Online Appendix: Heterogeneous Workers and Federal Income Taxes in a Spatial Equilibrium, Mark Colas and Kevin Hutchinson

A1. Numerical and Theoretical Appendix

Firm's Choice of Capital. — The firm chooses capital such that the marginal revenue product of capital is equal to the rental price of capital. The optimal ratio of labor to capital is given by

$$\frac{L_{jt}}{K_{jt}} = \left(\frac{\bar{\mathcal{R}}_t}{A_{jt}\left(1-\eta\right)}\right)^{1/\eta}. \tag{A1}$$

Therefore, the ratio of labor to the capital is determined by the price of capital $\bar{\mathcal{R}}_t$, TFP A_{jt}, and the parameter η. Combining capital demand (A1) with the equation for the marginal revenue products of capital yields the following labor demand curves:

$$\begin{aligned} w_{jt}^S &= \tilde{A}_{jt} L_{jt}^{1-\rho} \theta_{jt} S_{jt}^{\rho-1} \\ w_{jt}^U &= \tilde{A}_{jt} L_{jt}^{1-\rho} \left(1-\theta_{jt}\right) U_{jt}^{\rho-1}, \end{aligned} \tag{A2}$$

where

$$\tilde{A}_{jt} = \eta A_{jt} \left(\frac{\bar{\mathcal{R}}_t}{A_{jt}\left(1-\eta\right)}\right)^{\frac{\eta-1}{\eta}}.$$

Note that, because of the assumptions on capital supply and the functional form of the production function, these labor demand curves do not take capital, K_{jt} as an argument. We can therefore estimate the labor demand curves without data on physical capital.

Competitive Equilibrium Definition. — We begin our proof by defining a feasible allocation and a competitive equilibrium. We then show that there does not exist a feasible allocation that dominates the competitive equilibrium with lump-sum taxes. Throughout this section we drop all t subscripts for simplicity, and add i subscripts to individual level choices.

Let an allocation be given by $\{\mathbf{c}, \mathbf{h}, \mathbf{j}, \mathbf{L}, \mathbf{K}, \mathbf{H}\}$, where $\mathbf{c}, \mathbf{h}, \mathbf{j}$ are vectors of household choices, $\mathbf{L}$ is a matrix of labor supply of all demographic groups across all cities, $\mathbf{K}$ is a vector of capital across all cities, and $\mathbf{H}$ is a vector of housing across cities. Let $\mathbf{L}_j$ be a vector of labor supply of all demographic groups in city j. An allocation is feasible if it satisfies the following feasibility constraint:

$$\sum_j Y_j\left(\mathbf{L}_j, K_j\right) = G + \sum_i c_i + \sum_j \left(\int_0^{H_j} \left(z_j x^{k_j}\right) dx\right) + \sum_j \bar{\mathcal{R}} K_j$$

and $H_j = \sum_i h_{ij}$, for all cities j. That is, total production is equal to the sum of government spending, consumption, housing production, and purchases of capital.

Now we define a competitive equilibrium. Let $\{\mathbf{c}^\star, \mathbf{h}^\star, \mathbf{j}^\star, \mathbf{L}^\star, \mathbf{K}^\star, \mathbf{H}^\star, \mathbf{r}^\star, \mathbf{w}^\star, \mathbf{\Pi}^\star\}$ denote a competitive equilibrium, where $\mathbf{r}$ is a vector of rents across all cities, $\mathbf{w}$ is a matrix of all wage levels across all cities and demographic groups, and $\mathbf{\Pi}$ is total landowner profits. A competitive equilibrium must satisfy feasibility and the following conditions:

1) Household maximization: $j_i^\star$, $c_i^\star$ and $h_{ij}^\star$ maximize $\max_{j,c,h_j} u_i(j, c, h_j)$ subject to the budget constraint $c_i + r_j^\star h_j = w_j^{d\star} + s^d \mathbf{\Pi}^\star - \mathcal{T}_j^d \left(w_j^{d\star} + s^d \mathbf{\Pi}^\star \right)$, for all households i. Let $N_j^{d\star}$ denote the number of households of demographic d who optimally chose location j.

2) Firm maximization: $\mathbf{L}_j^\star$ and $K_j^\star$ solve $\max_{\mathbf{L}_j, K_j} \left[Y_j(\mathbf{L}_j, K_j) - \sum_d L_j^d w^{d\star} - \bar{\mathcal{R}} K_j \right]$ in each city j.

3) Landowner maximization: $H_j^\star$ solves $\max_H \left(\int_0^H \left(r_j^\star - z_j x^{k_j} \right) dx \right)$ in all cities j. The sum of maximized profits are given by

$$\mathbf{\Pi}^\star = \sum_j \left(\int_0^{H_j^\star} \left(r_j^\star - z_j x^{k_j} \right) dx \right)$$

4) Labor market clearing: $L_j^{d\star} = N_j^{d\star}$ for all demographic groups d and cities, j.

5) Housing market clearing: $H_j^\star = \sum_i h_{ij}^\star$

6) Government budget constraint: $\sum_j \sum_d N_j^{d\star} \mathcal{T}_j^d \left(w_j^{d\star} + s^d \mathbf{\Pi}^\star \right) = G$

PARETO OPTIMALITY PROOF. — A competitive equilibrium with lump-sum taxes is a competitive equilibrium where taxes for each household are lump-sum. That is, taxes for a household of demographic group d are independent of any of the individual's decisions such that $\mathcal{T}_j^d \left(I_j^d \right) = \tau_d$ and the sum of the lump-sum taxes across individual equals the government revenue requirement. The proof can easily be extended to allow for individual-specific lump-sum taxes.

