_i = (t - (1-t)\rho_i^{1+\eta})w_i\lambda_i\overline{L} = (t - (1-t)\rho_i^{1+\eta})w_i(L_{hi} + L_{mi}). \tag{9}$$

[6]That is, an unemployed resident has a different amenity value from a region as the same individual when they are employed. Rather than introducing a second Fréchet distribution for the amenity value of unemployed residents, we simply take a new draw from $G_i(a)$.

[7]Notice that λ_j is the probability that that a mobile individual from anywhere in the country chooses to work in region j, regardless of whether they work in manufacturing or construction. The local demand in those sectors determines the allocation for workers between them, with individuals being indifferent between working in one sector or the other (given the identical wage in both sectors). In contrast, Charles et al. (2018) allow individuals to draw 'comparative advantage' parameters from a Fréchet distribution for their relative efficiencies in each sector, so that their allocation across sectors reflects both relative demand and the relative supply arising from this Fréchet distribution.

Finally, to ensure that the benefits given to those not in the labor force are financed through the payroll tax, we add the external trade balance condition: $\sum_{i=1}^{N-1} B_i = B$, where B is the exogenous external trade balance. If $B < 0$, for example, then this deficit is financed through borrowing from the foreign country. Then we solve for t to ensure that the government budget deficit equals the external trade deficit, B.[8] Substituting that solution for t back into the above expression for B_i we obtain:

$$B_i = B \frac{(1+\rho_i^{1+\eta}) w_i (L_{hi} + L_{mi})}{\sum_{j=1}^{N-1} (1+\rho_j^{1+\eta}) w_j (L_{hj} + L_{mj})} - w_i (L_{hi} + L_{mi}) R_i, \tag{10}$$

where

$$R_i \equiv \frac{\sum_{j=1}^{N-1} \left(\rho_i^{1+\eta} - \rho_j^{1+\eta}\right) w_j (L_{hj} + L_{mj})}{\sum_{j=1}^{N-1} (1+\rho_j^{1+\eta}) w_j (L_{hj} + L_{mj})}. \tag{11}$$

Note that R_i reflects the extent to which unemployment benefits replace after-tax wages in region i relative to the national average.[9]

Regional Employment

While the above equations to determine regional expenditure look relatively complex, they provide a rather simple solution for employment. As derived in the Appendix, the value of employment in manufacturing equals

$$w_i L_{mi} = \alpha E_i + B_i. \tag{12}$$

To interpret this expression, the share α of regional expenditure E_i is spent on the manufactured good, and in addition, this good can be exported so the trade balance B_i also appears in (12) to determine employment. Using the regional trade balance from (10), we can solve for manufacturing employment as:

$$L_{mi} = \left[\frac{\alpha - (1-\alpha)\theta_{Li} R_i}{1 + R_i} \right] \frac{E_i}{w_i} + \frac{B}{W} \tilde{\lambda}_i, \tag{13}$$

where $\theta_{Li} \equiv w_i L_{hi} / (r_{hi} H_i)$ is the cost share of labor in housing construction, while

$$W \equiv \left[\frac{\sum_{j=1}^{N-1} w_j (L_{hj} + L_{mj})}{\sum_{j=1}^{N-1} (L_{hj} + L_{mj})} \right] = \sum_{j=1}^{N-1} w_j \tilde{\lambda}_j, \text{ and } \tilde{\lambda}_j \equiv \left[\frac{(L_{hj} + L_{mj})}{\sum_{k=1}^{N-1} (L_{hk} + L_{mk})} \right]. \tag{14}$$

Thus, W is interpreted as the average wage across regions and $\tilde{\lambda}_j$ is the share of the working population residing in region j, which differs slightly from $\lambda_j = (L_{hj} + L_{mj})/\bar{L}$ because the latter is defined relative to the entire mobile population (workers and nonworkers).

[8] See the Appendix.

[9] We can have $R_i >< 0$, but note that with $\rho_j < 1, j = 1, ..., N-1$, then $R_i > -1$.

Given the Cobb-Douglas utility function, the rental value of housing is proportional to regional expenditure, $r_{hi}H_i = (1-\alpha)E_i$. It follows that we can rewrite (13) so that rather than regional expenditure appearing on the right, we instead have the rental value of the housing stock:

$$L_{mi} = \left[\frac{\alpha - (1-\alpha)\theta_{Li}R_i}{(1-\alpha)(1+R_i)}\right]\frac{r_{hi}H_i}{w_i} + \frac{B}{W}\tilde{\lambda}_i. \tag{15}$$

To interpret this expression, an increase in the rental value of the housing stock $r_{hi}H_i$ occurs whenever there is an increase in regional expenditure E_i, which generates demand for manufactured goods and local employment according to its coefficient in (15). This is a source of variation in local employment that is distinct from changes in the external trade balance B, which has its own coefficient $\tilde{\lambda}_i$.

For example, holding the external balance B fixed, suppose that the attractiveness of region i as measured by the amenity parameter A_i increases. Normalizing the wage of this region at unity, this will draw population to the region according to (6) and (7), thereby increasing local expenditure E_i. This increase in expenditure will raise manufacturing employment in (13), though the precise effect will depend on the changes in transfers within R_i from (11). Equivalently, since the rental value of housing is proportional to regional expenditure, $r_{hi}H_i = (1-\alpha)E_i$, we will obtain an increase in manufacturing employment from the rise in the rental value of housing in (15). In either (13) or (15), the inflow of workers also raises the coefficient $\tilde{\lambda}_i$ and *further* impacts manufacturing employment depending on the sign of B: if $B > (<) 0$, then the enlarged region due to migration will experience some added (offset) manufacturing employment as the national trade surplus (deficit) takes on a greater role in that region.

Besides differences in local amenities, regions also differ in their amount of land, T_i. Again normalizing the wage of region i at unity, an increase in T_i will lower the price of land, thereby lowering construction costs and the price of housing. The mobile population is attracted to this region according to (6) and (7), but there will still be fewer person per acre than in smaller regions (assuming that their amenity values have the same mean). The inflow of person will raise local expenditure E_i, thereby raising manufacturing employment according to the same arguments as just above. So with differing values of A_i and T_i across regions, we achieve a steady-state equilibrium in each region with differing proportions of the working population $\tilde{\lambda}_i$, and therefore differing impacts of the external trade balance B according to its coefficient $\tilde{\lambda}_i/W$ in (13) and (15).

We can readily re-express the employment equation to reflect employment in housing and manufacturing combined. Using the labor share in construction once again to obtain $L_{hi} = \theta_{Li}r_{hi}H_i/w_i$, we can add this to (15) to obtain total employment in region i:

$$L_{mi} + L_{hi} = \left[\frac{\alpha + (1-\alpha)\theta_{Li}}{(1-\alpha)(1+R_i)}\right]\frac{r_{hi}H_i}{w_i} + \frac{B}{W}\tilde{\lambda}_i. \tag{16}$$

The term $\alpha + (1-\alpha)\theta_{Li}$ reflects the overall labor share in production in region i, including housing construction, and notice that the coefficient on real expenditure in (16) exceeds that in (15). As expected, the impact of local demand on employment is greater when considering total employment $L_{mi} + L_{hi}$ in (16), than when only considering manufacturing employment.

Estimating Equation

The specification in (15) and (16) should be adjusted because the employment share $\tilde{\lambda}_i$ on the right, which is defined in (14), is based on the employment levels that appear on the left. So any error in this equation which influences employment will be correlated with $\tilde{\lambda}_i$. One source of error, for example, arise because the coefficient on the housing variable differs across regions i depending on the value of R_i, as well as depending on the labor share in construction costs θ_{Li}. This is an example of heterogeneous coefficients in a cross-sectional regression. Running (15) or (16) as linear regressions with an average value of the housing coefficient on the housing variable, denoted by β, would lead to an error term that incorporates the difference between actual coefficient and β, times the housing variable itself, in the error term. That error would be correlated with $\tilde{\lambda}_i$ on the right.

To avoid this endogeneity, we solve for the employment shares $\tilde{\lambda}_i$ using the model. Notice that from (14) we have

$$\frac{\tilde{\lambda}_i}{W} = \left[\frac{(L_{hi} + L_{mi})}{\sum_{j=1}^{N-1}(L_{hj} + L_{mj})}\right]\left[\frac{\sum_{j=1}^{N-1}(L_{hj} + L_{mj})}{\sum_{j=1}^{N-1} w_j(L_{hj} + L_{mj})}\right] = \frac{(L_{hi} + L_{mi})}{\sum_{j=1}^{N-1} w_j(L_{hj} + L_{mj})},$$

so that equation (16) is rewritten as:

$$L_{mi} + L_{hi} = \left[\frac{\alpha + (1-\alpha)\theta_{Li}}{(1-\alpha)(1+R_i)}\right]\frac{r_{hi}H_i}{w_i} + (L_{mi} + L_{hi})\frac{B}{\sum_{j=1}^{N-1} w_j(L_{hj} + L_{mj})}.$$

We can readily solve for $(L_{mi} + L_{hi})$ from this equation. Then taking natural logs and differencing over time, while relying on our assumption that construction costs are Cobb-Douglas so that θ_{Li} does not vary, we obtain

$$\Delta \ln(L_{mi} + L_{hi}) = \Delta \ln\left(\frac{r_{hi}H_i}{w_i}\right) - \Delta \ln\left(1 - \frac{B}{WL}\right) + \epsilon_i, \tag{17}$$

with

$$WL = \sum_{j=1}^{N-1} w_j(L_{hj} + L_{mj}) \quad \text{and} \quad \epsilon_i = -\Delta \ln(1 + R_i). \tag{18}$$

We see that by solving for the employment shares $\tilde{\lambda}_i$, we end up with a log-linear specification for employment, as in AADHP (2016). On the right hand side of (17) we have the change in the log of the real housing value, along with the change in the trade balance relative to wage earnings, $-\Delta \ln(1 - \frac{B}{WL}) \approx \Delta \frac{B}{WL}$, where the approximation holds because the economy-wide wage earnings

WL are large compared to the trade balance B. The error term in (18) depends on R_i, and for small value of this variable then $\epsilon_i \approx -\Delta R_i$. In other words, the error term depends on changes in the extent to which unemployment benefits in a region replace wages there, as compared to the national average. ADH (2013) and AADHP (2016) document that the China shock has led to significant increases in the use of transfer payments nationally including unemployment insurance, disability payments, etc. We will not attempt to measure the amount of these payments by region, but simply include them in the error term. The change in these transfers is very likely correlated with the external balance in (17), however, and with the real rental value of housing. To address this correlation we shall use instrumental variables, as discussed in the next section.

In practice, we are willing to apply these instruments to the *real value* of the housing stock rather than *real rental value*. Increases in housing prices are likely to have a wealth effect (not included in our static model) that influences regional expenditure E_i , which is the driving force behind employment in (13). So using the housing value rather than rental value may be a better indication of the employment impact, including this wealth effect. The value of housing is constructed as the real price of housing times its stock, where the stock of housing evolves according to

$$H_{it} = (1-\delta)H_{it-1} + I_{it}, \tag{19}$$

where I_{it} are new housing starts.

