Online Appendix for "IT and Urban Polarization"

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A Employment and Establishment Coverage: Comparison to NETS Data

A.1 NETS Data

The National Establishment Time Series (NETS) is an annual series consisting of establishment-level longitudinal microdata covering, in principle, the universe of US Business. The starting point for the NETS database was annual snapshots (taken every January) of the full Duns Marketing Information (DMI) file that followed over 58.8 million establishments between January 1990 and January 2020. These snapshots actually used the DMI file to determine which establishments were active in January of each year in question. The database includes information on: business name, address and contact information, headquarters ID, number of establishments per firm, industry classification, type of proprietorship, employment by location and estimated annual establishment sales. Finally, NETS includes unique firm and establishment identifiers through D&B hqduns and duns numbers.

As highlighted in Section B.1, there are some key distinctions between NETS and the databases provided by official sources such as the CBP. First, NETS information is not collected at a particular time of year, but throughout the year. Second, in NETS an establishment is defined as a "unique line of business (SIC8) at a unique location." So, it is possible to have more than one establishment at a location. Third, NETS data include not only firm owners among establishment employees, but also self-employed, contract, and temporary workers. Finally, there are some drawbacks to the data, highlighted by Barnatchez, Crane and Decker (2017) and Crane and Decker (2020), in particular due to data staleness as well as issues with data imputation. While the data are reported to be regularly collected, some employment level information seems to be updated less frequently than official sources counterparts. Similarly, imputed data points differ quite significantly from their administrative data counterparts.

A.2 Comparison to Ci Aberdeen Data: IT Budget Sample

Ci Aberdeen data have lots of similarities to the NETS data. First, both are indexed by duns numbers and have imputed values for establishment sales. Second, establishment and employment data tend to follow similar definitions in both samples, including non-employment establishments. However, as we compare the two samples, we do observe some key distinctions. First, headquarter IDs are quite distinct between the two databases. Second, employment levels are quite distinct among large establishments. We present more details below.

Table OA-1: Coverage Ci Aberdeen relative to NETS

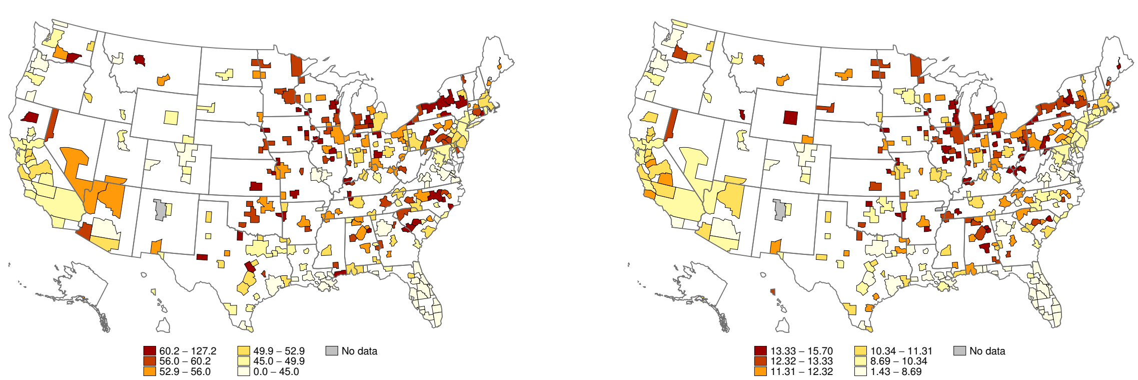
	Mean	**S.D.**	**p10**	**p25**	**p50**	**p75**	**p90**	**N**
IT Budget Sample								
Fraction Emp. in Ci	52%	12%	42%	47%	53%	59%	62%	279
Fraction Est. in Ci	11%	2%	8%	10%	11%	13%	14%	277
Fraction Sales in Ci	52%	9%	44%	49%	53%	56%	60%	279
ERP Sample								
Fraction Emp. in Ci	20%	7%	13%	16%	20%	23%	27%	279
Fraction Est. in Ci	1%	0%	1%	1%	1%	1%	1%	277
Fraction Sales in Ci	17%	6%	10%	13%	16%	20%	23%	279

Similar to the comparison to the CBP presented in Section B, while our IT budget sample covers more than 50 percent of employment in NETS, it only covers about 11% of establishment (see Table OA-1. However, the low establishment coverage is due to low coverage of small establishments. In fact, our sample covers above 50 percent of NETS establishments for establishments with 10 employees or more (see Table OA-2).

In terms of industry coverage, we see that our sample has a low coverage in leisure and hospitality, trade, transportation, and utility, as well as other services in both establishment and employment coverage (see Tables OA-3 and OA-4).

Table OA-2: Coverage Ci Aberdeen relative to NETS by establishment size

	Mean	**S.D.**	**p10**	**p25**	**p50**	**p75**	**p90**	**N**
IT Budget Sample								
1 to 4 Employees	2%	1%	2%	2%	2%	3%	3%	279
5 to 9 Employees	23%	4	19%	21%	23%	25%	26%	279
10 to 19 Employees	42%	8%	35%	40%	43%	47%	49%	279
20 to 49 Employees	48%	8%	42%	46%	49%	52%	55%	279
50 to 99 Employees	53%	8%	47%	50%	54%	57%	60%	279
100 to 249 Employees	60%	11%	51%	56%	61%	66%	72%	279
250 to 499 Employees	72%	22%	50%	62%	71%	82%	95%	279
500 to 999 Employees	91%	41%	55%	70%	83%	106%	133%	279
1,000 or more Employees	142%	71%	75%	100%	125%	167%	225%	277
ERP Sample								
1 to 4 Employees	0%	0%	0%	0%	0%	0%	0%	279
5 to 9 Employees	0%	0%	0%	0%	0%	0%	0%	279
10 to 19 Employees	1%	0%	1%	1%	1%	2%	2%	279
20 to 49 Employees	5%	1%	4%	4%	5%	6%	7%	279
50 to 99 Employees	12%	4%	9%	11%	12%	14%	17%	279
100 to 249 Employees	28%	7%	20%	24%	28%	33%	38%	279
250 to 499 Employees	37%	18%	21%	28%	35%	45%	53%	279
500 to 999 Employees	57%	34%	27%	38%	49%	67%	100%	279
1,000 or more Employees	95%	59%	45%	60%	79%	110%	167%	277



(a) Employment Coverage

(b) Establishment Coverage

Figure OA-1: Geographical distribution of Ci coverage relative to NETS: IT budget sample

Finally, in terms of geographic coverage, the IT budget sample shows a higher coverage in the Midwest and East Coast regions, while coverage rates are somewhat lower in the West Coast and Western regions. Patterns are quite similar for both employment (figure OA-1a) and establishments (figure OA-1b). That said, coverage rates even in areas with low coverage are still meaningful (above 45 percent for employment and above 8 percent for establishments).