PROPOSITION 1: *Let* $\{\boldsymbol{c}^\star, \boldsymbol{h}^\star, \boldsymbol{j}^\star, \boldsymbol{L}^\star, \boldsymbol{K}^\star, \boldsymbol{H}^\star, \boldsymbol{r}^\star, \boldsymbol{I}^\star, \mathbf{\Pi}^\star\}$ *be a competitive equilibrium with lump-sum taxes. There is no other feasible allocation* $\left\{ \boldsymbol{c}', \boldsymbol{h}', \boldsymbol{j}', \boldsymbol{L}', \boldsymbol{K}', \boldsymbol{H}' \right\}$ *such that*

$$u_i\left(j_i', c_i', h_{ij}'\right) \geq u_i\left(j_i^\star, c_i^\star, h_{ij}^\star\right)$$

for all $i \in I$ *and*

$$u_{\hat{i}}\left(j_{\hat{i}}', c_{\hat{i}}', h_{\hat{i}j}'\right) > u_{\hat{i}}\left(j_{\hat{i}}^\star, c_{\hat{i}}^\star, h_{\hat{i}j}^\star\right)$$

for at least one individual $\hat{i}$.

PROOF:

Suppose there exists an allocation $\left\{\mathbf{c}', \mathbf{h}', \mathbf{j}', \mathbf{L}', \mathbf{K}', \mathbf{H}'\right\}$ such that

$$u_i\left(j_i', c_i', h_{ij}'\right) \geq u_i\left(j_i^\star, c_i^\star, h_{ij}^\star\right)$$

for all $i \in I$ and

$$u_{\hat{i}}\left(j_{\hat{i}}', c_{\hat{i}}', h_{\hat{i}j}'\right) > u_{\hat{i}}\left(j_{\hat{i}}^\star, c_{\hat{i}}^\star, h_{\hat{i}j}^\star\right)$$

for at least one individual $\hat{i}$.

As the bundle $\left\{j_{\hat{i}}', c_{\hat{i}}', h_{\hat{i}j}'\right\}$ is preferred to $\left\{j_{\hat{i}}^\star, c_{\hat{i}}^\star, h_{\hat{i}j}^\star\right\}$ for this individual $\hat{i}$, this bundle must have not been affordable at the competitive equilibrium prices. Therefore, we must have

$$c_{\hat{i}}' + r_{j'}^\star h_{\hat{i}j'}' > w_{j'}^{d\star} + s^d \mathbf{\Pi}^\star - \tau_d$$

for this individual.

By similar logic, and by nonsatiation of preferences given our utility function, we must also have

$$c_i' + r_{j'}^\star h_{ij'}' \geq w_{j'}^{d\star} + s^d \mathbf{\Pi}^\star - \tau_d$$

for all agents i.

Summing these inequalities across agents yields

$$\sum_i c_i' + \sum_j r_j^\star H_j' > \sum_d \sum_j w_j^{d\star} L_j^{d\prime} - G + \mathbf{\Pi}^\star$$

Plugging in the feasibility constraint for $\sum_i c_i'$ yields

$$\sum_j Y_j'\left(\mathbf{L}_j', K_j'\right) - G - \sum_j \left(\int_0^{H_j'} \left(z_j x^{k_j}\right) dx\right) - \sum_j \bar{\mathcal{R}} K_j' + \sum_j r_j^\star H_j' > \sum_d \sum_j w_j^{d\star} L_j^{d\prime} - G + \mathbf{\Pi}^\star.$$

Plugging in profits $\mathbf{\Pi}\left(\mathbf{r}, \mathbf{H}\right) = \sum_j \left(\int_0^{H_j} \left(r_j - z_j x^{k_j}\right) dx\right)$ and simplifying yields

$$\text{(A3)}\quad \sum_j Y_j'\left(\mathbf{L}_j', K_j'\right) - \sum_d \sum_j w_j^{d\star} L_j^{d\prime} - \sum_j \bar{\mathcal{R}} K_j' + \sum_j \left(\int_0^{H_j'} \left(r_j^\star - z_j x^{k_j}\right) dx\right) > \sum_j \left(\int_0^{H_j^\star} \left(r_j^\star - z_j x^{k_j}\right) dx\right)$$

But in order for equation (A3) to be true, there must be either one city j such that either

$$Y_j\left(\mathbf{L}_j', K_j'\right) - \sum_d w_j^{d\star} L_j^{d\prime} - \bar{\mathcal{R}} K_j' > 0 \tag{A4}$$

or

$$\int_0^{H_j'} \left(r_j^\star - z_j x^{k_j}\right) dx > \int_0^{H_j^\star} \left(r_j^\star - z_j x^{k_j}\right) dx \tag{A5}$$

Neither of these conditions can hold. Condition (A4) cannot hold because $\mathbf{L}_j^\star$ and $K_j^\star$ maximize firm profits at the competitive equilibrium prices and maximum profits are equal to zero in the competitive equilibrium because production exhibits constant returns to scale. Condition (A5) cannot hold because $H_j^\star$ maximizes landowner profits given prices $r_j^\star$. Therefore the competitive equilibrium with lump-sum taxes is Pareto optimal.

Bartik Instrument. — The instrument interacts the lagged industry composition of each city with current national changes in total hours worked in each industry. Conceptually, cities that historically have large concentrations of industries that are currently growing will see faster wage growth than cities which historically have large concentrations of industries which are currently declining.