One surprising feature of our specification (17) is that the trade balance term $-\Delta \ln(1 - \frac{B}{WL}) \approx \Delta \frac{B}{WL}$, as well as the housing variable, both have coefficients of unity. We regard these coefficients as a special feature of our model that arise because of the simplifying assumptions that we have made, including: a single manufacturing sector which means that all regions compete equally with imports of that differentiated good, so that regions differ only in their amount of land and in their average amenities; and a Cobb-Douglas utility function over the manufacturing aggregate and housing, along with a Cobb-Douglas production function for construction. The equation for the log-difference in construction employment in (2) is even simpler, since it does not include the external trade balance or any error term. That simple form follows from our Cobb-Douglas assumptions as well as our focus on steady-states in the model. We have no doubt that relaxing these assumptions can lead to coefficients that differ from unity in the estimating equations (2) and (17), as well as more complex errors. Rather than explore these features in our model, we move to the empirical specification, where we will introduce both of the right-hand side variables from (17) into construction employment in (2), with coefficients differing from unity. Our theory suggests that the external balance – and therefore the China shock – should have less impact on construction employment, as we will confirm.

3 Empirical Specification

We estimate the impact of the China shock with the following regression:

$$\Delta \ln L_{it} = \beta_1 \Delta IPW_{it} + \beta_2 \Delta HPQ_{it} + X_{it}'\beta_3 + \gamma_t + \gamma_r + e_{it}, \tag{20}$$

where L_{it} is the sectoral employment in commuting zone i at year t: we first look at the employment in manufacturing, and then we go beyond manufacturing and look at the employment in construction.[10] ΔIPW_{it} is the same 'China shock' variable used by ADH (2013) and AADHP (2016). It measures the change in commuting zone i's import exposure from China, and is instrumented by China's exports to eight other developed countries.[11] ΔHPQ_{it} is the housing variable measured as the change of the log of real housing value in commuting zone i at year t, which is constructed as commuting zone i's housing price times housing stock, deflated by its wage. It is instrumented by the housing supply elasticity from Saiz (2010) and the estimated housing structural break following Charles et al. (2018), as mentioned above and will be discussed in more details below. The vector X_{it} contains a set of economic and demographic controls at the start of each decade.[12] We follow ADH (2013) and estimate the model for stacked ten-year equivalent first differences over two periods: 1990 to 2000 and 2000 to 2007. The variable γ_t, $t = 0, 1$ is a time dummy for each decadal period, and γ_r, $r = 2, 3, ..., 10$ augments the model with geographic dummies for the nine Census divisions to absorb region-specific trends.

Before considering housing, the parameter β_1 measures both the 'direct' and the 'overall' effect of the change in import exposure from China on local labor market. After introducing housing, β_1 captures only the 'direct' effect of the China shock, holding other variables constant, and the overall effect of the China shock would come from not only the 'direct' effect but also the 'indirect' effect operating through the changes of the housing value, with coefficient β_2. We will quantify these direct and indirect impacts using a variance decomposition.

[10] To be consistent with our theoretical model, our empirical regression uses a log-linear specification with the natural log of employment counts as the dependent variable. We also perform the estimation using the shares of employment to working-age population as the dependent variable. The results are qualitatively similar and reported in the Appendix, Table A.3.

[11] More specifically, ΔIPW_{it} is constructed as 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 (ADH, 2013, p. 2128). The eight other developed countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[12] 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.

Data and Measurement

Data on labor market outcomes are obtained from the Census Integrated Public Use Micro Samples (IPUMS) for the years 1990 and 2000, and the American Community Survey (ACS) for 2006 to 2008.[13] We follow the detailed instructions in ADH (2013) and Acemoglua and Autor (2011) to construct the employment and wage variables for different education levels and industries. Import exposure variables are obtained from ADH (2013) directly.

Local housing price is measured using the housing price index data from the Federal Housing Finance Agency (FHFA). Housing stock is obtained partly from the Department of Housing and Urban Development (HUD) State of the Cities Data Systems.[14] The database reports total housing units at the metropolitan statistical area (MSA) level for the years 1970, 1980, 1990, and 2000 from the Census. We calculate the housing stock in other years according to the stock-flow equation (19). The new housing starts I_{it} for each year is measured using the number of new privately owned housing units authorized by building permits, obtained from the Census Building Permits Survey data. We begin with the total housing units in 1990 and calibrate the depreciation rate δ by fitting the 2000 value predicted by the stock-flow equation to the 2000 total units data. The resulting depreciation rate is 0.09%. Based on this estimated δ and new construction, we construct the housing stock for each year. The real housing value is then constructed as housing price times housing stock, deflated by the wage.

Housing Instruments

We employ two instruments for the change in housing value to address its endogeneity. One is the land topology-based measure of housing supply elasticity introduced by Saiz (2010). Saiz (2010) proposes that housing development is effectively 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 (2010) constructs a measure of exogenous land availability and uses this measure to estimate the housing supply elasticity for local areas. The estimated supply elasticity is believed to be 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). The more elastic housing supply areas are expected to experience smaller housing price changes with respect to demand shocks. We adopt this elasticity as our first instrument for the decadal change in housing value.[15]

[13] As in the literature, we pool the Census ACS data from 2006 to 2008 to reflect the year 2007 to increase sample size and hence the measurement precision.

[14] Web link: https://www.huduser.gov/portal/datasets/socds.html.

[15] Davidoff (2013) points out that the Saiz elasticity may possibly reflecting demand shocks as well. However, for our application, we emphasize the endogenous response of the housing market in magnifying the China shock. Areas with inelastic housing supply are expected to be affected more by the China shock and therefore have more transmission through the housing market. Thus introducing the Saiz elasticity can represent the heterogeneity in how local areas with different housing elasticities magnify the shock's impact on the labor market.

The other instrument is the estimated structural break from rapid changes in housing prices that occurred in the local area (Ferreira and Gyourko, 2011; Charles et al. 2018). Such high-frequency breaks lie outside our theoretical model which focuses on steady-state equilibria. It can be expected, however, that there are some higher-frequency changes occurring within regions that impact both employment and the dynamics of the housing market. These higher-frequency dynamics are a source of variation in housing prices that would be distinct from the secular trends captured by the China shock instrument ΔIPW_{it} constructed as a long-difference.[16] To obtain the instrument, we follow Charles et al. (2018) and 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 regression:

$$\ln p_{it} = \phi_{0i} + \phi_{1i} t + \kappa_i (t - t_i^*) D_{it} + \epsilon_{it}, \tag{21}$$

where $\ln p_{it}$ is the log value of quarterly housing price index for each area i in year-quarter t, and ϕ_{0i} 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 ϕ_{1i} is the linear time trend before the structural break, while κ_i captures the size of the structural break. We estimate separately over the periods 1990-2000 and 2000-2007, and use the annualized size of the structural break κ_i as the instrument for the decadal changes in housing value.[17]

To estimate the structural break, we use the high-frequency quarterly housing data at the MSA level. Figure 1 illustrates how the structural breaks are found and estimated for six areas. The left panel shows three areas over the 1990-2000 period and the right panel shows three other areas over the 2000-2007 period. The first row shows two areas that experienced smooth evolution of prices in each period, suggesting close to zero structural break. The second row shows areas that experienced 'sharp' price increases at some point, suggesting a positive structural break. Similarly, the last row shows a negative structural break during each sample period. On average, most areas experienced housing booms after 2000 and had a relative slowdown before 2000, so the average correlation between the estimated structural break and housing price growth is negative for the first period and positive for the second period.

[Figure 1 here]

Figure 2 goes further to plot the correlations between the two instruments and the decadal change in real housing value at the commuting zone level. The first row is for the structural break and the second row is for the Saiz elasticity. There is a clear correlation between both instruments and the change in housing values, especially in the second period 2000-2007, when most areas experienced

[16] As mentioned in note 2, some unmeasured, high-frequency aspects of the China shock could be correlated with the structural breaks in housing prices.

[17] In estimation, we restrict the break date to be between 1991Q1 to 2000Q4 for the first period and between 2001Q1 and 2005Q4 for the second period. We restrict the break to be before 2006 since housing booms had started to burst in 2006 for some areas. Extending the search of the break date to 2006Q4, however, leads to qualitatively similar results.

housing booms. In the first period, when most areas experienced a slow down, the relationship is negative and much less obvious.[18] More evidence will be provided when we discuss the first-stage results in a later section.

[Figure 2 here]

Summary Statistics

Before going to the regression results, we discuss the summary statistics of our key variables of interest, including import exposure, employment and housing variables. Table 1, Panel A replicates the sample in ADH (2013), which covers 722 commuting zones over two periods. Panel B reports our final sample with non-missing housing data. We have altogether 260 MSAs that have full information on housing price, housing stock and the Saiz elasticity. We then match them to the commuting zone level. This produces a final sample consisting of 249 commuting zones over two periods. The excluded commuting zones are mainly rural areas lacking data on housing.[19]

Our final sample accounts for 85 percent of the U.S. population and closely resemble the original ADH sample in the statistics of key variables. It shows that import exposure from China increased substantially during the sample period, especially in the second decade: in the first decade, import exposure increased by 1.09 thousand US dollars per worker on average, while in the second decade, the average increase is 2.57 dollars per worker. Corresponding to the high increase in the average exposure, the standard deviation of import exposure in the second decade is also much higher than that in the first decade, suggesting large differences across commuting zones in their exposures from import competition.

Table 1 shows that manufacturing employment, both the counts and as a share of working-age population, decreased during the two decades. By contrast, non-manufacturing employment increased on average. Construction employment, for example, experienced a large increase during the two sample periods, especially in the second decade. The increase of construction employment is 25.97 log points during the 2000s, with a wide standard deviation of 16.04 log points.

Real housing value increased substantially in the 2000s and varied across regions, with an average increase of 58.86 log points and a standard deviation of 32.76 log points. The Saiz elasticity and the structural break are the two instruments we use for housing value. The time-invariant Saiz elasticity ranges from 0 to 12, and the average elasticity in our sample is 2.57. The structural break is estimated separately for two decades. The average number is 1.08 in the first decade and 3.72 in the second period, suggesting positive housing growth on both periods with a much larger growth rate in the second period.

[18] In our regression analysis, we therefore construct our instrument by taking their negative values over 1990-2000. We also experiment with interacting the instruments with the period dummies, and the results are qualitatively similar.

[19] Appendix Figure A.2 plots a map of the United States showing the distribution of the areas.

[Table 1 here]

4 Empirical Results

We first estimate the regression on manufacturing employment, and then go beyond manufacturing and look at the distinct effects on non-manufacturing employment, in particular employment in the construction sector. We also examine whether the results differ by the education level of workers. For each employment group, we start with the same case as in ADH (2013) ignoring housing, but using our matched sample with reduced number of commuting zones. We then introduce the housing variable into the regression and experiment with various housing instruments.