Table OA-3: Ci coverage relative to NETS: Employment by Industry

	Mean	S.D.	p10	p25	p50	p75	p90	N
IT Budget Sample								
Manufacturing	75%	22%	53%	64%	73%	83%	97%	279
Construction	46%	11%	35%	41%	45%	52%	58%	279
Information	64%	27%	43%	52%	61%	70%	84%	279
Finance	54%	21%	36%	42%	51%	62%	76%	279
Professional & Bus Services	39%	16%	22%	29%	36%	45%	55%	279
Education and Health	75%	18%	59%	66%	75%	81%	92%	279
Leisure and Hospitality	19%	9%	11%	14%	18%	23%	29%	279
Public Adm	77%	60%	49%	59%	69%	82%	97%	279
Trade, Transp., and Util.	36%	11%	25%	30%	35%	40%	46%	279
Mining	56%	47%	10%	34%	52%	71%	94%	279
Other Services	35%	20%	21%	26%	32%	39%	48%	279
ERP Sample								
Manufacturing	35%	18%	15%	24%	32%	42%	54%	279
Construction	7%	7%	2%	4%	6%	10%	14%	279
Information	24%	17%	8%	15%	21%	30%	44%	279
Finance	14%	13%	3%	5%	11%	19%	28%	279
Professional & Bus Services	11%	12%	3%	5%	9%	14%	19%	279
Education and Health	34%	14%	21%	26%	33%	40%	47%	279
Leisure and Hospitality	7%	7%	1%	3%	5%	8%	12%	279
Public Adm	31%	39%	11%	18%	25%	33%	48%	279
Trade, Transp., and Util.	11%	9%	3%	6%	9%	13%	17%	279
Mining	11%	24%	0%	0%	0%	12%	36%	279
Other Services	9%	15%	2%	4%	7%	11%	17%	279

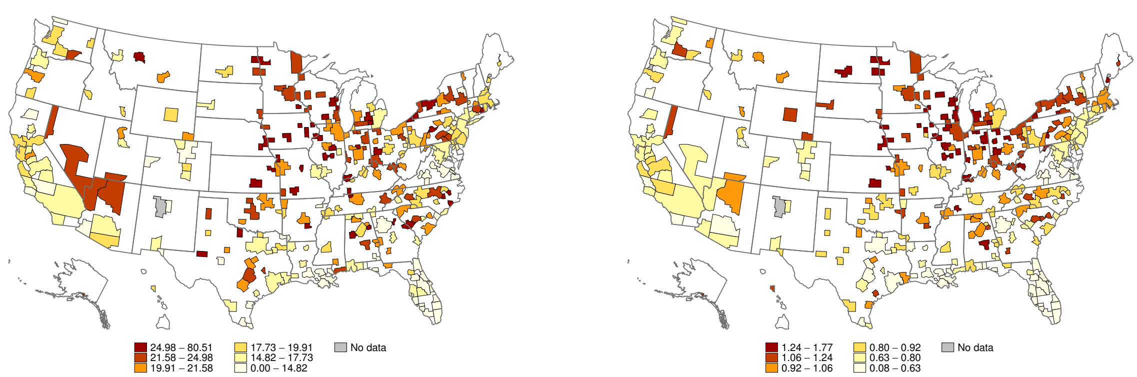
A.3 Comparison to Ci Aberdeen Data: ERP Sample

As discussed in Section I, our ERP sample is limited. Our information on ERP adoption covers on average only 20 percent of workers and 1 percent of establishments in the MSA, compared to NETS (see table OA-1). Moreover, as presented in Table A-6, even after controlling for establishment size, MSA average coverage is above 28 percent only for establishments that have 100 employees or more. Finally, Table OA-4 shows that the ERP sample covers less than 35 percent of establishments in all industry sectors but public administration. However, since the coverage is tilted toward larger establishments, employment coverage varies from 10 (Leisure and Hospitality) to 36 percent (Manufacturing) of the NETS industry employment (Table OA-3).

Finally, in terms of geographic coverage, the ERP sample shows a higher coverage in the Midwest and East Coast regions, while coverage rates are somewhat lower in the West Coast and Western regions. Patterns are quite similar for both employment (Figure OA-2a) and establishments (Figure OA-2b). That said, coverage rates even in areas with low coverage are still meaningful (above 15 percent for employment and above 0.6 percent for establishments).

Table OA-4: Ci coverage relative to NETS: Establishments by industry

	Mean	S.D.	p10	p25	p50	p75	p90	N
IT Budget Sample								
Manufacturing	32%	8%	23%	27%	32%	38%	41%	279
Construction	8%	2%	5%	7%	8%	9%	11%	279
Information	23%	7%	13%	18%	22%	27%	33%	279
Finance	18%	5%	12%	15%	18%	21%	24%	279
Professional & Bus Services	5%	1%	3%	4%	5%	5%	6%	279
Education and Health	28%	6%	22%	25%	28%	31%	34%	279
Leisure and Hospitality	7%	2%	5%	6%	7%	8%	9%	279
Public Adm	59%	9%	51%	56%	61%	64%	68%	279
Trade, Transp., and Util.	8%	2%	6%	7%	8%	9%	10%	279
Mining	23%	12%	8%	15%	22%	31%	38%	279
Other Services	6%	2%	4%	5%	6%	6%	7%	279
ERP Sample								
Manufacturing	4%	2%	2%	3%	4%	6%	7%	279
Construction	0%	0%	0%	0%	0%	1%	1%	279
Information	3%	1%	1%	2%	2%	3%	5%	279
Finance	1%	0%	0%	0%	1%	1%	1%	279
Professional & Bus Services	0%	0%	0%	0%	0%	0%	1%	279
Education and Health	2%	1%	1%	2%	2%	2%	3%	279
Leisure and Hospitality	1%	0%	0%	1%	1%	1%	1%	279
Public Adm	5%	2%	3%	4%	5%	6%	8%	279
Trade, Transp., and Util.	1%	0%	0%	0%	1%	1%	1%	279
Mining	2%	3%	0%	0%	0%	3%	6%	279
Other Services	0%	0%	0%	0%	0%	1%	1%	279



(a) Employment Coverage

(b) Establishment Coverage

Figure OA-2: Geographical distribution of Ci coverage relative to NETS: ERP sample

B Measures of Skill Concentration

We now calculate measures of the concentration of skills across regions. These measures allow us to test if we have observed an increase in the spatial dispersion of skills across MSAs in the last 25 years. Moreover, these measures abstract from issues of long-run trends in the composition of the labor force. Consequently, we are able to focus on the correlation between the spatial dispersion of skills and an MSA's characteristics – in particular size and cost of housing. We consider three simple measures: the location quotient that compares the skill distribution in the MSA against the overall skill distribution in the economy, the Ellison and Glaeser (1997) index of industry concentration, and an adjusted version of this index proposed by Oyer and Schaefer (2016). The latter two indexes attempt to measure concentration by comparing it against a distribution that would be obtained by chance (the "dartboard approach").