Formally, we can write the instrument as follows:

$$\text{Bartik}_{jt}(e) = \sum_{m=1}^{M} \kappa_{mj}^{80}(e)\text{NatHoursInd}_{mt}(e),$$

where m indexes industries, $\kappa_{mj}^{80}(e)$ is total hours of labor by households of skill level e in city j in 1980 as a fraction of the total hours worked in all industries in city j in 1980, and NatHoursInd_{mt} is the total hours worked nationally in industry m in time t. The instrument creates variation in city-level wages that are assumed to be orthogonal to changes in unobserved amenities.

We include both the Bartik instrument and the Bartik instrument interacted with our measure of housing supply elasticity as instruments.

Card and Moretti Instruments. — In particular, the Card instrument is constructed as

$$\text{Card}_{jt}(e) = \sum_{g=1}^{G} \mu_{gj}^{80}(e)\text{Imm}_{gt}(e),$$

where $\text{Imm}_{gt}(e)$ is the national inflow rate of immigrants with education level e from country g in time t and $\mu_{gj}^{80}(e)$ is the share of total immigrants from country g of education level e living in labor market j in 1980. The intuition is that the historical distribution of immigrants from a given country g is correlated with the distribution of new immigrants from country g but is uncorrelated with current labor market conditions.

We also use the Moretti instrument to predict changes in the quantities of skilled and unskilled labor. In particular, the instrument interacts the long-term trend of increasing educational attainment with the lagged age structure of labor market. For instance, labor markets that are disproportionately young or old are predicted to have larger increases in skilled labor. This is because the young are more likely to obtain education and the old are less likely to be educated and will be leaving the labor force. More formally, we predict hours as

$$\text{Moretti}_{jt}(e) = \sum_{l=1}^{L} \omega_{lj}^{80}(e)\text{NatHoursAge}_{lt}(e),$$

where $\omega_{lj}^{80}(e)$ is the share of hours worked by age group l in labor market j with education level e and $\text{NatHoursAge}_{lt}(e)$ is national hours worked by group l with education level e in time t. To be clear, the denominator of $\omega_{lj}^{80}(e)$ is total hours worked by skill group e in labor market j. The predicted hours measures are then used to predict changes in relative labor supply across cities.

Choice Probabilities and Likelihood Function. — Given that the idiosyncratic preference draw, ϵ_{ijt} is distributed as Type 1 Extreme Value, the choice probabilities have the following closed-form solution:

$$P_{ijt}^{d} = \frac{e^{\delta_{jt}^{d} + \beta_{hp}^{d}\mathbb{I}(j \in Bstate_i) + \beta_{\text{dist}}^{d}\phi(j, Bstate_i) + \beta_{\text{dist2}}^{d}\phi^2(j, Bstate_i)}}{\sum_{j'=1}^{J} e^{\delta_{j't}^{d} + \beta_{hp}^{d}\mathbb{I}(j' \in Bstate_i) + \beta_{\text{dist}}^{d}\phi(j', Bstate_i) + \beta_{\text{dist2}}^{d}\phi^2(j', Bstate_i)}}, \tag{A6}$$

and the corresponding log-likelihood function is

$$\mathcal{L}_t^d(\boldsymbol{\beta}^d, \boldsymbol{\delta_t^d}) = \sum_{i=1}^{N_t^d} \sum_{j=1}^{J} \mathbb{I}_j^i \log(P_{ijt}^d), \tag{A7}$$

where $\mathbb{I}_j^i$ is an indicator equal to one if individual i lives in location j and zero otherwise.

Numerical Algorithm. — In this section we briefly outline the algorithm we use to solve for equilibria.

1) Start with an initial guess of each household's probability of choosing each location.

2) Given the current distribution of households, calculate implied wage-income levels for each household in each location using equation 5.

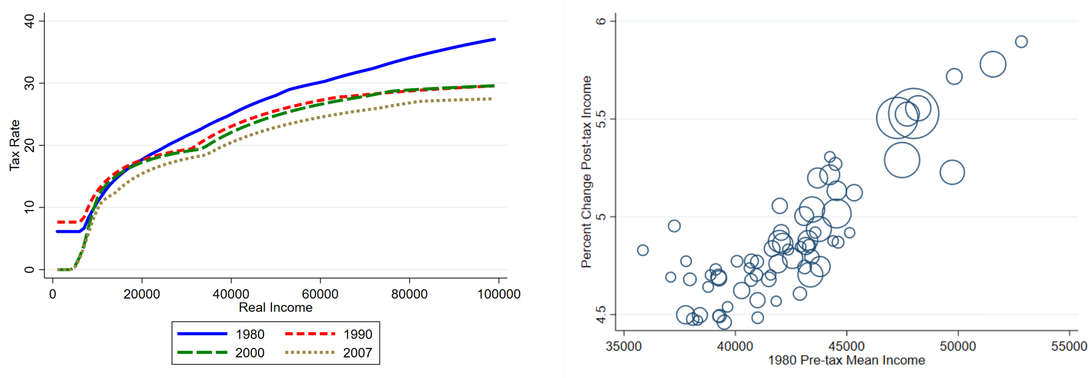
3) Guess total amount of landowner profits.
4) Given the current guess of landowner profits, calculate each household's total income.
5) Apply taxes to current income level to calculate each household's after-tax income in each location.
6) Given after-tax income and a distribution of workers, calculate the implied rent in each location using equation 9.
7) Calculate the total amount of landowner profits. If this is equal to the current guess of landowner profits, move to next step. If not, update guess of landowner profits and return to step 4.
8) Given current implied after tax wages and rents, calculate each household's indirect utility implied with living in each location.
9) Use indirect utility to calculate each household's probability of choosing each location. If this is equal to the current guess of household choice probabilities, an equilibrium has been found. If not, update guess of household choice probabilities and return to step 1.