4.1 Effects on Manufacturing Employment

Table 2 reports our estimation results for manufacturing employment. The dependent variable is $100\times$ the decadal change in natural log of the employment in manufacturing. Column (1) reports the results ignoring housing. It confirms the findings in ADH (2013): import exposure from China substantially reduces the number of workers employed in the manufacturing sector. More specifically, a $1,000 per worker increase in import exposure reduces the number of manufacturing employment by 5.84 percent. This estimated effect is even larger than the estimate in ADH (2013) with the full sample of 722 commuting zones. Appendix Table A.1, column (1) reproduces the estimates in ADH (2013) and shows a decrease of 4.23 percent in manufacturing employment for a $1,000 per worker increase in import exposure. This difference in results is related to the fact that our reduced sample of 249 commuting zones consists of mainly large cities. Rural areas are excluded from the sample because housing data are lacking.[20] Looking at workers with different education levels, we find that both the college workers and the non-college workers in the manufacturing sector are affected adversely: the number of college workers employed in the manufacturing sector decreased by 5.75 percent and the number of non-college workers employed in the manufacturing sector decreased by 6.02 percent.

[Table 2 here]

We then introduce housing into the regression in column (2) and use the Saiz elasticity as its instrument. Together with the import exposure variable and its instrument (i.e., changes in China's exports to eight other economies, which we call the ADH instrument), we have two endogenous variables and two instruments. The first-stage results are reported in Table 3, columns (2)-(3). Both instruments are relevant with a joint F statistic of 19.44. Looking at the two instruments separately, we

[20] On average, these areas did not experience housing booms and busts to the same extent as large cities. So by excluding areas with less affected housing markets, we actually start with a stronger version of the ADH results, focusing on areas that have more negative reduced-form impacts of import exposure because these are areas where endogenous housing market responses are more important.

find that the ADH instrument predicts both the changes of import exposure and the changes of housing value significantly, suggesting that import exposure from China will also affect the local housing value.[21] 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 reduction of the housing value, which further magnifies the adverse effect of import exposure on employment. Table 2, column (2) confirms this. It shows that the direct effect of import exposure on employment is now reduced to -4.40 percent for a $1,000 per worker change in import exposure. Comparing with the effect in column (1), it is a 25% reduction in magnitude, suggesting that part of the effect of import exposure on employment appears to be transmitted through the contracting housing value in the housing market. A one percent reduction in real housing value will decrease employment by 0.22 percent. Areas with inelastic housing supply are expected to be affected more by the China shock and therefore have more transmission through the housing market. Thus, even if the China shock is the only shock in the economy, this two-variable case with both import exposure and housing can represent the heterogeneity in how local areas with different housing market elasticities magnify the shock's impact on the labor market.

We introduce the estimated structural break as a second instrumental variable for housing in Table 2, column (3). The first-stage results are reported in Table 3, columns (4)-(5). Both the supply elasticity and the structural break predict the variation in housing value significantly, with a joint F statistic of 12.03. The second-stage coefficients reported in Table 2, column (3) are quite close to those reported in column (2), which used only the Saiz elasticity as an instrument: the coefficient of the China shock changes from -4.40 to -4.64, while the coefficient of the change in housing value changes from 0.22 to 0.19. The small size of these changes accords with our expectations that adding a second instrument does not affect the consistency of our estimates, but can improve their efficiency. With these small changes, the direct effect of import exposure is reduced slightly: a $1,000 per worker change in import exposure reduces the number of manufacturing employment by 4.64 percent, which is a 20% reduction in magnitude comparing with the effect ignoring housing. Since we have two endogenous variables but three instruments in this case, we can also perform the over-identification test. The p-value of the Hansen J statistic is 0.532, so the exogeneity of the instruments is accepted.

Similar patterns are observed when we examine the effects for workers with different education levels, in the rest of Table 2. Controlling for housing reduces the direct effect of import exposure on manufacturing employment for both college workers and workers without college education. For college workers, the reduction of the direct effect of import exposure is around 20-31%; and for workers without college education, the reduction of the direct effect is around 21-23%. Thus, even for the manufacturing sector, which faces the China trade shock directly, part of the employment

[21] Feler and Senses (2016) also 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.

effect of import exposure is transmitted and magnified through the housing market.

[Table 3 here]

4.2 Effects on Construction and FIRE Employment

We next go beyond manufacturing and examine the effects of import exposure on employment in non-manufacturing sectors, in particular construction employment and FIRE (finance, insurance and real estate). Table 4 provides the results for construction. The dependent variable is $100\times$ the decadal change in log construction employment counts. Ignoring housing, column (1) shows that import exposure from China reduces construction employment in the U.S. significantly, for both workers with college education and workers without college education. On average, a $1,000 per worker increase in import exposure reduces the employment in construction by 3.42 percent. Again, this estimated effect is stronger in our reduced sample of large cities than that in the full sample with more rural areas (comparing with the results in Appendix Table A.1, column 2). The more rural areas did not experience housing booms and busts to the same extent as large cities, so the magnification effect of housing market is less important in those areas. By excluding them, our sample focuses on areas that have more negative reduced-form impacts of import exposure.

Columns (2) and (3) introduce housing into the regression. Strikingly, now the detrimental effect of the China shock on construction employment disappears: the change in import exposure from China becomes entirely insignificant (with t-values of roughly unity) in columns (2) and (3). To be sure, the China shock is still having an impact on housing values, as shown by the first-stage coefficients in Table 3. But given this first-stage effect, the change in import exposure from China does not significantly impact construction employment in the second-stage variable. This result is consistent with our very simple specification of construction employment in equation (2), which depends on the rental value of housing but not on the external trade balance. Despite the strong assumption of our model (i.e. Cobb-Douglas utility and production functions and steady-state equilibria), this simple theoretical prediction is borne out in our estimated results.

[Table 4 here]

We also take a look at the impact of the China shock on the employment of the FIRE sector (Finance, Insurance, and Real Estate), which might be related to the housing market as well. Table 5 reports the results. When ignoring housing, import exposure has a negative but statistically insignificant impact on FIRE employment. After controlling housing, the impact becomes positive and statistically significant at the 10% level. Distinguishing workers by the education level, we observe a significantly positive impact of import exposure for workers without college education.

[Table 5 here]

For the whole non-manufacturing, which includes all sectors other than manufacturing, we observe a similar pattern (see Appendix, Table A.2), though not as significant as that for construction or FIRE. Generally speaking, the possibly negative impact of the China shock disappears after controlling housing. Instead, the estimated coefficient of import exposure becomes positive, though insignificant. These results suggest that import exposure might have positive impacts on non-manufacturing sectors and relates to the findings in Bloom et al., (2019), who show that import competition from China has had a *significantly positive* effect on U.S. service sector jobs by reallocating employment from manufacturing to services. Using U.S. establishment-level data, they are able to find significant evidence of industry switching for U.S. firms: plants change their reported industry code from manufacturing to services, which reduces measured manufacturing employment and increases service sector employment. Since we have only employment totals from the household side, it is relatively harder for us to catch the reallocation of employment significantly.

4.3 Variance Decomposition

To further understand how each instrument contributes to the explanation of the endogenous variables and how changes in import exposure and changes in housing value contribute to the changes in sectoral employment, we perform a decomposition of variance like that in Eaton et al., (2004). In the Appendix Table A.5 we report this decomposition separately for manufacturing and construction employment. But our preferred specification for conducting the decomposition is to sum these two sectoral employments before taking their natural log, to obtain an broader view of the impacts of import exposure and fluctuations in the housing market. Looking at both manufacturing and construction employment is consistent with the approach of Charles et al. (2016, 2018), who find that the general housing boom over 2000-2007 'masked' the drop in employment decline due to the manufacturing decline over that period, so that the overall drop in employment was apparent only after the bust came. In our analysis we are interested in how the magnitude of the boom and bust and the total employment of manufacturing and construction respond to the China shock, and for this purpose it is helpful to sum manufacturing and construction.

In Table 6 we report again the employment regressions, where now the dependent variable is the log change in the sum of manufacturing and construction employment. Without controlling for housing, there is an increase in the negative coefficient on import exposure as compared to Table 2 where just manufacturing employment is used. When the housing variable is introduced, however, then the coefficient on import exposure falls substantially and housing plays an important role. Our goal here is to determine the extent to which the instruments for import exposure and housing – with the first-stage regressions still as shown in Table 3 – explain the variance in the sum of manufacturing and construction employment across regions.

[Table 6 here]

Consider first the first-stage regressions to construct predicted changes of import exposure and housing value:

$$\hat{y}_{it} = \sum_{k=1}^{N} \hat{\alpha}_k IV_{kit} + X'_{it}\hat{\beta} + \hat{\gamma}_t D_t + \hat{\gamma}_r D_r, \tag{22}$$

where $\hat{y}_{it}$ is either the predicted change of import exposure $\widehat{\Delta IPW}_{it}$, or the predicted change of log housing real value $\widehat{\Delta HPQ}_{it}$; IV_{kit} represents the instrumental variable used in the regression, which includes the ADH instrument for import exposure from China (i.e., China's exports to other eight countries), the Saiz supply elasticity and the estimated structural break; X_{it} represents the same control variables as in equation (20); and D_t and D_r are the dummy variables used to capture the time and region fixed effects γ_t and γ_r in equation (20).

A demeaned transformation of the above equation at both the time-level and the region-level implies that $\tilde{\hat{y}}_{it} = \sum_{k=1}^{N} \hat{\alpha}_k \tilde{IV}_{kit} + \tilde{X}_{it}'\hat{\beta}$. Taking the variance on both sides, we have

$$\begin{aligned} \text{Var}(\tilde{\hat{y}}_{it}) &= \text{Cov}(\tilde{\hat{y}}_{it}, \textstyle\sum_{k=1}^{N} \hat{\alpha}_k \tilde{IV}_{kit} + \tilde{X}_{it}'\hat{\beta}) \\ &= \textstyle\sum_{k=1}^{N} \text{Cov}(\tilde{\hat{y}}_{it}, \hat{\alpha}_k \tilde{IV}_{kit}) + \text{Cov}(\tilde{\hat{y}}_{it}, \tilde{X}_{it}'\hat{\beta}). \end{aligned}$$

Dividing through by $\text{Var}(\tilde{\hat{y}}_{it})$, we get

$$1 = \sum_{k=1}^{N} \hat{\alpha}_k b_k + \mathbf{b}'\hat{\beta},$$

where $b_k = \text{Cov}(\tilde{\hat{y}}_{it}, \tilde{IV}_{kit})/\text{Var}(\tilde{\hat{y}}_{it})$ is the slope coefficient of an auxiliary regression of $\tilde{IV}_{kit}$ on $\tilde{\hat{y}}_{it}$, or equivalently:[22]

$$IV_{kit} = b_k \hat{y}_{it} + \gamma_t + \gamma_r + \epsilon_{kit}. \tag{23}$$

Then the estimated coefficient $\hat{\alpha}_k \hat{b}_k$ is a convenient way of summarizing the percentage of the variance in the predicted changes of import exposure (or housing value) that is explained by each of the instrumental variables.