B.1 Location Quotient

As a first pass, we consider a concentration measure that compares the distribution in a given MSA against the distribution in the overall economy. In particular, we consider that the degree of concentration of skill i in city j (λ_{ij}) is given by:

$$\lambda_{ij} = \frac{\frac{m_{ij}}{S_j}}{\frac{M_i}{\sum_{l=1}^{N} M_l}} \tag{OA.1}$$

Intuitively, if a MSA is more concentrated in skill level i than the economy at large, this index's value would be above 1. Moreover, this measure has two additional benefits. First, by focusing on shares, it reduces the impact of the MSA's overall size on the analysis. Second, by comparing the region against the economy-wide distribution, it takes into account the potential changes in the national labor market. Consequently, it allows us to focus on the increase or decrease in concentration across regions as well as how it correlates to these regions' characteristics.

Following what has been show in other sections, we consider two time periods: 1990 and 2015. Moreover, following Cortes, Jaimovich and Siu (2017), we divide the occupations in four groups: non-routine manual, routine manual, routine cognitive, and non-routine cognitive. We divide the regions into two groups around the median. We use the log rent index in 1980, i.e. cheap vs. expensive, as the measure to separate the MSAs. Results are presented in Table OA-5.

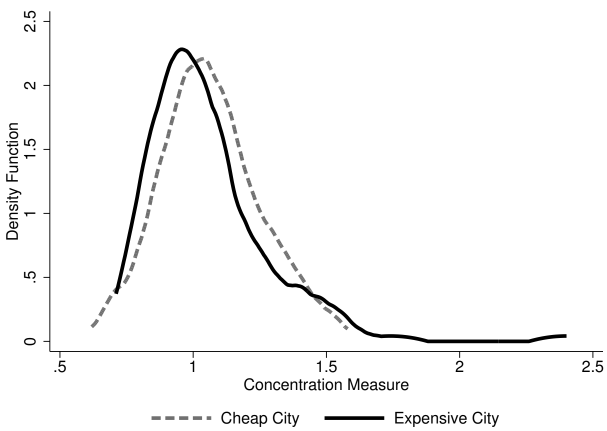
As we can see from Table OA-5, in 1990, cheaper cities had on average a higher concentration in routine manual jobs, a lower concentration in cognitive jobs (both routine and non-routine), and close to at par in non-routine manual jobs when compared to expensive cities. Differently, in 2015 we see cheap cities being on average more concentrated in routine cognitive jobs, while we see minor changes in the other occupation categories. These results are in line with what our theoretical results would predict.

Finally, Figures OA-3 and OA-4 present the density distributions of the location quotients for small and large cities across occupation groups and time. While we observe that there is significant variance in this index across MSAs, the overall message is the same as the one presented in Table OA-5.

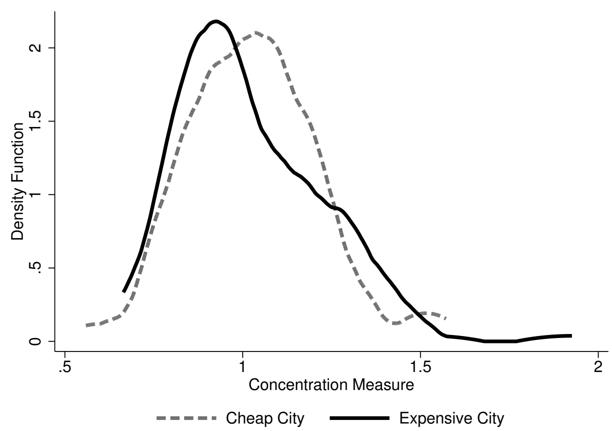
Table OA-5: Simple measure of concentration across skill and city size groups

Panel A: 1990								
	Non-Routine Manual		*Routine Manual*		*Routine Cognitive*		*Non-Routine Cognitive*	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Expensive City	1.05	1.01	1.03	1.00	0.98	0.98	0.97	0.95
Cheap City	1.06	1.06	1.26***	1.23†††	0.92***	0.91†††	0.86***	0.86†††
Panel B: 2015								
	Non-Routine Manual		*Routine Manual*		*Routine Cognitive*		*Non-Routine Cognitive*	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Expensive City	1.02	0.97	1.07	1.04	0.99	1.00	0.95	0.95
Cheap City	1.03	1.02	1.25***	1.23†††	1.02*	1.03††	0.87***	0.87†††

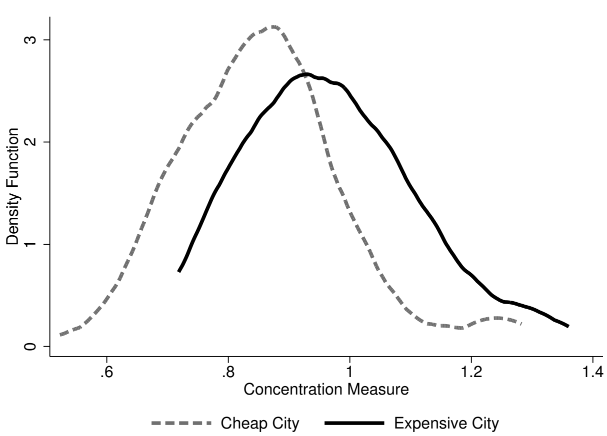
***,**,* represent significance at 1, 5, and 10% respectively in a t-test of means with unequal variances.
†††,††, † represent significance at 1, 5, and 10% respectively in a Wilcoxon rank-sum test of medians.