Several counterfactuals involve choosing flat taxes or lump sum taxes to keep revenue constant. For these, we include an outer loop around the equilibrium finding algorithm outline above in which we guess flat taxes or lump sum taxes and iterate until tax revenue is equal to the desired level.

A2. Results Appendix

Suggestive Evidence of Variation Created by National Tax Changes. — Figure A1 provides some suggestive evidence that changes in the national tax code in the data have led to significant changes in differences in after-tax income. Panel A summarizes the evolution of federal income taxes in the US between 1980 and 2007. In particular, Panel A displays effective income tax schedules, for single individuals with no children, in all four of our sample years, where effective tax rates are defined as the fraction of income paid in taxes. For example, someone making $50,000 in 1980 (in year 2000 dollars) paid approximately 28% of their income in taxes, while someone making $50,000 in 1990 (again, in year 2000 dollars) paid about 25.5% of their income in taxes.

Panel B of Figure A1 shows an example of the local labor market variation generated by these tax changes. In particular, this figure plots $\Delta Z_j^S(1990)$ for single households with at least a college degree, by CBSA. To reiterate, we hold income levels constant at their 1980 pretax levels and calculate the corresponding after-tax income under both the 1980 and 1990 tax codes. Changes are then constructed as the within-CBSA percent change in after-tax income that results from moving to the 1990 tax code from the 1980 tax code. We can see that there is substantial heterogeneity in these changes, ranging from 4.5%



Panel A: Tax Changes   Skilled Households

Figure A1. : Panel A displays effective federal income tax schedules over time, which are calculated using TAXSIM for single individuals with no children. Panel B uses data from the 5% samples of the 1980 census (Ruggles et al. 2010) to construct composition-adjusted skilled wage levels by CBSA.

to 6%. This heterogeneity suggests that these changes to the tax code provided skilled households with an incentive to live in the higher-wage CBSAs as a direct implication of a less progressive tax schedule.

Additional Model Fit. — We perform the same model fit exercises as in Section IV.B for the years 1980, 1990, and 2000. The results are displayed in Figure A2. The fit for all years is quite good.

Alternative Estimates of Labor Supply Parameters. — In our main specification, we use both Bartik instruments and tax instruments in our estimation of labor supply parameters. In Table A1, we display estimates of β_r^e and β_w^e in which we 1) only use tax instruments, 2) only use Bartik instruments, and 3) use both tax and Bartik instruments. We can wee that the results are qualitatively similar across all three specifications, though the magnitude of both parameters is slightly larger in the case in which we only use one instrument.

Selected Housing Supply Elasticities. — To facilitate interpretation, Table A2 displays estimates of the inverse housing supply elasticity (k_j) for selected CBSAs. We can see that there is substantial variation in the inverse housing supply elasticity across cities, ranging from 0.20 to 1.80.

Figure A3 shows the relationship between inverse housing supply elasticity and city level earnings. We can see that the two measures are highly correlated—higher wages cities tend to have more inelastic housing supplies.

Counterfactual Tax Codes with Harmonized State Taxes. — In this section we repeat the simulations in Section V.B, but with state taxes harmonized. The main effects of each counterfactual tax code are summarized in Figure A4 and Table A3. For each of the three counterfactual tax codes, we chose either the flat tax or the parameter $\bar{\kappa}_t$ to keep total tax revenue equal to the baseline tax revenue. We consider the case with current state taxes in Section V.B. The results with harmonized state taxes are qualitatively similar but with slightly larger efficiency gains. The effects on between-group inequality are given in Table A4.

A3. Data Appendix

We construct our data using the 5% samples of the 1980, 1990, and 2000 US census. We also use the 3%, three-year aggregated American Community Survey (ACS) for the years 2005-2007.[1] The data are downloaded from the US Integrated Public Use Microdata Series (IPUMS) website (Ruggles et al., 2010). To maintain comparability with the broader wage inequality literature, we follow Autor, Katz and Kearney (2008) (AKK) as closely as possible in constructing the samples. However, because our analysis is at the local labor market level, there are necessarily some differences. We try to be explicit about these differences throughout the Data Appendix.

Before describing the distinct procedures used to construct each series, we first highlight a few definitions and sample selection rules that are consistent throughout the analysis. Individuals residing in group quarters such as prisons and psychiatric institutions are always dropped. Wages are deflated using the PCE deflator, with 1999 as the baseline.[2] All individual-level calculations are weighted by the product of total hours worked, the census sampling weights, and the geographic weights described below. All local labor market level calculations are weighted by the corresponding population in 1980.

Some of the series below use industry and occupation in their construction. Creating a balanced panel of occupations and industries over time is complicated by the fact that the Census Bureau redefines the classification systems for each decennial census. Although Meyer and Osborne (2005) provide a crosswalk between the different census years, there are still instances where some occupations and industries are available in one year but not another. Therefore, we use David Dorn's crosswalks to aggregate occupations and industries into a balanced panel.[3] See Dorn (2009), Autor and Dorn (2013), and Autor,

[1] We do not use ACS data after 2007 because hours worked are only reported in intervals.

[2] We use the PCE in the year preceding the decennial census surveys (i.e., 1979, 1989, and 1999) because the questionnaire asks about income earned in the previous year. The procedure for deflating the ACS data is slightly different. All three years are reported in real terms, where 2007 is the baseline. However, the ACS questionnaire asks about income earned in the previous twelve months rather than the previous calendar year. Therefore, we deflate wages in the ACS using the average value of the PCE in 2006 and 2007 to reflect the change in the question.