Table 7 Panel A reports the decomposition results (i.e., $\hat{\alpha}_k \hat{b}_k$).[23] Column (1) shows that in the case with only import exposure, the ADH instrument (i.e., China's exports to other eight countries) explains about 68% of the variation in the changes of import exposure from China. Column (2) introduces housing and uses the Saiz supply elasticity as the housing instrument. The variation in import exposure remains to be explained mainly by the ADH instrument (67%), with the supply elasticity playing a negligible role (0.41%). On the other hand, the variation in the housing value is mainly explained by the Saiz elasticity (66.1%), with the ADH instrument explaining only 6.68%. Adding the structural break as one more instrument in columns (3) does not improve the explanation for import exposure,[24] but substantially increases the explanatory power for housing value. All three

[22] Similarly for the coefficient vector $\mathbf{b}$, which can be obtained from regressions of each control variables on $\tilde{\hat{y}}_{it}$.

[23] Appendix Table A.4 Panel A reports the estimation results for each auxiliary regression ($\hat{b}_k$).

[24] The structural break explains -0.19%, which is essentially zero, of the variation in changes of import exposure. One

instruments can explain over 86% of the variation in housing value, with the structural break alone explains 67.76% of the variation.

Then imagine running the second-stage regressions using the predicted changes of import exposure and housing:

$$\Delta \ln L_{it} = \hat{\beta}_1 \Delta \widehat{IPW}_{it} + \hat{\beta}_2 \Delta \widehat{HPQ}_{it} + X'_{it}\hat{\beta}_3 + \hat{\gamma}_t D_t + \hat{\gamma}_r D_r + \hat{e}_{it}. \tag{24}$$

By construction, these predicted values are orthogonal to the observed error in the second-stage regression. So again, we can use the same technique to get a percentage of the variance in the changes of employment that is explained by the predicted changes of import exposure and the predicted changes of housing value, with the following auxiliary regressions:

$$Z_{kit} = \theta_k \Delta \ln L_{it} + \gamma_t + \gamma_r + \varepsilon_{kit}, \tag{25}$$

where Z_{kit} represents $\Delta \widehat{IPW}_{it}$ or $\Delta \widehat{HPQ}_{it}$. Table 7 Panel B reports the decomposition results (i.e., $\hat{\beta}_k \hat{\theta}_k$).[25] It shows that for the sum of manufacturing and construction employment, predicted changes in import exposure explain about 8-13% of its variation, and predicted changes in housing value explain 16-24% of its variation.

Finally, we can put the above two steps together by multiplying various percentages to get the contribution of each instrument in explaining the variation of employment. Panel C in Table 7 reports the percentages. When ignoring housing, the ADH China shock instrument explains 9.05% of the variation in manufacturing and construction employment. After controlling for housing using the Saiz elasticity, the ADH China shock instrument contributes to the variation in manufacturing and construction employment through two channels: one is its contribution through the changes of import exposure (the 'direct' channel), the other is its contribution through the changes of housing value (the 'indirect' channel). Column (2) shows the direct channel explains 5.5% of the variation ($67.24\% \times 8.18\% = 5.5\%$) and the indirect channel accounts for 1.12% of the variation ($6.68\% \times 16.71\% = 1.12\%$), the sum of the two channels explains 6.62% of the variation. These results lead to our conclusion that the indirect magnification of the ADH China shock instrument through the housing market explains *one-fifth* as much of the variance in manufacturing plus construction employment (or 1.12/5.5) as does its direct effect through import exposure.

While still using a single instrument for housing, the results in column (2) of Table 7 Panel C show that the Saiz elasticity explains 11.08% of the variation in manufacturing and construction employment, through almost entirely its explanation of the changes in housing values.[26] This substantially

disadvantage of our approach of variance decomposition is that it's possible to yield negative numbers since it is based on covariances.

[25]Appendix Table A.4 Panel B reports the estimates for the auxiliary regressions ($\hat{\theta}_k$).

[26]$0.41\% \times 8.18\% + 66.10\% \times 16.71\% = 0.03\% + 11.05\% = 11.08\%$.

exceeds the combined direct plus indirect effects of the ADH instrument, which accounted for 6.62%. We conclude that there is substantial impact of the housing market on employment obtained using the Saiz instrument, which is nearly twice as large as that obtained from the China shock and appears to be independent of it.

We next look at the two housing instruments, as reported in column (3) of Table 7. The China shock now explains 5.93% of the variation in manufacturing plus construction employment through the direct channel of import exposure ($67.31\% \times 8.81\% = 5.93\%$), and 0.65% of the variation ($2.69\% \times 24.33\% = 0.65\%$) through the indirect channel, and the sum of the two channels explains 6.58% of the variation. The indirect channel has fallen noticeably in importance, which occurs because the explanatory power of the Saiz elasticity decreases. It now explains only 3.89% of the variation in employment, which comes almost entirely from the changes in housing value ($0.46\% \times 8.81\% + 15.84\% \times 24.33\% = 0.04\% + 3.85\% = 3.89\%$). In contrast, the structural break instrument for housing is very important: it explains 16.47% of the variance in manufacturing and construction employment, entirely through the changes in housing values.[27] Taken together, the two housing instruments explain some 20% of the variation in manufacturing and construction employment.[28]

[Table 7 here]

5 Conclusion

The rapid growth in imports from China has been found to be responsible for the great U.S. employment sag by several studies. In this paper, we propose one reason for the strong impact of the China trade shock on U.S. labor market, which is the magnification effect through the U.S. housing market. We start with a model of monopolistic competition that expands on ADH (2013) by adding three new features: a housing sector; workers can choose in which region to reside and whether to work or not; and payroll taxes that are collected in each region by the national government to fund unemployment benefits in each region. We get an estimation equation for employment that is very similar to that used in ADH (2013) or in AADHP (2016), except with the addition of a housing variable. Before considering housing, the estimated effect measures both the 'direct' and the 'overall' effect of the change in import exposure on local labor market. After introducing housing, the overall effect of import exposure comes from both the 'direct effect' of import competition and the 'indirect effect' operating through the housing market.

[27] $-0.19\% \times 8.81\% + 67.76\% \times 24.33\% = -0.017\% + 16.49\% = 16.47\%$.

[28] As we have observed in notes 2 and 4, some of the high-frequency movements in housing prices reflected in the structural break instrument could be correlated with unmeasured, higher-frequency aspect of the China shock. So we do not conclude that the 16.47% of the variance in manufacturing and construction employment due to the housing instruments is fully independent of the China shock.

Our estimation results show that controlling for housing reduces the negative coefficient of import exposure on U.S. manufacturing employment by 20-25%, with a significant indirect magnification through the contracting housing value in the housing market. Combining manufacturing and construction employment, the indirect effect of the China shock through the housing market explains one-fifth as much of the variance in employment as the direct effect of import exposure, with further employment impacts through independent fluctuations in the housing market. 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 an outside trade shock. This may also be an important factor behind the differences in employment changes across countries.

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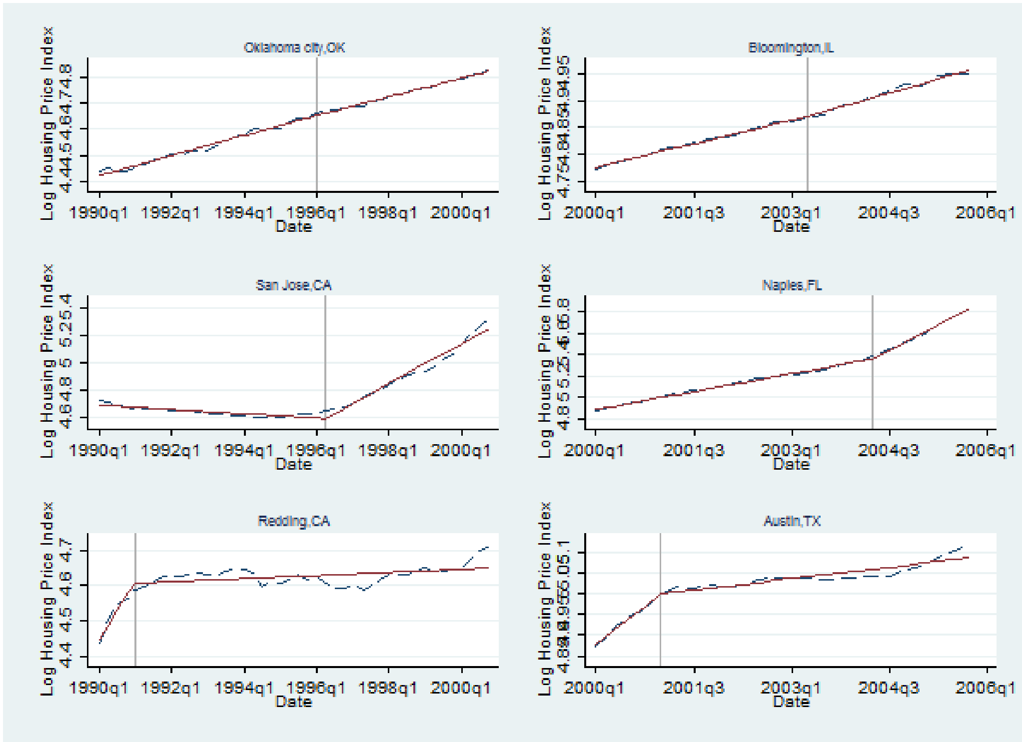
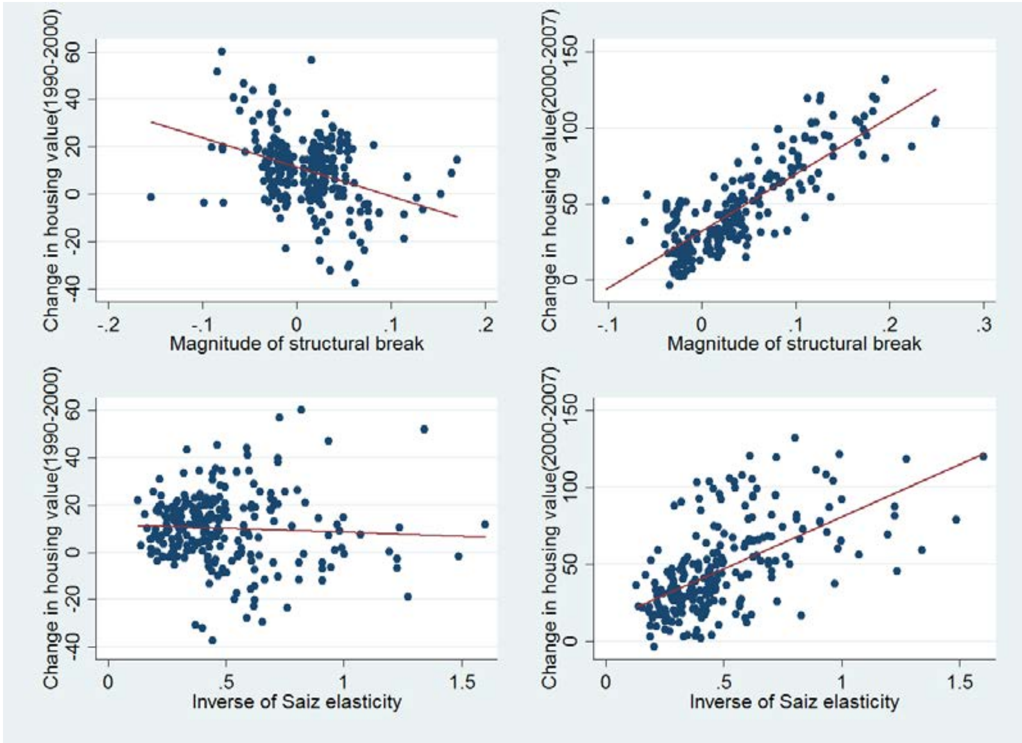
Figure 1: Structural Breaks Across Different Areas



Note: This figure plots the quarterly housing price data for selective metropolitan areas. 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 (21).