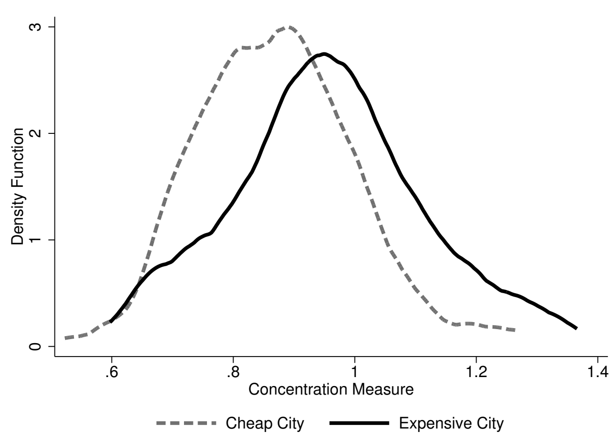
(a) Non-Routine Manual: 1990



(b) Non-Routine Manual: 2015

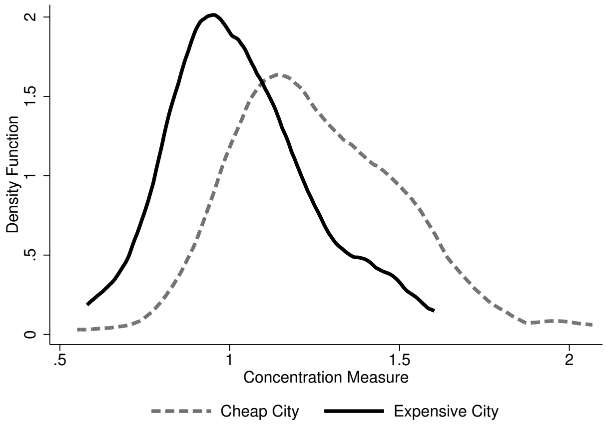


(c) Non-Routine Cognitive: 1990

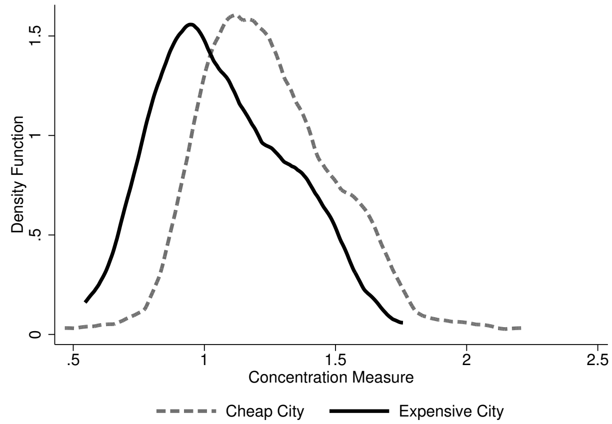


(d) Non-Routine Cognitive: 2015

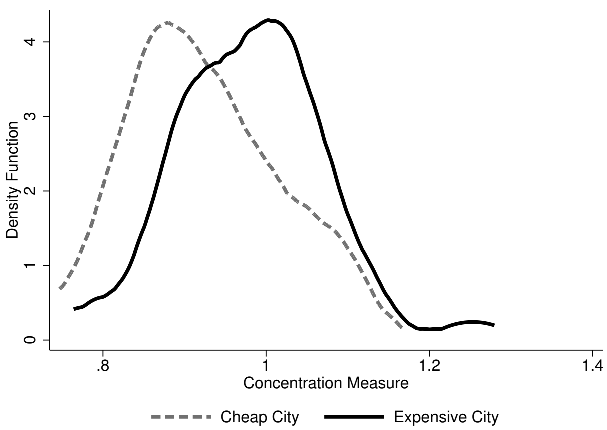
Figure OA-3: Non-routine occupations LQ distributions



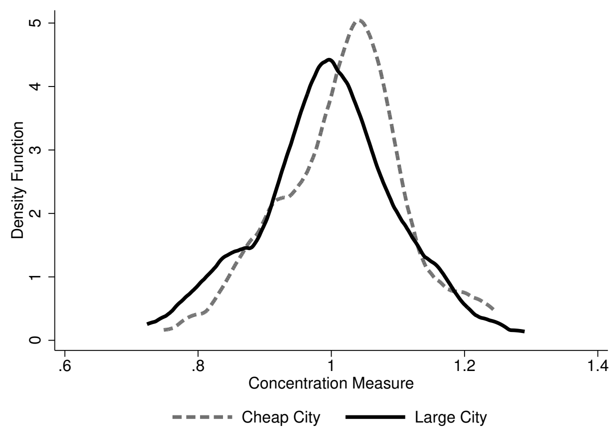
(a) Routine Manual: 1990



(b) Routine Manual: 2015



(c) Routine Cognitive: 1990



(d) Routine Cognitive: 2015

Figure OA-4: Routine occupations LQ distributions

B.2 Ellison-Glaeser (1997) Index

We now adapt the concentration index presented by Ellison and Glaeser (1997) for the skill distribution context. Denote λ_i as the EG concentration index for skill i. To define this index, we first introduce some notation. Define s_{ij} as the share of workers of skill i in city j, i.e., $s_{ij} = \frac{m_{ij}}{M_i}$. Let x_j be the share of total employment in city j, i.e., $x_j = \frac{S_j}{\sum_{l=1}^{N} M_l}$. Then, our measure of spatial concentration of skill i is given by:

$$\lambda_i = \frac{\sum_j (s_{ij} - x_j)^2}{1 - \sum_j x_j^2} \tag{OA.2}$$

According to Ellison and Glaeser (1997), there are several advantages in using this index. First, it is easy to compute with readily available data. Second, the scale of the index allows us to make comparisons with a no-agglomeration case in which the data are generated by the simple dartboard model of random location choices (in which case $E(\lambda_i) = 0$). Finally, the index is comparable across populations of different skill sizes. Notice that in this case, we have one index per skill group per year. Consequently, we are unable to compare expensive and cheap cities. However, we are able to see if skill groups became more or less concentrated across cities over time.

Table OA-6: Ellison-Glaeser Index

	1990	**2015**	**% Change**
Non-Routine Manual	0.00032	0.00038	18.66
Routine Manual	0.00075	0.00076	0.75
Routine Cognitive	0.00007	0.00014	108.90
Non-Routine Cognitive	0.00029	0.00030	3.38

Results are presented in Table OA-6. As we can see, while routine manual occupations have seen no clear change in concentration, and all other occupational groups have seen an increase in concentration. These results complement the findings regarding the location quotient, by indicating how the concentration of each occupation group has changed across cities. While these results are generally in line with what we should expect given our model's outcomes, we are not able to precisely link them to city characteristics. In order to do that, in the next section we follow Oyer and Schaefer (2016) and adapt the Ellison and Glaeser (1997) to create a city's skill concentration index.

B.3 Oyer-Schaefer (2016) Index

We now consider an adapted version of the EG concentration index based on Oyer and Schaefer (2016), which we call the Oyer-Schaefer index (henceforth OS index). Hence, denote ζ_j the OS concentration index for city j. To define this index, we first introduce some notation. Define $\tilde{x}_i$ as the overall share of workers of skill i in the economy, i.e., $\tilde{x}_i = \frac{M_i}{\sum_{l=1}^{N} M_l}$. Similarly, define $\tilde{s}_{ij}$ the share of workers of skill i in city j, i.e., $\tilde{s}_{ij} = \frac{m_{ij}}{S_j}$, where S_j is city j's labor force size. Then, the OS index is defined as:

$$\zeta_j = \frac{S_j}{S_j - 1} \frac{\sum_i \left(\tilde{s}_{ij} - \tilde{x}_i\right)^2}{1 - \sum_i \tilde{x}_i^2} - \frac{1}{S_j - 1} \tag{OA.3}$$

Differently from the EG index, in the OS index we are able to compare the degree of concentration across cities with different housing costs. Unfortunately, we are unable to pin down the source of the increase/decrease in within-city concentration. In particular, we are unable to tie the changes in concentration to changes in the shares of each particular skill group. In this sense, although the EG and OS indexes complement each other, both have weaknesses and do not give a complete picture of the changes in concentration.