[3] These crosswalks are available for download on Dorn's website.

Dorn and Hanson (2013) for more details.

The same methods for assigning individuals to education levels and constructing potential experience are used throughout. In particular, we create five different education categories: dropout, high school graduate, some college, college graduate and post college. Beginning with the 1990 census, the educational attainment question changed its focus from years of education to degree receipt. We use the method proposed by Jaeger (1997) to make the categories listed above comparable across surveys. In the 1980 sample, individuals with less than twelve years of schooling completed are defined as high school dropouts; those with exactly twelve years as high school graduates; those with some college but less than one year and those with between one and three years of college completed as some college; those with either four or five years of college as college graduates; and those with six or more years of college as post college. In the later samples, individuals whose highest grade completed is grade 11 or less are defined as high school dropouts; those with a high school degree, a GED, or those who completed grade 12 but did not receive a diploma as high school graduates; those with an associate degree or that attended college but did not receive a degree as some college; those with a bachelor's degree as college graduates, and those with a master's degree, professional degree, or doctorate as post college. Broader education definitions, such as high school and college equivalents, are weighted averages of these five education levels, where the weights depend on the particular definition and will be defined when necessary.

Potential experience is defined as age less assigned years of schooling less six. We assign zero years of schooling to observations coded as no schooling, nursery school, preschool or kindergarten in all samples. In 1980, assigned years of schooling simply corresponds to the educational attainment question.[4] In later samples, we follow Park (1994) to assign years of schooling to each degree category.[5] Both the Jaeger (1997) method described in the above paragraph and the Park (1994) method described here capitalize on the sampling structure of the Current Population Survey, which implemented the same question change as the census, to create their rules. In particular, they match individuals that were asked the old education question in 1991 and the new education question in 1992.

Local Labor Market Geography: PUMA/County Group to CBSA Crosswalks. — After 1990, the Public Use Microdata Area (PUMA) is the smallest geographic unit available in the IPUMS microdata. PUMAs are defined to have between 100,000 and 200,000 residents, are an aggregate of both counties and census tracts, and are contained entirely within states. Defining local labor markets as PUMAs has two shortcomings. First, they are too small; for example, there are upwards of 50 PUMAs in Los Angeles County alone. Second, the PUMA definitions, and their corresponding boundaries, changed drastically between 1990 and 2000, which complicates making comparisons over time. The corresponding concept in 1980 is the county group (CG), which is an aggregation of counties

[4]Recall that the education attainment question explicitly asked about years of schooling in 1980.

[5]Note that we round up all assignment values in Park (1994) that are non-integers to keep the number of experience cells manageable.

only, whose boundaries are also different from those of the 1990 and 2000 PUMAs.

To overcome these problems, we use core based statistical areas (CBSAs), defined by the Office of Management and Budget (OMB), as our geographic concept of local labor markets. The OMB replaced the old concept of metropolitan statistical areas (MSAs) with CBSAs in 2003. CBSAs include both "micropolitan" and "metropolitan" areas, where the former is based on Census Bureau-defined urban clusters of between 10,000 and 50,000 people and the latter is based on Census Bureau-defined urbanized areas of at least 50,000 people. CBSAs provide us with a more natural concept of a local labor market, and we are able to hold their boundaries fixed over time.[6]

The primary challenge with using CBSAs is that their definitions do not line up with the geographic information contained in the census. In particular, the key complication is that sometimes PUMAs (and CGs) are not completely contained in a particular CBSA. We solve this problem by following a strategy similar to the one used by Autor and Dorn (2013) and Dorn (2009), who define local labor markets as commuting zones (CZs).[7] In particular, we relate PUMAs (and county groups) to CBSAs by utilizing the county-PUMA overlap files constructed by the Census Bureau.[8] Specifically, we construct weights that correspond to the fraction of the overall PUMA population contained in a CBSA. For example, suppose that PUMA A is completely contained in CBSA 1 and PUMA C is completely contained in CBSA 2. Suppose further that PUMA B overlaps with CBSAs 1 and 2, where the fraction of PUMA B's total population contained in CBSA 1 is 50% and the fraction contained in CBSA 2 is 50%. To calculate CBSA-level aggregates using individual-level data, we replicate the observations in PUMA B so that one observation is labeled as CBSA 1 and one is labeled CBSA 2. Calculations are then weighted according to the population overlap.

Wage Series. — The sample used to construct the relative wage series includes nonfarm, nonmilitary households, between the ages of 16 and 64, that were not participating in unpaid family work. Households with positive business income are dropped. Given concerns about measurement error in wages (see Baum-Snow and Neal (2009)), we drop individuals that worked less than 40 weeks annually and less than 35 hours weekly (i.e., we use only full-time, full-year [FTFY] households). Respondents with missing or imputed values for education are dropped. Observations with values of zero for wage income, usual hours worked or weeks worked, as well as those with imputed values for any of these variables, are also dropped. Finally, immigrants with missing or imputed birthplaces are dropped.

Hourly wages are constructed by dividing total wage income by the product of usual

[6] Note that the metropolitan area variable, *metarea*, in the IPUMS data is essentially unusable. For reasons of confidentiality, any persons living in a PUMA whose border overlaps with a metropolitan area is counted as not living in that metropolitan area. As noted by IPUMS, these omissions are not necessarily representative. See https://usa.ipums.org/usa/volii/incompmetareas.shtml for more details.

[7] Note that we use CBSAs, rather than commuting zones, so we can use the Gyourko, Saiz and Summers (2008) housing supply elasticity measures.