Figure 2: Correlations Between Instruments and Changes in Real Housing Value



Note: This figure plots the correlations between the decadal change of real housing value and the two instruments (structural break and Saiz elasticity) over two periods: 1990-2000 in the left panel and 2000-2007 in the right panel.

Table 1: Summary Statistics

		1990-2000		2000-2007	
Variable	Obs	Mean	Std.Dev	Mean	Std.Dev
Panel A: The ADH Sample (722 CZ)					
Δ imports exposure from China	1444	1.14	0.99	2.63	2.01
Δ manuf. employment share	1444	-2.07	1.63	-2.73	1.80
Δ non-manuf. employment share	1444	1.29	2.38	3.70	2.71
Δ log manuf. employment	1444	-7.03	16.09	-16.90	15.55
Panel B: Our Sample with Housing (249 CZ, Pop Share=85%)					
Δ imports exposure from China	498	1.09	0.74	2.57	1.86
Δ manuf. employment share	498	-2.26	1.42	-2.71	1.67
Δ non-manuf. employment share	498	1.14	2.35	3.74	2.68
Δ log manuf. employment	498	-8.73	15.37	-16.55	14.60
Δ log non-manuf. employment	498	14.47	9.17	19.33	10.83
Δ log constr. employment	498	11.53	17.00	25.97	16.04
Δ log housing value	498	5.20	16.84	58.89	32.76
Saiz Elasticity	498	2.57	1.21	2.57	1.21
Structural Break	498	1.08	4.33	3.72	6.17

Note: The ADH sample (N = 1,444 = 722 commuting zones × 2 time periods) is the same as that in ADH (2013). Our matched sample includes only commuting zones that have information on housing variables and the instruments. We keep the sample balanced over two periods.

Table 2: The Impact of Housing and Imports on Manufacturing Employment

	(1)	(2)	(3)
Dep. var: 100 × change in log manuf. employment			
All education levels			
ΔImport exposure from China	-5.835***	-4.401***	-4.640***
	(1.233)	(1.129)	(1.049)
ΔHousing value		0.217***	0.188***
		(0.043)	(0.040)
Hansen J p-value			0.532
College education			
ΔImport exposure from China	-5.751***	-3.982**	-4.602***
	(1.624)	(1.607)	(1.534)
ΔHousing value		0.267***	0.192***
		(0.067)	(0.050)
Hansen J p-value			0.216
No College education			
ΔImport exposure from China	-6.015***	-4.767***	-4.634***
	(1.432)	(1.347)	(1.293)
ΔHousing value		0.188***	0.204***
		(0.050)	(0.039)
Hansen J p-value			0.749
Reduction in Direct Import Coefficient			
All education levels		25%	20%
College education		31%	20%
No College education		21%	23%
Instruments for Housing		Elasticity	Elasticity+Break

Note: N = 498 (249 CZs over two time periods). Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) performs the estimation without controlling housing. The import exposure is instrumented by China's exports to eight other economies as in ADH. Column (2) introduce housing and instrument it with the Saiz elasticity. Together with the ADH China shock instrument, we have two endogenous variables and two instruments in this case. Column (3) adds one more instrument for housing, i.e., the estimated structural break. Hansen J p-values are reported for over-identified cases. We perform the estimations for the group of all workers, the group of workers with college education and the group of workers without college education. All regressions include a dummy for the 2000-2007 period, a set of census division dummies, and the full vector of controls: start of period 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 average offshorability index of occupations. All regressions are weighted by start of period commuting zone's share of national population.

Table 3: First Stage Results for Different Instruments

	ΔIPW	ΔIPW	ΔHPQ	ΔIPW	ΔHPQ
	(1)	(2)	(3)	(4)	(5)
ADH IV	0.573***	0.567***	-2.567**	0.568***	-1.790
	(0.104)	(0.105)	(1.100)	(0.104)	(1.151)
Saiz Elasticity		0.045	-10.837***	0.050	-4.527***
		(0.066)	(2.096)	(0.066)	(1.068)
Structural Break				0.002	2.538***
				(0.010)	(0.226)
Number of Endogenous Var.	1	2		2	
Number of Instruments	1	2		3	
K-P Wald F Statistics	30.275	19.443		12.027	
Stock-Yogo cv: 10% size	16.38	7.03		13.43	
Stock-Yogo cv: 15% size	8.96	4.58		8.18	

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 tables 2, 4, 5 and 6. 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 4: The Impact of Housing and Imports on Construction Employment

	(1)	(2)	(3)
Dep. var: 100 $\times$ change in log construction employment			
All education levels			
ΔImport exposure from China	-3.416**	1.285	0.620
	(1.366)	(1.122)	(1.042)
ΔHousing value		0.709***	0.629***
		(0.047)	(0.053)
Hansen J p-value			0.082
College education			
ΔImport exposure from China	-3.773***	0.124	-0.302
	(1.369)	(1.098)	(1.052)
ΔHousing value		0.588***	0.537***
		(0.077)	(0.057)
Hansen J p-value			0.407
No College education			
ΔImport exposure from China	-3.011**	2.208	1.337
	(1.482)	(1.505)	(1.359)
ΔHousing value		0.788***	0.683***
		(0.058)	(0.068)
Hansen J p-value			0.034
Instruments for Housing		Elasticity	Elasticity+Break

Note: N = 498 (249 CZs over two time periods). Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) performs the estimation without controlling housing. The import exposure is instrumented by China's exports to eight other economies as in ADH. Column (2) introduces housing and instrument it with the Saiz elasticity. Together with the ADH China shock instrument, we have two endogenous variables and two instruments in this case. Column (3) adds one more instrument for housing, i.e., the estimated structural break. Hansen J p-values are reported for over-identified cases. We perform the estimations for the group of all workers, the group of workers with college education and the group of workers without college education. All regressions include a dummy for the 2000-2007 period, a set of census division dummies, and the full vector of controls: start of period 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 average offshorability index of occupations. All regressions are weighted by start of period commuting zone's share of national population.

Table 5: The Impact of Housing and Imports on FIRE Employment

	(1)	(2)	(3)
Dep. var: 100 $\times$ change in log FIRE employment			
All education levels			
ΔImport exposure from China	-0.177	1.798*	1.696*
	(0.788)	(1.013)	(0.901)
ΔHousing value		0.501***	0.460***
		(0.040)	(0.047)
Hansen J p-value			0.711
College education			
ΔImport exposure from China	-0.520	1.417	1.336
	(0.920)	(1.105)	(1.000)
ΔHousing value		0.292***	0.283***
		(0.064)	(0.055)
Hansen J p-value			0.782
No College education			
ΔImport exposure from China	0.706	3.481**	3.111**
	(0.953)	(1.474)	(1.350)
ΔHousing value		0.419***	0.374***
		(0.092)	(0.070)
Hansen J p-value			0.389
Instruments for Housing		Elasticity	Elasticity+Break

Note: N = 498 (249 CZs over two time periods). Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) performs the estimation without controlling housing. The import exposure is instrumented by China's exports to eight other economies as in ADH. Column (2) introduces housing and instrument it with the Saiz elasticity. Together with the ADH China shock instrument, we have two endogenous variables and two instruments in this case. Column (3) adds one more instrument for housing, i.e., the estimated structural break. Hansen J p-values are reported for over-identified cases. We perform the estimations for the group of all workers, the group of workers with college education and the group of workers without college education. All regressions include a dummy for the 2000-2007 period, a set of census division dummies, and the full vector of controls: start of period 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 average offshorability index of occupations. All regressions are weighted by start of period commuting zone's share of national population.

Table 6: The Impact of Housing and Imports on Manufacturing and Construction Employment

	(1)	(2)	(3)
Dep. var: 100 × change in log manuf.+constr. employment			
All education levels			
ΔImport exposure from China	-6.336***	-3.716***	-4.004***
	(1.441)	(1.090)	(1.066)
ΔHousing value		0.395***	0.361***
		(0.040)	(0.036)
Hansen J p-value			0.346
College education			
ΔImport exposure from China	-6.158***	-3.715***	-4.142***
	(1.380)	(1.145)	(1.198)
ΔHousing value		0.369***	0.317***
		(0.052)	(0.040)
Hansen J p-value			0.303
No College education			
ΔImport exposure from China	-5.861***	-2.834***	-3.176***
	(1.483)	(1.045)	(0.991)
ΔHousing value		0.457***	0.416***
		(0.039)	(0.039)
Hansen J p-value			0.224
Reduction in Direct Import Coefficient			
All education levels		41%	37%
College education		40%	33%
No College education		52%	46%
Instruments for Housing		Elasticity	Elasticity+Break

Note: N = 498 (249 CZs over two time periods). Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) performs the estimation without controlling housing. The import exposure is instrumented by China's exports to eight other economies as in ADH. Column (2) introduces housing and instrument it with the Saiz elasticity. Together with the ADH China shock instrument, we have two endogenous variables and two instruments in this case. Column (3) adds one more instrument for housing, i.e., the estimated structural break. Hansen J p-values are reported for over-identified cases. We perform the estimations for the group of all workers, the group of workers with college education and the group of workers without college education. All regressions include a dummy for the 2000-2007 period, a set of census division dummies, and the full vector of controls: start of period 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 average offshorability index of occupations. All regressions are weighted by start of period commuting zone's share of national population.