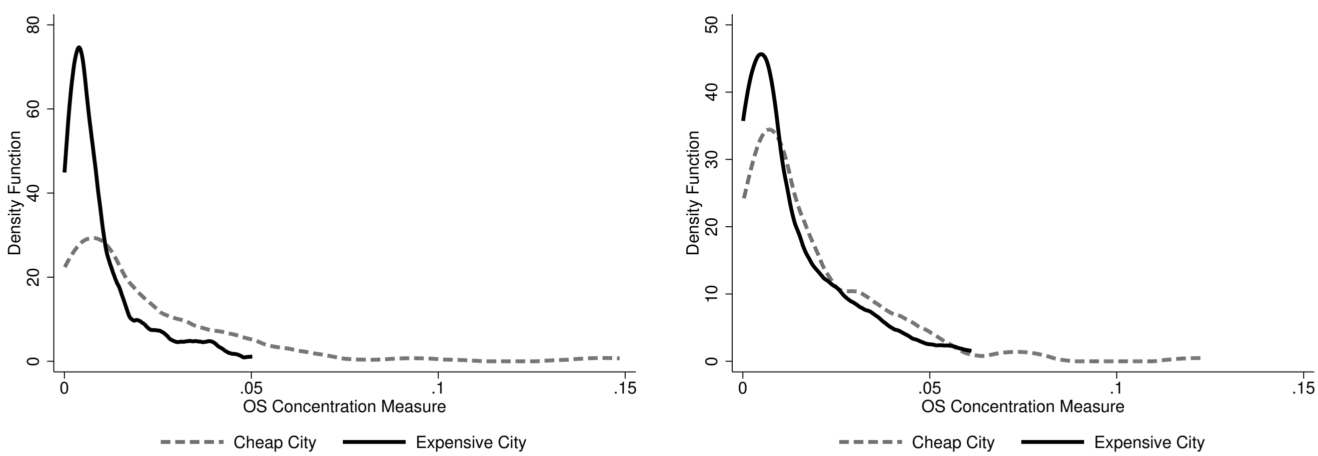
Table OA-7 presents the results for 1990 and 2015. As we can see, in both periods, cheap cities are consistently more concentrated than expensive cities, although the statistical significance of the difference has decreased over time. Furthermore, while cheap cities have seen a reduction in concentration, expensive cities have become more concentrated over time.

Table OA-7: OS index across city cost and time

	Mean	Median	St. Dev.	Min	Max
Panel A: 1990					
	Mean	Median	St. Dev.	Min	Max
Expensive City	0.00955	0.00558	0.01041	0.00002	0.05026
Cheap City	0.02089***	0.01217†††	0.02476	0.00011	0.14851
Panel B: 2015					
	Mean	Median	St. Dev.	Min	Max
Expensive City	0.01293	0.00736	0.01395	0.00007	0.06114
Cheap City	0.017503**	0.01185††	0.01900	0.00029	0.12240

***,**,* represent significance at 1, 5, and 10% respectively in a two-tailed t-test of means. †††,††, † represent significant at 1, 5, and 10% respectively in a Wilcoxon rank-sum test of medians.

Finally, we present the changes in the density distribution of the OS index in Figure OA-5. Notice that Figures OA-5(a) and OA-5(b) corroborate the results from Table OA-7, showing an increase in concentration among expensive cities and a decrease in concentration among cheap cities.



(a) 1990

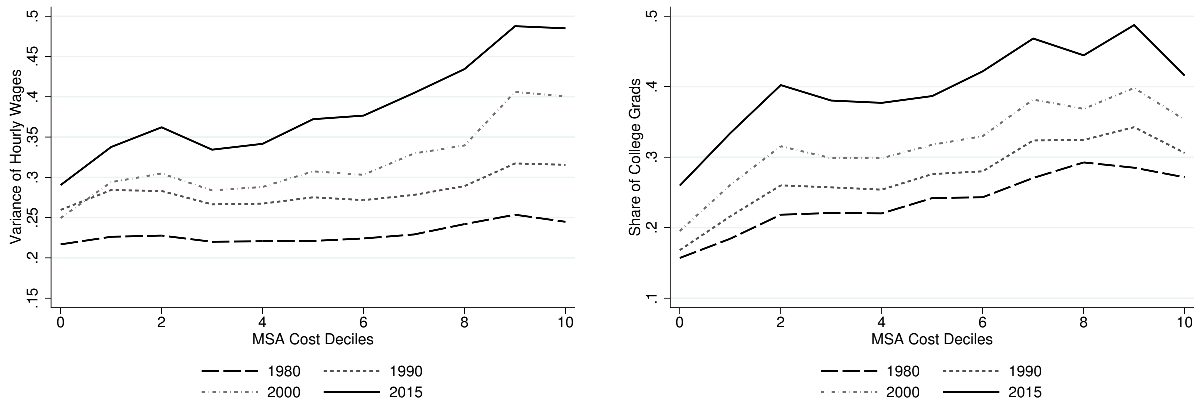
(b) 2015

Figure OA-5: Distribution of OS index across city sizes and time

C Wage Inequality Within and Between Cities

In this section we look at the patterns of wage inequality within and between cities and how these patterns changed over time and across occupational groups. As a result, we are able to infer the role of within-occupational-group worker heterogeneity in explaining the variations observed in the data.

First, as pointed out in the literature (see Baum-Snow and Pavan (2013), Eeckhout, Pinheiro and Schmidheiny (2014), and Santamarıa (2018), among others), large cities are more unequal and inequality has gone up over time. As we see in Figure OA-6a,[1] wage dispersion is larger in big cities.



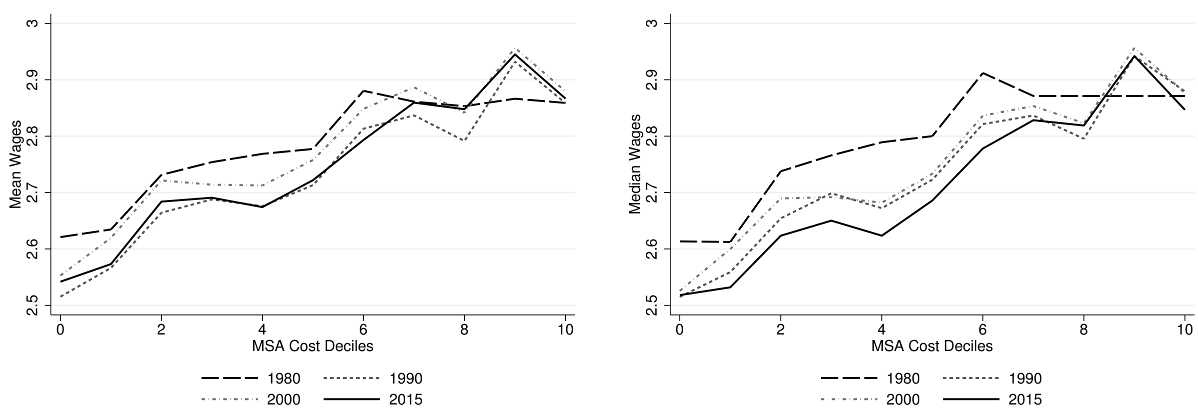
(a) Variance of Hourly Wages

(b) Share of College Graduates

Figure OA-6: Inequality within cities over time and by city's housing cost

Moreover, while we have seen that college attainment has been marginally higher in larger MSAs (Figure OA-6b), the results in Figure OA-6a still hold even after we control for several observable characteristics.