[8] The PUMA files can be downloaded at http://mcdc.missouri.edu/websas/geocorr2k.html. The county group files are not available in a downloadable form from the Census Bureau, but the information can be found at https://usa.ipums.org/usa/resources/volii/cg98stat.txt. Please email Kevin Hutchinson if you would like a copy of the Stata file we built containing this data.

hours worked (per week) and weeks worked (per year). We drop observations where the hourly wage is less than 80% of the nominal minimum wage in that year. Following Autor and Dorn (2013), top coded wage incomes are multiplied by a factor of 1.5 and hourly wages are set not to exceed this value divided by 50 weeks times 35 hours. A few issues related to top coding complicate comparisons over time. First, in 1980, 1990, and 2000, the nominal thresholds for top coding are $75,000, $140,000 and $175,000, respectively. The corresponding values in real terms are $153,178, $175,667, and $175,000, implying a more severe right truncation in 1980. Second, in 1980, all values above $75,000 are coded as $75,000. In contrast, values above the threshold are expressed as state medians in 1990 and state means in 2000, again implying a more restrictive right truncation in 1980. Because wages tend to be higher in large cities, relaxing the right censoring disproportionately raises mean wages in large cities, even if the underlying city-level wage distributions are unchanged. Although only a small fraction of the sample is top coded, it is concerning that right censoring might be driving changes in wages.

The problem is even more pronounced in the ACS, where top codes are state specific, equal to the 99.5th percentile of the state income distribution, and values above the top code are equal to the state mean of all observations above the cutoff. We address this issue by imposing a comparable top code on the 1990, 2000, and 2007 data. Specifically, we set the nominal top codes in each year so the real value of the top code is $153,178 across all three samples.[9] We then set all values of wage income above the top code to equal the top code.

We follow AKK and create composition-adjusted wages by using the predicted values from a series of log wage regressions. More specifically, we run separate log wage regressions by gender, CBSA, and year on the following covariates:

- Five indicators for race (White, Black, Asian, Native American, or Other);
- Five indicators for marital status (Married, Separated, Divorced, Widowed, or Single);
- An indicator for veteran status;
- Five education categories (H.S. Dropout, H.S. Graduate, Some College, College Graduate, or Post College);
- A quartic in experience;
- Interactions between the experience quartic and a broader education indicator, called College Plus, that includes College Graduates and Post College;
- An immigrant indicator (Native or Immigrant);
- An interaction between immigrant status and three indicators for English proficiency (Speaks English, Poor English, or None).

[9]The respective nominal values for 1980, 1990, 2000, and 2007 are $75,000, $122,078, $153,178, and $181,138.

- An interaction between immigrant status and three indicators for years in the United States (0-10 years, 11-20 years, or 21+ years);
- A full set of interactions between immigrant status and education categories;
- Time effects in the ACS regressions.[10]

We then use the estimated coefficients to predict log wages by gender-education-experience-CBSA cells in each year.[11] Again, as in AKK, we use four different experience groups; 5 years, 15 years, 25 years, and 35 years, which yields 40 cells per commuting zone. The key difference between our procedure and the one used by AKK is that we run separate regressions for *each* local labor market. Mean log wages for each CBSA, in each year, are weighted averages of the corresponding cells, where the weights are the share of total hours worked in 1980. This holds the composition of the labor force constant across locations and over time.

Labor Supply Series. — The relative supply series, again following AKK, is constructed by forming two samples: "quantity" and "price." The quantity sample includes nonfarm, nonmilitary households, between the ages of 16 and 64, that were not participating in unpaid family work. However, in contrast to the relative wage series, the quantity sample includes all employed households (i.e., including part-time and self-employed households). Respondents with missing or imputed values for education are dropped. Observations with values of zero for wage income *and* business income are dropped. Individuals with values of zero for usual hours worked or weeks worked are dropped. Finally, observations with imputed values for any of the preceding variables are also dropped.

The quantity sample divides total hours worked by all employed households into gender-education-experience cells. In particular, the experience cells are single-year categories of 0-39 years of potential experience. Households with greater than 39 years of potential experience are included in the 39-year cell. The education cells are the five categories described above. This yields 400 gender-education-experience cells.

The price sample is created using full-time, full-year wage earners (i.e., the same households used to construct relative wages). More specifically, each cell in the price sample is the mean FTFY real hourly wage for that gender-education-experience combination. Wages in each of the cells, in each year, are normalized by dividing by the wage of male high school graduates with 10 years of potential experience. An efficiency unit is computed for each gender-education-experience combination by averaging price samples across 1980, 1990, 2000, and 2007 and multiplying by 2000 to convert from hourly wages to yearly incomes. Efficiency units for married households are multiplied by $(1 + \Lambda)$, where Λ is the average income of the spouse relative to the household head. The price and quantity samples are then merged to create the final supply measure for each cell, which is the efficiency

[10] Recall that the ACS data are an aggregate of 2005, 2006, and 2007 data.

[11] Predictions are evaluated for white, married, nonveteran natives. ACS predictions are evaluated using the estimated 2007 time effect.

unit multiplied by the total hours worked in that cell. Aggregated quantities, such as high school and college equivalents, are simply sums of the relevant cells.