Table 7: Variance Decomposition

	(1)	(2)	(3)
Panel A: Variance Decomposition for First Stage Regression			
Explanatory variable: Predicted ΔImport exposure			
ADH IV	67.96%	67.24%	67.31%
Saiz Elasticity		0.41%	0.46%
Structural Break			-0.19%
Explanatory variable: Predicted ΔHousing value			
ADH IV		6.68%	2.69%
Saiz Elasticity		66.10%	15.84%
Structural Break			67.76%
Panel B: Variance Decomposition for Second Stage Regression			
Explanatory variable: ΔManuf.+Constr. Employment			
Predicted ΔImport	13.31%	8.18%	8.81%
Predicted ΔHousing		16.71%	24.33%
Panel C: Variance Decomposition Combined			
Explanatory variable: ΔManuf.+Constr. Employment			
ADH IV	9.05%	6.62%	6.58%
Saiz Elasticity		11.08%	3.89%
Structural Break			16.47%

Note: This table reports the variance decomposition for both the first-stage and the second-stage regressions of the employment of manufacturing plus construction. The procedures are discussed in section 4.3. The numbers reported are the estimated coefficients $\hat{b}_k$ from auxiliary regression (23) and $\hat{\theta}_k$ from auxiliary regression (25), times the estimated coefficients from the corresponding first-stage regressions ($\hat{\alpha}_k$, reported in Table 3) or the second-stage regressions ($\hat{\beta}_k$, reported in Table 6) respectively. Column (1) refers to the case with only one endogenous variable: import exposure, which is instrumented by China's exports to eight other economies as in ADH. Column (2) refers to the case introducing housing and instrumenting it by the Saiz supply elasticity. Column (3) adds one more instrument for housing, i.e., the estimated structural break.

ONLINE APPENDIX

A Theory Appendix

Regional Model with Monopolistic Competition

As explained in the main text, there are N regions, the first $N-1$ of which are located in the home country, while the final region N is the foreign country. Each region produces a traded differentiated good using only labor and also imports varieties from every other region. Housing is a nontraded good produced with labor and land. In a steady state with H_i housing units and a fraction δ of these depreciating, then δH_i new houses are built with the production function $\delta H_i = f(L_{hi}, \delta T_i)$, where T_i denotes the fixed endowment of land in region i with δT_i made available through depreciation of the housing stock, and L_{hi} denotes the amount of labor devoted to new construction. We assume that housing is rented to the local population by landowners who, like the rest of the local population, consume a CES bundle of local and imported varieties and housing. We adopt a Cobb-Douglas utility function over the differentiated good and housing:

$$U_i = \left(\frac{1}{\alpha} \sum_{j=1}^{N} \int_0^{M_j} c_{ji}(\omega)^{(\sigma-1)/\sigma} d\omega \right)^{\frac{\alpha\sigma}{\sigma-1}} \left(\frac{H_i}{1-\alpha} \right)^{1-\alpha}, \tag{A.1}$$

where i and j denote regions, $c_{ji}(\omega)$ denotes consumption of variety ω sent from region j to i, M_i is the mass of varieties, α is the share of income spent on the traded industries, and $1-\alpha$ spent on the nontraded good, i.e., housing units of H_i. There will also be a random portion of utility denoting the amenity value of each region that is introduced later.

For simplicity we will assume that firms in the differentiated industry, which we refer to as manufacturing, produce one unit of output with one unit of labor (though nothing of substance would change if firms were heterogeneous in their productivities.) With the wage w_i, prices are $p_i = \frac{\sigma}{\sigma-1} w_i$. It follows that $c_{ji}(\omega) = c_{ji}$ and the utility function is simplified as

$$U_i = \left(\frac{1}{\alpha} \sum_{j=1}^{N} M_j c_{ji}^{(\sigma-1)/\sigma} \right)^{\frac{\alpha\sigma}{\sigma-1}} \left(\frac{H_i}{1-\alpha} \right)^{1-\alpha}.$$

With output of y_i and fixed costs of F, profits are then $p_i y_i - w_i(F + y_i) = w_i[y_i/(\sigma-1) - F]$. In order to have zero profits in equilibrium, the output of firms is therefore *fixed* at $y_i = (\sigma-1)F$. The total employment in the manufacturing sector is then

$$L_{mi} = M_i(y_i + F) = \sigma M_i F. \tag{A.2}$$

We introduce iceberg costs of τ_{ji} to ship a good from region j to i, with $\tau_{ii} = 1$. Denote the total expenditure in each region by E_i, which we solve for below. Then consumption of each manufactured variety sent from region j to i is

$$c_{ji} = \left(\frac{\tau_{ji} p_j}{P_i}\right)^{-\sigma} \frac{\alpha E_i}{P_i}, \tag{A.3}$$

where P_i refers to region i's overall price index in manufacturing, which is:

$$P_i = \left(\sum_{j=1}^{N} M_j (\tau_{ji} p_j)^{(1-\sigma)}\right)^{\frac{1}{1-\sigma}}. \tag{A.4}$$

The demand for housing is obtained from the Cobb-Douglas structure in (A.1) as

$$H_i = \frac{(1-\alpha)E_i}{r_{hi}}, \tag{A.5}$$

where r_{hi} is the rental price of housing. We suppose that the rental price of housing r_{hi} reflects the depreciation rate times the construction cost per housing unit, which equal $c_i(w_i, p_{Ti})$ where c_i is the unit-cost function dual to f_i. That is, the rental price of housing is $r_{hi} = \delta c_i(w_i, p_{Ti})$. If we define the rental price of an acre of land by $r_{Ti} \equiv \delta p_{Ti}$, then we can alternatively express the rental price of housing as $r_{hi} = c_i(\delta w_i, r_{Ti})$, depending on the amortized labor costs in construction plus the rental price of land per housing unit.

Goods market clearing

For simplicity, we take the variety M_N, price index P_N, and expenditure E_N in the foreign country $j = N$ as exogenous, and we also normalize the foreign wage at unity, $w_N = 1$. Our goal is to determine equilibrium across the home regions. With output of each variety in region i determined by $y_i = (\sigma - 1)F$, market clearing in the manufactured varieties requires that

$$y_i = \sum_{j=1}^{N} \tau_{ij} c_{ij} = \sum_{j=1}^{N} \left(\frac{\tau_{ij} p_i}{P_j}\right)^{1-\sigma} \left(\frac{\alpha E_j}{p_i}\right), \quad i = 1, ..., N-1, \tag{A.6}$$

where output includes the iceberg costs τ_{ij} and we have used consumption from (A.3). Another $N-1$ equilibrium conditions come from the labor used in construction as derived in the main text:

$$L_{hi} = \frac{\theta_{iL} r_{hi} H_i}{w_i}, \quad i = 1, ..., N-1, \tag{A.7}$$

where the Cobb-Douglas labor share θ_{iL} is a parameter. A final goods-market condition comes from the balance of trade in each home region,

$$\sum_{j=1,j\neq i}^{N} M_i p_i \tau_{ij} c_{ij} - \sum_{k=1,k\neq i}^{N} M_k p_k \tau_{ki} c_{ki} = B_i, \quad i = 1, ..., N-1. \tag{A.8}$$

The first term on the left of (A.8) is total exports from region i to all other home regions and to the foreign country, while the second term is total imports. Region i has a trade balance of B_i determined by the tax and transfers in (3), and we will further solve for it below. In the main text, we discuss how the allocation of labor between regions, and between those residents in and out of the labor force. Those conditions together with (A.3)-(A.8) fully determine labor allocations across regions, and the employment in construction and manufacturing, along with product variety, wages and rentals.

Derivation of equations (10) and (11) in the main text:

Using $B_i = \left[t - (1-t)\rho_i^{1+\eta}\right] w_i \lambda_i \bar{L}$ and $\sum_{j=1}^{N-1} B_i = B$ we obtain,

$$\sum_{j=1}^{N-1} \left[t - (1-t)\rho_j^{1+\eta}\right] w_j \lambda_i \bar{L}_j = B \Rightarrow t = \frac{B + \sum_{j=1}^{N-1} \rho_j^{1+\eta} w_j (L_{hj} + L_{mj})}{\sum_{j=1}^{N-1} (1 + \rho_j^{1+\eta}) w_j (L_{hj} + L_{mj})}.$$

Substituting this back into $B_i = \left[t - (1-t)\rho_i^{1+\eta}\right] w_i \lambda_i \bar{L}$, gives

$$\begin{aligned} B_i &= \left[t(1 + \rho_i^{1+\eta}) - \rho_i^{1+\eta}\right] w_i \lambda_i \bar{L} \\ &= \left[(1 + \rho_i^{1+\eta}) \frac{B + \sum_{j=1}^{N-1} \rho_j^{1+\eta} w_j (L_{hj} + L_{mj})}{\sum_{j=1}^{N-1} (1 + \rho_j^{1+\eta}) w_j (L_{hj} + L_{mj})} - \rho_i^{1+\eta}\right] w_i (L_{hi} + L_{mi}) \\ &= \left[\frac{(1 + \rho_i^{1+\eta}) B + \sum_{j=1}^{N-1} (\rho_j^{1+\eta} - \rho_i^{1+\eta}) w_j (L_{hj} + L_{mj})}{\sum_{j=1}^{N-1} (1 + \rho_j^{1+\eta}) w_j (L_{hj} + L_{mj})}\right] w_i (L_{hi} + L_{mi}), \end{aligned}$$

which implies (10) and (11). With this solution for B_i, regional expenditure $E_i = I_i - B_i$ using (4) becomes

$$\begin{aligned} E_i &= I_i - B_i = w_i (L_{hi} + L_{mi}) + r_{Ti} T_i - B_i \\ &= (1 + R_i) w_i (L_{hi} + L_{mi}) + r_{Ti} T_i - B \frac{(1 + \rho_i^{1+\eta}) w_i (L_{hi} + L_{mi})}{\sum_{j=1}^{N-1} (1 + \rho_j^{1+\eta}) w_j (L_{hj} + L_{mj})}. \end{aligned} \tag{A.9}$$

Employment in each region:

Since profits are zero in each region, labor income from manufacturing equals sales, as so using (A.6) we obtain

$$w_i L_{mi} = M_i p_i y_i = M_i p_i c_{ii} + M_i p_i \sum_{j=1, j\neq i}^{N} \tau_{ij} c_{ij}.$$

The final summation on the right is the labor used to produce manufacturing exports from region i, but we can use trade balance in (A.8) to replace this with the value of labor used in imports plus the local trade balance B_i , so that

$$w_i L_{mi} = M_i p_i c_{ii} + \sum_{k=1, k\neq i}^{N} M_k p_k \tau_{ki} c_{ki} + B_i = \alpha E_i + B_i,$$

where the final equality is obtained using consumption from (A.3). We report this employment equation in the main text in (12).

Using the expression for the regional trade balance in (10), we obtain

$$w_i L_{mi} = \alpha E_i + B \frac{(1+\rho_i^{1+\eta}) w_i (L_{hi} + L_{mi})}{\sum_{j=1}^{N-1} (1+\rho_j^{1+\eta}) w_j (L_{hj} + L_{mj})} - w_i (L_{hi} + L_{mi}) R_i. \tag{A.10}$$

As explained in the main text, in a steady-state the rental price of housing will reflect the depreciation rate times construction costs, $r_{hi} = \delta c_i (w_i, r_{Ti})$. Multiplying both sides by H_i, it follows that the total rental value of the housing stock, $r_{hi} H_i$, equals the total construction costs needed to maintain that stock, $(\delta H_i) c_i (w_i, r_{Ti})$. We make the simplifying assumption that $f_i(.)$ and $c_i(.)$ are Cobb-Douglas, so that the share of labor in construction costs, $\theta_{Li} \equiv w_i L_{hi} / (r_{hi} H_i)$, is constant in each region. It follows that labor used in construction equals $L_{hi} = \theta_{Li} (1-\alpha) E_i / w_i$, which can be used to simplify (A.10), obtaining

$$L_{mi} = \frac{[\alpha - \theta_{Li}(1-\alpha) R_i]}{(1+R_i)} \frac{E_i}{w_i} + \frac{B}{(1+R_i)} \frac{(1+\rho_i^{1+\eta})(L_{hi} + L_{mi})}{\sum_{j=1}^{N-1} (1+\rho_j^{1+\eta}) w_j (L_{hj} + L_{mj})}. \tag{A.11}$$

This can be rewritten using R_i from (11) as (13) and (14) in the main text.