Instead, inequality *between* cities as measured by the city wage premium has not changed over time. Figure OA-7 shows that the increase in the mean and median wages with city housing cost has not changed significantly over time.[2]



(a) Mean Hourly Wages

(b) Median Hourly Wages

Figure OA-7: Inequality between cities: the Urban Wage Premium over time

[1] Observe that in Figures OA-6 and OA-7, as well as the figures in online appendix section C.1, we present deciles in terms of cities' cost of living, proxied by log(rent index) in 1980, and not in terms of the city size as in Baum-Snow and Pavan (2013) for example.

[2] In fact, once we control for observable characteristics, as presented in Appendix section C.1, differences over time in mean and median residual wages are even smaller.

Finally, we decompose the overall variance in wages in terms of a within- and between-city contribution. Following the decomposition proposed by Lazear and Shaw (2009), the total variance in wages, σ^2, is given by

$$\sigma^2 = \sum_{j=1}^{J} s_j \sigma_j^2 + \sum_{j=1}^{J} s_j (\overline{w}_j - \overline{\overline{w}})^2. \tag{OA.4}$$

The first term on the RHS of equation (OA.4) is the within-city component of the variance. s_j is the share of workers in the economy employed in city j, while σ_j^2 is the variance of wages in city j. The second term on the RHS of equation (OA.4) represents the between-city component of the wage variance. In this expression, $\overline{w}_j$ is the mean wage in MSA j, and $\overline{\overline{w}}$ is the mean wage in the economy.

The results in Table OA-8 show that most of the wage dispersion is due to the within-city component (around 95 percent). Moreover, the decomposition in terms of within- and between-city components is persistent over time. Consequently, the contribution of each component to the overall increase in wage inequality has stayed proportional to each component's contribution to the overall dispersion. These results are preserved even when we focus on wage dispersion within occupational groups (See Table OA-9 in Appendix Section C.1) as well as when we control for observables (Tables OA-10 and OA-11 in Appendix Section C.1).

Table OA-8: Variance decomposition log hourly wages

			Variance		
Year	Total	Within City	Between City	% Within	% Between
1980	0.237	0.226	0.011	95%	5%
1990	0.297	0.280	0.017	94%	6%
2000	0.336	0.320	0.017	95%	5%
2015	0.408	0.385	0.023	94%	6%

We need to keep in mind though that, while the bulk of wage dispersion is due to the within-MSA component, this does not mean that geographical components do not play a key role in explaining wage dispersion. As technology is adopted unevenly across space and workers and firms choose to search for workers and post jobs in different cities, these decisions affect both the within- and between-MSA components of wage inequality. Consequently, our decomposition exercise mostly says that, in terms of wage inequality, while cities vary in terms of wage inequality, the bulk of the wage inequality happens within the average city.

C.1 Residual Wage Distributions

We calculate residual wages as the residual of a Mincer regression. In particular, we estimate a separate Mincer regression for each year:

$$\log(w_{it}) = \alpha_t + \beta_t X_{i,t} + \varepsilon_{i,t} \tag{OA.5}$$

We include the typical controls in a Mincer regression (age, age squared, a gender dummy, and a full set of race fixed effects). We also control for educational groups (less than high school, high school graduate, some college, college and more), a dummy for foreign born, and industry groups. Results are qualitatively the same if we do not include industry or educational groups. Results are presented in Figure OA-8. As we can see, results are qualitatively the same as the ones presented in Figure OA-6a.[3] Similarly, we can calculate the mean and median residual wages, as well as the inter-quantiles residual wage differences.

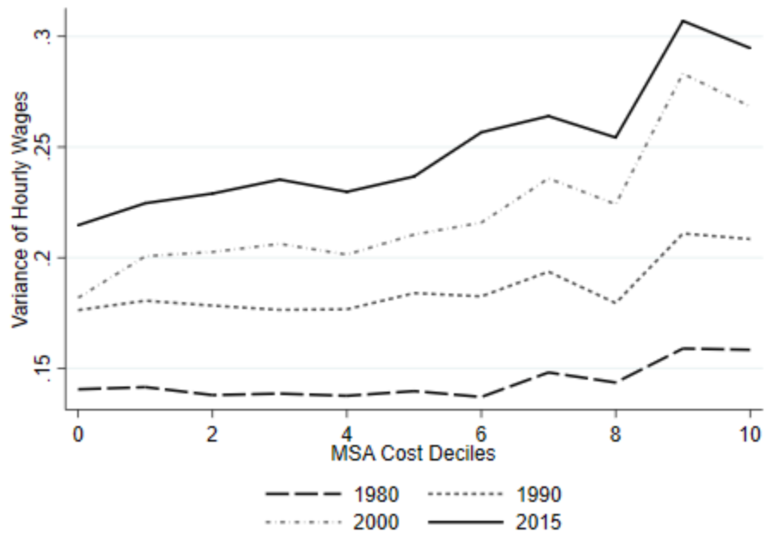


Figure OA-8: Variance Residual Wages

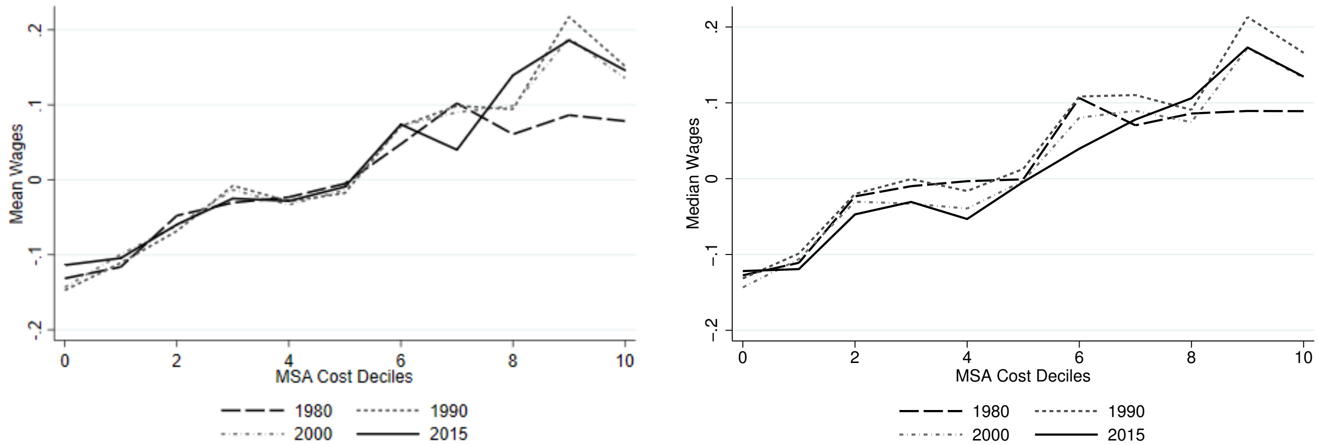
D Introducing Land and Firm Ownership

We have considered absentee land and firm owners up to now. In this section, we consider the case of land and firm ownership.[4] Following Fajgelbaum and Gaubert (2020), we consider that each type $\mathbf{s}$ worker in location j and occupation i earns a wage $w_{i,j}(\mathbf{s})$ and owns a fraction $b(\mathbf{s})$ of the national returns to fixed factors Π. Workers of different types may differ in their ownership of fixed factors, but they hold the same portfolio regardless of where they locate.[5] In this case, the income of an agent of type $\mathbf{s}$ in city j and occupation i, $I_{i,j}(\mathbf{s})$ (called expenditure in Fajgelbaum and Gaubert (2020)) is given by:

[3]Notice that, while our results are qualitatively the same, some of the controls absorb part of the contribution of city's cost of living to wage inequality. This result is similar to differences in the industrial composition of cities of different sizes explaining up to one-third of the city size effect, as pointed out by Baum-Snow and Pavan (2013).