*

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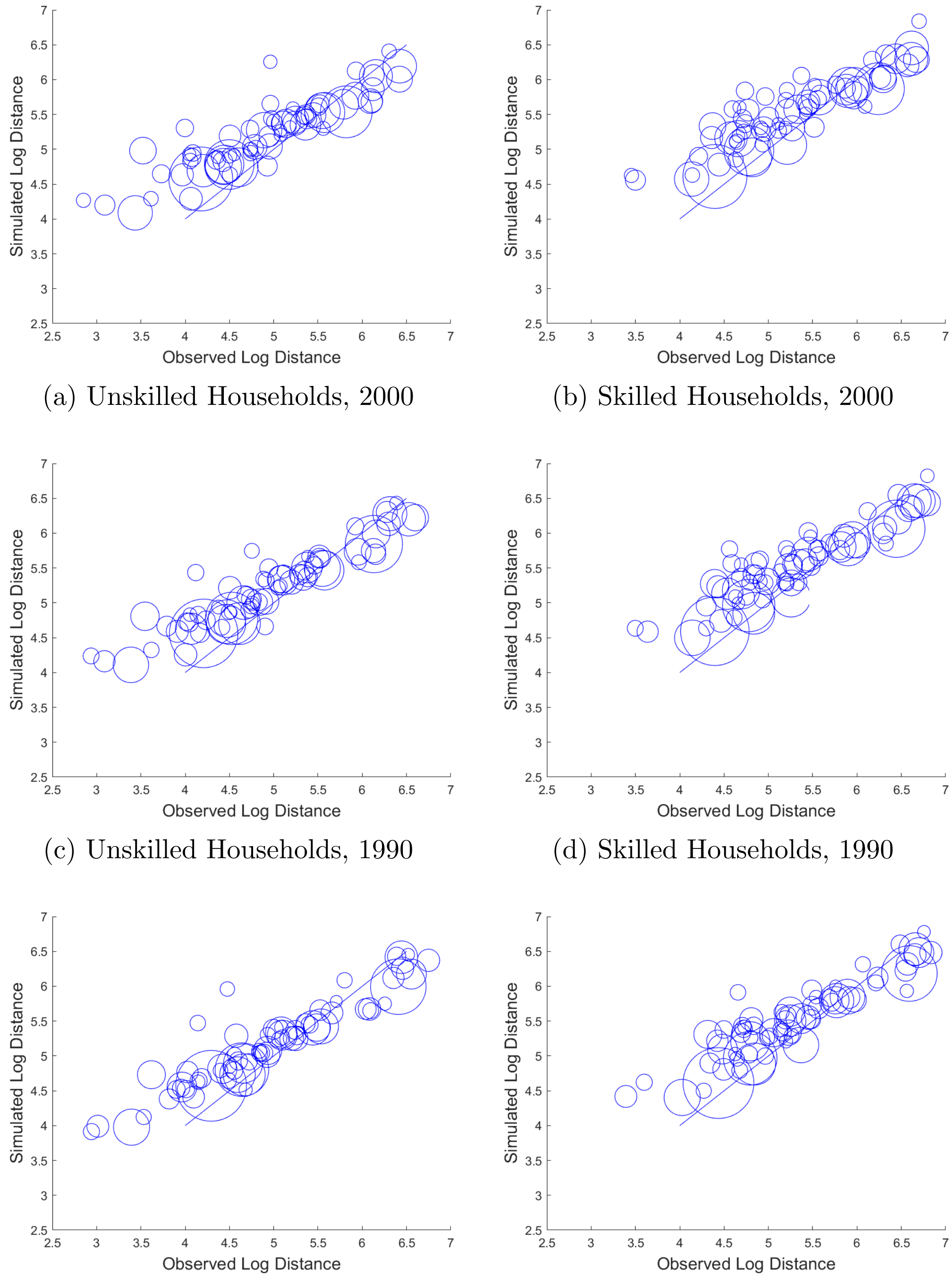


(a) Unskilled Households, 2000

(b) Skilled Households, 2000

(c) Unskilled Households, 1990

(d) Skilled Households, 1990

(e) Unskilled Households, 1980

(f) Skilled Households, 1980

Figure A2. : This figure shows the average log distance traveled from birth state in each city in the data and predicted by the model for unskilled households and skilled households in 2000, 1990 and 1980. The horizontal access is the average log distance from birth state in the data; the vertical access is the model's prediction.

I. Only Tax Instruments		
	Low Skill	High Skill
β_w^e: Wage	9.57	13.83
	(1.97)	(3.91)
β_r^e: Rent	-7.58	-5.63
	(1.39)	(1.48)
α^e: Share Housing	0.79	0.41
	(0.04)	(0.02)
Cragg-Donald Wald F Statistic	20.16	7.59
II. Only Bartik Instruments		
	Low Skill	High Skill
β_w^e: Wage	11.83	15.81
	(6.61)	(6.00)
β_r^e: Rent	-7.38	-6.89
	(4.52)	(2.80)
α^e: Share Housing	0.62	0.44
	(0.04)	(0.02)
Cragg-Donald Wald F Statistic	1.93	3.76
III. All Instruments		
	Low Skill	High Skill
β_w^e: Wage	7.15	12.54
	(1.34)	(2.20)
β_r^e: Rent	-5.23	-5.23
	(0.96)	(0.95)
α^e: Share Housing	0.73	0.42
	(0.03)	(0.02)
Cragg-Donald Wald F Statistic	12.84	9.86

Table A1—: Estimates of Labor Supply Parameters. Standard errors in parentheses. Panel I shows parameter estimates in which we only use tax instruments. Panel II shows parameter estimates in which we only use Bartik instruments. Panel III shows parameter estimates in which we use both instruments.