B Discussion on Shift-Share Instruments

One concern raised by the very recent literature is that usual inference to a shift-share analysis may understate the true variability of the estimator and therefore corrections should be done to the standard errors. Borusyak et al. (2018) derive that the orthogonality between a shift-share instrument and an unobservable residual can be represented equivalently as the orthogonality between the underlying shocks and a shock-level unobservable, and therefore propose a transformation of CZ-level regressions to the industry-level regressions. 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 new inference methods that are valid under arbitrary cross-regional correlation in the regression residuals. Unfortunately, neither correction methods can be applied to our framework directly, since besides the endogenous 'shift-share' trade variable, we also have the region-level housing variable, which is also endogenous and cannot be measured at the industry level.

Having that said, we have done a quasi-TSLS experimentation by directly replacing the endogenous housing variable in our estimation equation (20) with the predicted housing variable that is constructed from a standard first-stage regression, and treating it as an exogenous control. In this case, we can apply the AKM method to correct the standard errors. We find that the AKM standard errors are much larger than the clustered standard errors. The significance of the estimated import exposure coefficient remains in the full sample of 722 commuting zones, whereas in the reduced sample of 249 commuting zones, the estimated import exposure coefficients are not significant any more. This is interesting and might be related to the fact that the reduced sample consists of mainly metropolitan areas, for which the cross-region correlations for the regression residuals are possibly much higher than those in the excluded rural areas. Now, on the one hand, housing reduces the magnitude of the estimated impact of the China shock; on the other hand, AKM inference increases the standard errors substantially, such that the estimated effects of the China shock are not significant. Further investigations on the corrections of standard errors in a shift-share framework with multiple endogenous variables remain to be done in the future.

C Supplementary Empirical Results

Table A.1 reports the estimation without housing as in ADH (2013) using the full sample of 722 commuting zones. The estimates for manufacturing (column 1) and non-manufacturing (column 4) replicate the numbers in ADH (2013). Table A.2 reports the employment regressions for non-manufacturing employment. Table A.3 reports the regressions using the shares of employment to working-age population rather than log employment as the dependent variables.

Table A.4, Panel A reports the estimates of $\hat{b}_k$ from the auxiliary regressions in equation (23). Table A.5, Panel A reports the decomposition results $\hat{\alpha}_k\hat{b}_k$, where $\hat{\alpha}_k$ comes from the first-stage regressions (22) as reported in Table 3. Because these auxiliary and first-stage regressions do not rely on the log employment used as the dependent variable in the second stage, panel A of Table A.5 and panel A of Table 7 are identical. Differences emerge in panels B and C, however, where Table A.5 reports results using the change in the log of manufacturing and construction employment separately, while Table 7 reports results using the change in the log of the sum of manufacturing and construction employment.

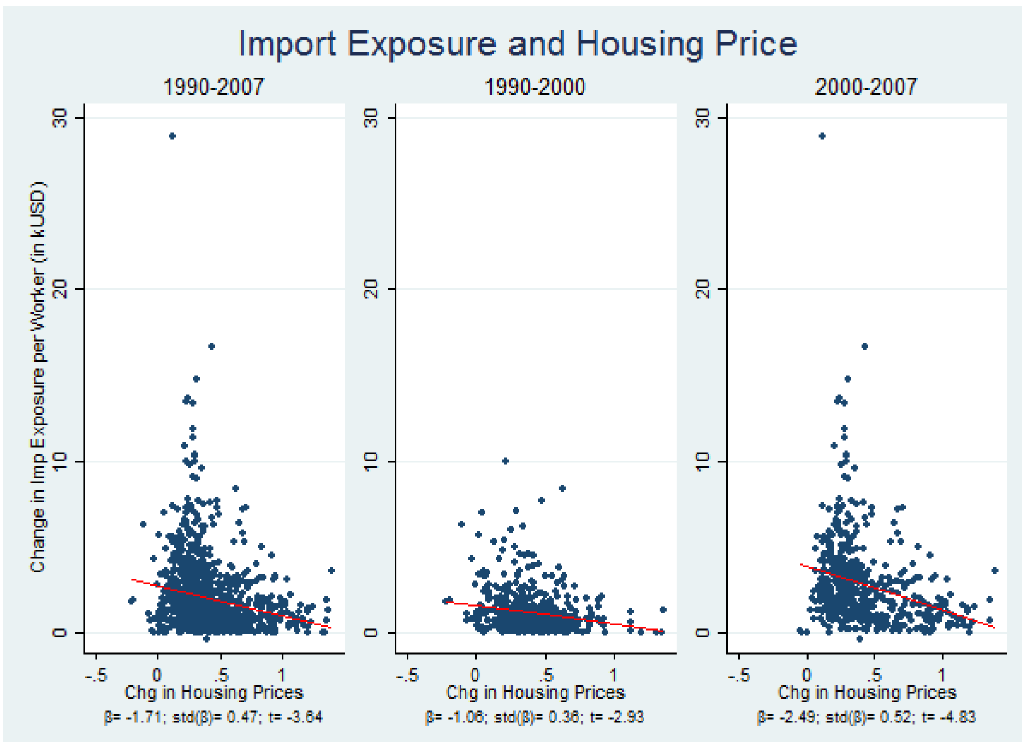
Table A.4, Panel B reports the estimates of $\hat{\theta}_k$ from the auxiliary regressions in equation (25). Table A.5, Panel B reports the decomposition results $\hat{\beta}_k\hat{\theta}_k$, where $\hat{\beta}_k$ comes from the second-stage regressions (24) as reported in Tables 2 and 4. It shows that predicted changes in import exposure accounts for about 8-10% of the variation in manufacturing employment, and predicted changes in housing value explains 4-6% of the variation in manufacturing employment. As for the construction sector, predicted changes in import exposure explains less than 0.4% of the variation, while predicted changes in housing value explains 20-30% of the variation.

The results are combined in Panel C of Table A.5. When ignoring housing, the ADH China shock instrument explains 6.74% of the variation in manufacturing employment and 0.28% of the variation in construction employment. After controlling for housing using the Saiz elasticity, the ADH China shock instrument contributes to the variation in employment through both the 'direct' channel of changes in import exposure and the 'indirect' channel of changes in housing value. For manufacturing employment, the direct channel plays the dominant role: it explains 5.33% ($67.24\% \times 7.92\% = 5.33\%$) of the variation, and the indirect channel accounts for 0.28% ($6.68\% \times 4.25\% = 0.28\%$) of the variation. Taken together, these direct and indirect effects of the China shock explain 5.61% of the variation in manufacturing employment. That is somewhat less than the 6.74% explained by the China shock when ignoring housing, but housing has an independent effect on manufacturing employment, too. That independent effect is reported as 2.84% in column (2), and nearly all of that is obtained the direct effect of the Saiz elasticity on the housing market and therefore on manufacturing employment ($66.10\% \times 4.25\% = 2.81\%$). By these comparisons, the ADH instrument explains twice as much of the variation in manufacturing employment as the Saiz elasticity. In contrast, for construction employment, all contribution comes through the indirect channel of the housing market ($6.68 \times 19.94\% = 1.33\%$) and the direct contribution through the changes of import exposure is virtually zero.

Results when using the two housing instruments are in column (3) of Table A.5. The China shock now explains 5.79% of the variation in manufacturing employment through mainly the direct channel of import exposure ($67.31\% \times 8.35\% = 5.62\%$) , and 0.68% of the variation in construction employment through entirely the indirect channel of housing market ($2.69\% \times 32.43\% = 0.87\%$). After adding the structural break as one more instrument for housing, the explanatory power of Saiz elasticity decreases to 1.05% for the variation in manufacturing employment and 5.14% for the variation in construction employment. In contrast, the structural break explains 4.31% of the manufacturing employment and 21.97% of the construction employment, both entirely through the changes in housing value. Taken together, the two housing instruments explain over 5% of the variation in manufacturing employment and 27% of the variation in construction employment.

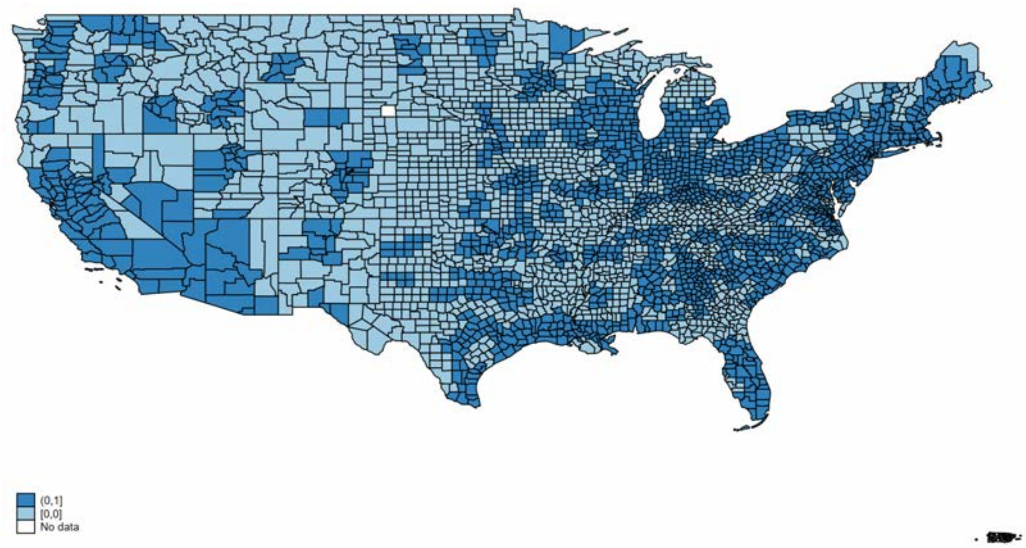
In Table A.6, we perform a variance decomposition for the shares of employment to working-age population. We skip the decomposition at the first-stage regression, since it is identical to Panel A of Table A.5 (or Table 7). The three instruments explain even higher fractions of the variance in employment shares than in employment counts. For example, the China shock instrument explains more than 15% of the variation in the share of manufacturing employment. The two housing instruments explain around 6% of the variation in manufacturing employment share and 32% of the variation in construction employment share. Patterns regarding the direct and indirect channels remain qualitatively similar.