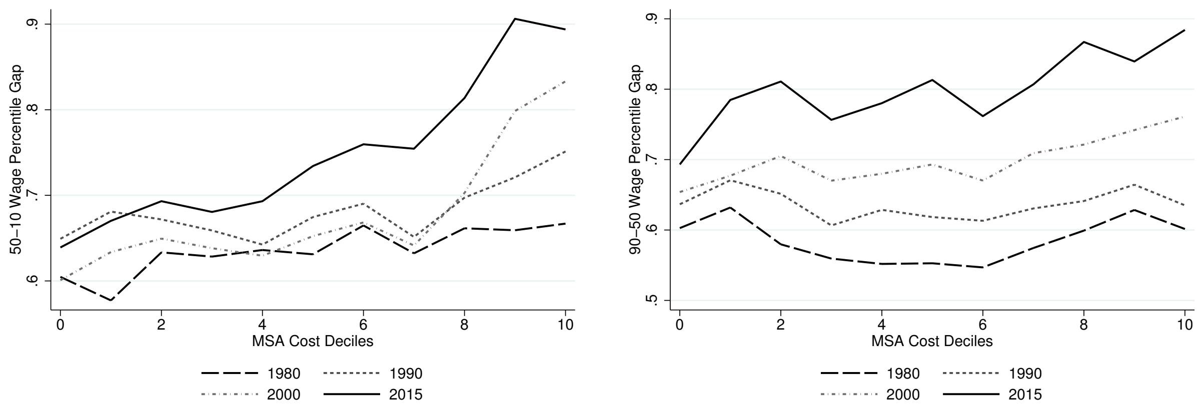
[4]Notice that because firms are immobile and there is no entry, firms have positive profits in equilibrium.

[5]According to Redding and Rossi-Hansberg (2017), distributing land rents locally to current residents – such as in Redding (2016) – generates inefficiencies because moving across locations imposes an externality on the rents received by other agents. To avoid this inneficiency and the interaction between location choice and rents, we follow Fajgelbaum and Gaubert (2020).



(a) Mean Residual Wages (b) Median Residual Wages

Figure OA-9: Mean and median residual wages across city costs and time



(a) 50-10 Percentile Gap (b) 90-50 Percentile Gap

Figure OA-10: Wage gaps across city costs and time

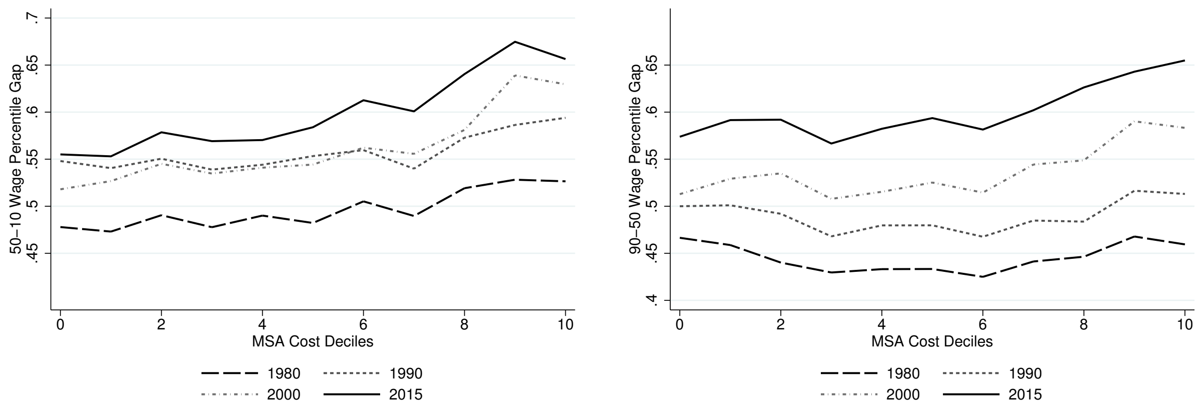
$$I_{i,j}(\mathbf{s}) = w_{i,j}(\mathbf{s}) + b(\mathbf{s})\Pi \tag{OA.6}$$

where:

$$\Pi = \sum_{j \in \mathcal{J}} \left\{ \pi_j + p_j H_j^S \right\} \tag{OA.7}$$

where π_j is the profit for representative firm in location j, p_j is the rent price in city j, and H_j^S the housing supply in city j.

Notice that this extension mostly changes the worker's problem. In particular, within a given city j and given a wage $w_{i,j} = \tilde{w}_{i,j} s_i$, a citizen chooses consumption bundles $\{c_{ij}, h_{ij}\}$ to maximize utility subject to the budget constraint:



(a) 50–10 Percentile Gap

(b) 90–50 Percentile Gap

Figure OA-11: Residual wage gaps across city costs and time

$$\begin{aligned} \max_{\{c_{ij},h_{ij}\}} u(c_{ij},h_{ij}) &= c_{ij}^{1-\alpha}h_{ij}^{\alpha} \\ \text{s.t. } c_{ij}+p_jh_{ij} &\leq I_{ij}(\mathbf{s}) \end{aligned} \tag{OA.8}$$

for all i,j. Solving for the competitive equilibrium allocation for this problem we obtain $c^{\star}_{ij}=(1-\alpha)I_{ij}(\mathbf{s})$ and $h^{\star}_{ij}=\alpha\frac{I_{ij}(\mathbf{s})}{p_j}$. Substituting the equilibrium values in the utility function, we can write $v(I_{ij}(\mathbf{s}),p_j)=(1-\alpha)^{(1-\alpha)}\alpha^{\alpha}\frac{I_{ij}(\mathbf{s})}{p_j^{\alpha}}$.