Rank	City	Inverse Housing Supply Elasticity
1	Honolulu, HI	1.80
2	Worcester, MA	1.55
3	Boston-Cambridge-Quincy, MA-NH	1.40
4	Providence-New Bedford-Fall River, RI-MA	1.35
5	Baltimore-Towson, MD	1.20
...		
66	Indianapolis, IN	0.30
67	Tulsa, OK	0.29
68	Kansas City, MO-KS	0.29
69	Baton Rouge, LA	0.29
70	New Orleans-Metairie-Kenner, LA	0.20

Table A2—: Estimates of inverse housing supply elasticity for selected CBSAs. The inverse housing supply elasticity is calculated as $k_j = \frac{\nu_1+\nu_2\psi_j^{WRI}}{1-\left(\nu_1+\nu_2\psi_j^{WRI}\right)}$.

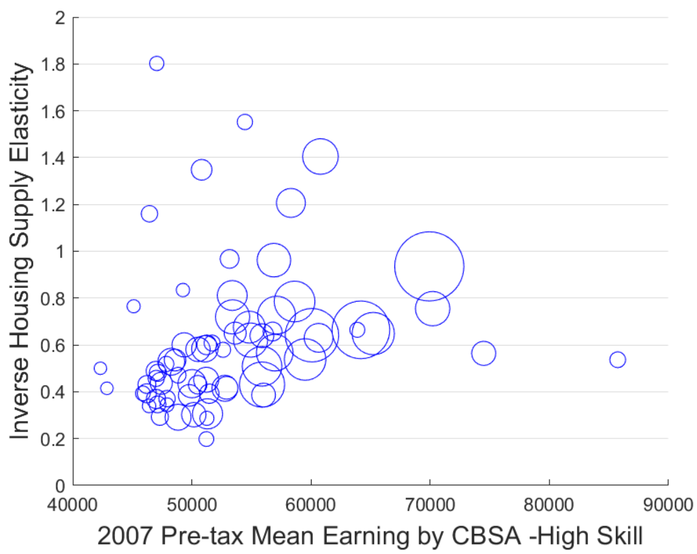
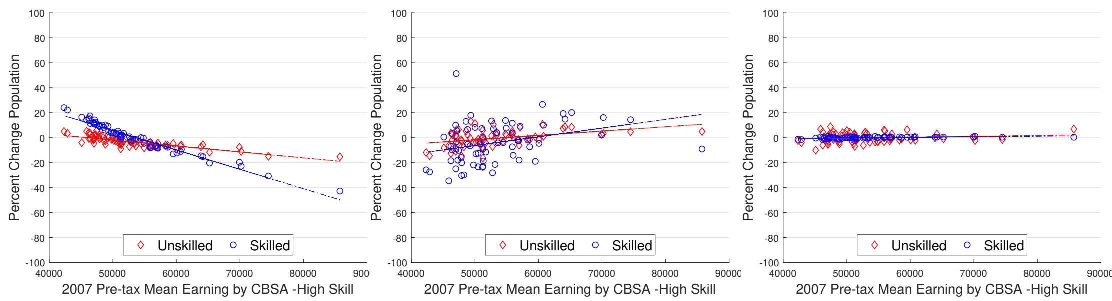


Figure A3. : Estimates of inverse housing supply elasticity and city level earnings. The inverse housing supply elasticity is calculated as $k_j = \frac{\nu_1+\nu_2\psi_j^{WRI}}{1-\left(\nu_1+\nu_2\psi_j^{WRI}\right)}$. The horizontal axis is the 2007 pretax mean earnings for skilled households.



Flat Tax Cost of Living Adjustment Local Wage Adjustment

Figure A4. : This figure shows the counterfactual population relative to non-distortionary lump-sum taxes for a flat tax, cost-of-living adjustments and local wage adjustments with harmonized stat income taxes. Each dot represents a CBSA. The horizontal axis is the 2007 pretax mean earnings for skilled households. Unobserved amenities, agent demographics, and labor demand parameters are held fixed at their 2007 levels.

	Baseline	Flat	COLA	Wage Adj
I. % High Income Cities				
Unskilled Workers	16.3	17.0	19.3	18.5
Skilled Workers	25.9	27.4	36.1	33.1
II. % Outside Large Cities				
Unskilled Workers	44.8	44.0	40.3	40.9
Skilled Workers	30.7	29.5	22.3	23.5
III. Deadweight Loss	0.25	0.13	0.10	0.01
IV. Landowner Profits	8.76	8.82	9.78	9.56

Table A3—: This table shows the main effects of counterfactual tax codes with harmonized state taxes. High income cities are the 10 cities with highest average skilled income of in 2007. Deadweight loss and landowner profits are measured as a percentage of baseline output.

	Flat	COLA	Wage Adj
I. Mechanical			
Unskilled	1.99	0.88	0.40
Skilled	-3.77	1.40	-0.07
Difference	5.76	-0.52	0.47
II. Mechanical+Sorting			
Unskilled	1.95	-0.02	0.13
Skilled	-3.94	-1.66	-1.70
Difference	5.89	1.64	1.84
III. Full effects			
Unskilled	2.00	0.63	0.36
Skilled	-3.80	-1.40	-1.24
Difference	5.80	2.03	1.61

Table A4—: This table shows the average equivalent variation of moving from the current tax code to each of the counterfactual tax codes with harmonized state taxes. Panel I shows the effect of changing from the current tax to each counterfactual tax code, holding all location choices constant at their baseline levels (the "mechanical effect".) In Panel II households are allowed to optimally chose their location in response to the tax change but prices and landowner profits are held at their baseline levels. Panel III incorporates equilibrium effects on price and landowner profits. Therefore, each entry captures the full effect of switching from the current tax code to each of the counterfactual tax codes.