Figure A.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 A.2: Areas with and without Housing Information



Note: This figure plots the map of the United States. Dark blue areas are areas with housing information, which constitutes our sample of 249 commuting zones. Light blue areas are areas without housing information. The sum of them represents the full sample of 722 commuting zones used in ADH (2013).

Table A.1: Results using the ADH Sample of 722 CZs without Controlling Housing

	Manuf.	Construction	FIRE	Non-Manuf.
	(1)	(2)	(3)	(4)
Dep.Var: 100 $\times$ change in log employment				
All education levels				
ΔImport exposure from China	-4.231***	-2.818**	0.190	-0.274
	(1.047)	(1.192)	(0.583)	(0.651)
College education				
ΔImport exposure from China	-3.992***	-2.503**	0.339	0.291
	(1.181)	(1.181)	(0.677)	(0.590)
No College education				
ΔImport exposure from China	-4.493***	-2.853**	0.035	-1.037
	(1.243)	(1.270)	(0.765)	(0.764)

Note: N = 1444. Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports the estimation results without housing using the full sample of 722 commuting zones as in ADH (2013). The estimates for manufacturing and non-manufacturing replicate the numbers reported in ADH (2013).

Table A.2: The Impact of Housing and Imports on Non-manufacturing Employment

	(1)	(2)	(3)
Dep. var: 100 $\times$ change in log non-manuf. employment			
All education levels			
ΔImport exposure from China	-0.635	0.206	0.499
	(0.858)	(0.679)	(0.673)
ΔHousing value		0.127***	0.162***
		(0.033)	(0.025)
Hansen J p-value			0.229
College education			
ΔImport exposure from China	-0.198	0.426	0.761
	(0.755)	(0.601)	(0.607)
ΔHousing value		0.094***	0.134***
		(0.031)	(0.022)
Hansen J p-value			0.184
No College education			
ΔImport exposure from China	-1.262	0.217	0.194
	(0.982)	(0.767)	(0.755)
ΔHousing value		0.223***	0.220***
		(0.044)	(0.035)
Hansen J p-value			0.923
Instruments for Housing		Elasticity	Elasticity+Break

Note: N = 498 (249 CZs over two time periods). Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1) performs the estimation without controlling housing. The import exposure is instrumented by China's exports to eight other economies as in ADH. Column (2) introduces housing and instrument it with the Saiz elasticity. Together with the ADH China shock instrument, we have two endogenous variables and two instruments in this case. Column (3) adds one more instrument for housing, i.e., the estimated structural break. Hansen J p-values are reported for over-identified cases. We perform the estimations for the group of all workers, the group of workers with college education and the group of workers without college education. All regressions include a dummy for the 2000-2007 period, a set of census division dummies, and the full vector of controls: start of period 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 average offshorability index of occupations. All regressions are weighted by start of period commuting zone's share of national population.

Table A.3: The Impact of Housing and Imports on Employment Shares

	Manuf. (1)	Construction (2)	FIRE (3)	Non-Manuf. (4)
Dep.Var: change in employment over working-age pop.				
Panel A: ADH Full Sample, ignoring housing				
All education levels				
ΔImports exposure from China	-0.596***	-0.143***	-0.023	-0.178
	(0.099)	(0.040)	(0.027)	(0.137)
College education				
ΔImport exposure from China	-0.592***	-0.086***	-0.016	0.168
	(0.125)	(0.030)	(0.033)	(0.122)
No College education				
ΔImport exposure from China	-0.581***	-0.174***	-0.020	-0.531***
	(0.095)	(0.067)	(0.025)	(0.203)
Panel B: Our Sample, ignoring housing				
All education levels				
ΔImports exposure from China	-0.733***	-0.151***	-0.037	-0.186
	(0.109)	(0.050)	(0.051)	(0.233)
College education				
ΔImport exposure from China	-0.744***	-0.106**	-0.046	0.225
	(0.150)	(0.041)	(0.058)	(0.179)
No College education				
ΔImport exposure from China	-0.699***	-0.177**	-0.021	-0.588*
	(0.119)	(0.088)	(0.046)	(0.335)
Panel C: Our Sample, housing instrumented by Saiz elasticity				
All education levels				
ΔImports exposure from China	-0.557***	0.058	0.069	0.276
	(0.100)	(0.055)	(0.075)	(0.293)
College education				
ΔImport exposure from China	-0.554***	0.010	0.078	0.473**
	(0.146)	(0.040)	(0.085)	(0.205)
No College education				
ΔImport exposure from China	-0.508***	0.156	0.062	0.162
	(0.119)	(0.110)	(0.059)	(0.427)
Panel D: Our Sample, housing instrumented by Saiz elasticity + structural break				
All education levels				
ΔImports exposure from China	-0.629***	0.021	0.032	0.191
	(0.105)	(0.053)	(0.067)	(0.293)
College education				
ΔImport exposure from China	-0.645***	-0.003	0.039	0.472**
	(0.148)	(0.038)	(0.075)	(0.192)
No College education				
ΔImport exposure from China	-0.574***	0.083	0.028	-0.060
	(0.122)	(0.103)	(0.055)	(0.432)

Note: This table reports the estimation results using the changes of the shares of employment to working-age population rather than log employment as the dependent variables. To save space, we only report the coefficients for import exposure. The coefficients for housing are all significantly positive. All regressions include a dummy for the 2000-2007 period, a set of census division dummies, and the full vector of controls. All regressions are weighted by start of period commuting zone's share of national population. Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Auxiliary Regressions for Variance Decomposition

	1IV Case	2IV Case		3IV Case		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First-Stage	ADH IV	ADH IV	Elasticity	ADH IV	Elasticity	Break
$\widehat{\Delta IPW}$	1.187***	1.185***	0.091**	1.185***	0.091**	-0.974*
	(0.056)	(0.057)	(0.037)	(0.056)	(0.038)	(0.317)
$\widehat{\Delta HPQ}$		-0.026***	-0.061***	-0.015***	-0.035***	0.267***
		(0.005)	(0.005)	(0.006)	(0.004)	(0.021)
Panel B: Second-Stage	$\widehat{\Delta IPW}$	$\widehat{\Delta IPW}$	$\widehat{\Delta HPQ}$	$\widehat{\Delta IPW}$	$\widehat{\Delta HPQ}$	
ΔManuf. + Constr. Emp	-0.021***	-0.022***	0.423***	-0.022**	0.674***	
	(0.005)	(0.005)	(0.064)	(0.005)	(0.081)	
ΔManuf. Emp	-0.017**	-0.018**	0.196***	-0.018**	0.340***	
	(0.007)	(0.007)	(0.068)	(0.007)	(0.104)	
ΔConstr. Emp	-0.002	-0.003	0.398***	-0.003	0.705***	
	(0.004)	(0.004)	(0.076)	(0.004)	(0.125)	

Note: Robust standard errors in parentheses, clustered on state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel A reports the estimates of $\hat{b}_k$ from the first-stage auxiliary regressions in equation (23). The dependent variable is the instrumental variable as indicated. The independent variable is either the predicted changes of import exposure ($\Delta\widehat{IPW_{it}}$) or the predicted changes of housing value ($\Delta\widehat{HPQ_{it}}$). Panel B reports the estimates of $\hat{\theta}_k$ from the second-stage auxiliary regressions in equation (25). The dependent variable is the predicted changes of import exposure ($\Delta\widehat{IPW_{it}}$) or the predicted changes of housing value ($\Delta\widehat{HPQ_{it}}$). The independent variable is the decadal change of employment, including the sum of manufacturing and construction employment, or manufacturing employment and construction employment separately. Column (1) refers to the case with only import exposure, which is instrumented by China's exports to eight other economies as in ADH. Columns (2)-(3) are the case introducing housing and instrumenting it by the Saiz elasticity. Columns (4)-(6) are the case adding the estimated structural break as one more instrument.

Table A.5: Variance Decomposition for Manufacturing and Construction Separately

	(1)	(2)	(3)
Panel A: Variance Decomposition for First Stage Regression			
Explanatory variable: Predicted ΔImport exposure			
ADH IV	67.96%	67.24%	67.31%
Saiz Elasticity		0.41%	0.46%
Structural Break			-0.19%
Explanatory variable: Predicted ΔHousing value			
ADH IV		6.68%	2.69%
Saiz Elasticity		66.10%	15.84%
Structural Break			67.76%
Panel B: Variance Decomposition for Second Stage Regression			
Explanatory variable: ΔManufacturing Employment			
Predicted ΔImport	9.92%	7.92%	8.35%
Predicted ΔHousing		4.25%	6.39%
Explanatory variable: ΔConstruction Employment			
Predicted ΔImport	0.41%	-0.39%	-0.29%
Predicted ΔHousing		19.94%	32.43%
Panel C: Variance Decomposition Combined			
Explanatory variable: ΔManufacturing Employment			
ADH IV	6.74%	5.61%	5.79%
Saiz Elasticity		2.84%	1.05%
Structural Break			4.31%
Explanatory variable: ΔConstruction Employment			
ADH IV	0.28%	1.07%	0.68%
Saiz Elasticity		13.18%	5.14%
Structural Break			21.97%

Note: This table reports the variance decomposition for the first-stage and second-stage regressions of the employment of manufacturing and construction separately. The procedures are discussed in section 4.3. Panel A reports the decomposition results $\hat{\alpha}_k \hat{b}_k$, where $\hat{\alpha}_k$ comes from the first-stage regressions (22) as reported in Table 3. Panel B reports the decomposition results $\hat{\beta}_k \hat{\theta}_k$, where $\hat{\beta}_k$ comes from the second-stage regressions (24). Column (1) refers to the case with only one endogenous variable: import exposure, which is instrumented by China's exports to eight other economies as in ADH. Column (2) refers to the case introducing housing and instrumenting it by the Saiz supply elasticity. Column (3) adds one more instrument for housing, i.e., the estimated structural break.

Table A.6: Variance Decomposition for Employment Shares

	(1)	(2)	(3)
Panel A: Variance Decomposition for Second Stage Regression			
Explanatory variable: ΔManuf. employment Share			
Predicted ΔImport	25.87%	20.00%	22.52%
Predicted ΔHousing		10.11%	8.05%
Explanatory variable: ΔConstruction employment Share			
Predicted ΔImport	0.60%	-0.63%	-0.24%
Predicted ΔHousing		30.00%	39.02%
Panel B: Variance Decomposition Combined			
Explanatory variable: ΔManuf. employment Share			
ADH IV	17.58%	14.12%	15.37%
Saiz Elasticity		6.76%	1.38%
Structural Break			5.41%
Explanatory variable: ΔConstruction employment Share			
ADH IV	0.41%	1.58%	0.89%
Saiz Elasticity		19.83%	6.18%
Structural Break			26.44%

Note: This table reports the variance decomposition for the shares of employment to working-age population. The first-stage results are identical to those in Panel A of Table 7. Column (1) refers to the case with only one endogenous variable: import exposure, which is instrumented by China's exports to eight other economies as in ADH. Column (2) refers to the case introducing housing and instrumenting it by the Saiz supply elasticity. Column (3) adds one more instrument for housing, i.e., the estimated structural break.