We consider the model with 4 skills and 3 cities. Moreover, we consider a production function such as:

$$A_jF(\mathbf{m}_j,\mathbf{k}_j,\mathbf{A}_j)=A_j\left\{\ \sum_i A_{l,ij}^{\frac{\gamma_i}{\lambda}}\left[m_{ij}^{\gamma_i}+A_{k,i}k_{ij}^{\gamma_i}\right]^{\frac{\lambda}{\gamma_i}}\ \right\}^{\frac{1}{\lambda}}. \tag{OA.9}$$

and a competitive housing market. Housing supply follows the price-quantity schedule

$$p_j(H)=\phi_jH^{\epsilon_{p,j}}. \tag{OA.10}$$

In other words, we consider a simplified version of our general model, in which workers cannot choose their occupation and have no idiosyncratic preferences for location. To calibrate the parameters, we use the estimated parameters in our initial submission, i.e.:

Finally, we need to discuss how to properly pin down $b(\mathbf{s})$. In Fajgelbaum and Gaubert (2020), they identify worker types with observable skill groups. In particular, they divide workers in two skill groups: high-skill (college) and low-skill (non-college). They then combine data from ACS and BEA to construct $I_{i,j}$. Based on the average share of capital income in the MSA owned by high-skill workers being 0.52, they set $b(s)$. We follow a similar procedure for a larger group of worker types.[6] In particular, we assume that high-skill workers own 52% of the portfolio, mid-skill

[6] Another possibility would be to split according to the log-normal for non-routine cognitive skills. We could make the case that higher non-routine cognitive skills is related to parents' wealth, both due to education attainment of

Table OA-9: Variance Decomposition: Log hourly wages – Occupational groups

Routine Cognitive

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.209	0.202	0.008	96%	4%
1990	0.259	0.243	0.016	93%	6%
2000	0.281	0.265	0.015	95%	6%
2015	0.347	0.329	0.018	95%	5%

Non-Routine Cognitive

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.228	0.217	0.010	96%	5%
1990	0.275	0.259	0.016	94%	6%
2000	0.324	0.308	0.016	95%	5%
2015	0.373	0.348	0.024	94%	7%

Routine Manual

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.194	0.175	0.019	90%	10%
1990	0.236	0.221	0.015	94%	6%
2000	0.235	0.224	0.012	95%	5%
2015	0.261	0.251	0.011	96%	4%

Non-Routine Manual

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.211	0.197	0.015	93%	7%
1990	0.276	0.254	0.022	92%	8%
2000	0.277	0.263	0.015	95%	5%
2015	0.286	0.275	0.012	96%	4%

Table OA-10: Variance Decomposition: Log hourly residual wages

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.194	0.187	0.007	96%	4%
1990	0.228	0.216	0.012	95%	5%
2000	0.262	0.251	0.010	96%	4%
2015	0.286	0.276	0.010	96%	4%

offspring, as well as higher non-cognitive skills that boost offspring's likelihood of white collar jobs (Karagiannaki (2017) and Johnson (2020)).

Table OA-11: Variance Decomposition: Log residual wages – Occupational Groups

Routine Cognitive

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.178	0.172	0.006	97%	3%
1990	0.216	0.204	0.012	94%	6%
2000	0.243	0.233	0.010	96%	4%
2015	0.271	0.261	0.010	96%	4%

Non-Routine Cognitive

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.190	0.183	0.007	96%	4%
1990	0.228	0.216	0.012	95%	5%
2000	0.274	0.263	0.011	96%	4%
2015	0.294	0.282	0.013	96%	4%

Routine Manual

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.185	0.172	0.013	93%	7%
1990	0.203	0.191	0.012	94%	6%
2000	0.216	0.207	0.009	96%	4%
2015	0.236	0.229	0.007	97%	3%

Non-Routine Manual

Year	Total	Variance Within City	Variance Between City	% Within	% Between
1980	0.184	0.176	0.008	96%	4%
1990	0.208	0.192	0.016	93%	7%
2000	0.220	0.209	0.011	95%	5%
2015	0.206	0.198	0.009	96%	4%

workers own 41%, and low-skill workers own 7%. Within occupation groups, the portfolio shares are evenly divided, regardless location.

Figure OA-12 shows the citywide occupation distribution by rent index for the cases of absentee owners (a) and profit portfolio (b). As we can see, the citywide occupation distributions are quite similar in both cases. In practice, since workers' income is not as dependent on location, low-rent cities become a bit larger. Similarly, in Table OA-13, we see how equilibrium rent indexes vary with local productivity in both cases. Again, the relationships are quite similar.

Table OA-12: Estimated Parameters 2015

Panel A: City level Parameters

Parameter	**low rent index**	**mid rent index**	**high rent index**
TFP A_j	59,000 (4200.0)	99,000 (12000.0)	120,000 (23000.0)
Measure of cities with A_j	154	75	24
Amenity a_j	1.0	1.2 (0.12)	1.6 (0.17)
House price shifter ϕ_j	0.059 (0.0079)	0.014 (0.0016)	0.0011 (0.00019)
Housing supply elasticity ϵ_j	0.48	0.69	1.1
Occupation Productivity $A_{l,ij}$			
non-routine manual	2.1 (0.2)	2.0 (0.21)	1.7 (0.2)
routine manual	3.0 (0.3)	2.9 (0.52)	3.9 (0.73)
routine cognitive	1.0	1.0	1.0
non-routine cognitive	1.0 (0.0088)	1.1 (0.017)	1.1 (0.025)

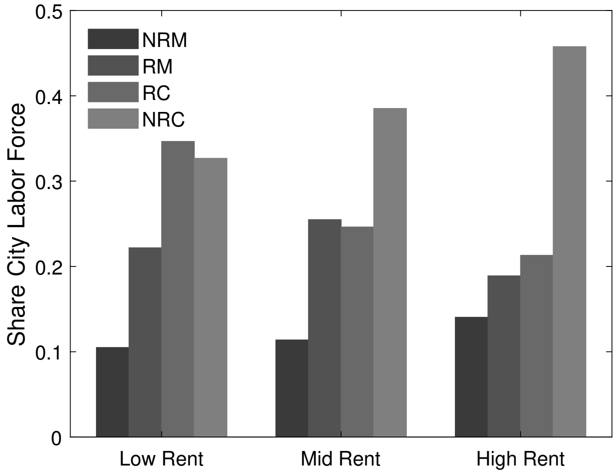
Panel B: Occupation level Parameters

Parameter	non-routine **manual**	routine **manual**	routine **cognitive**	non-routine **cognitive**
Capital Productivity $\frac{A_{k,i}}{A_{l,i}}$	0.11	0.013	0.02	0.15
Capital-Labor substitution parameter γ_i	0 0.23	0.62	0.62	-0.079
Measure of Workers in Occupation M_i	8,283,695	14,018,560	14,655,767	27,399,913

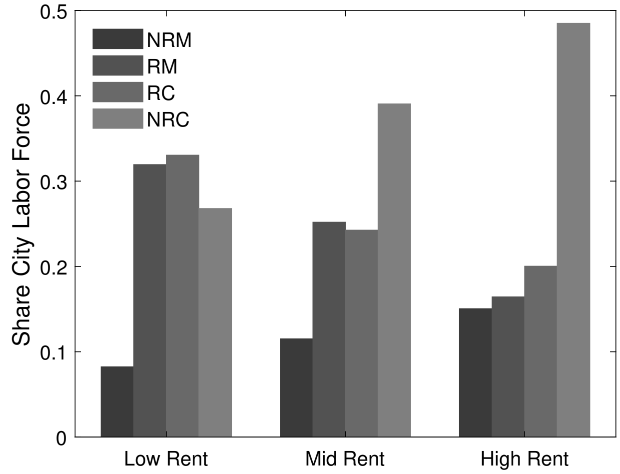
Panel C: Additional Parameters

Parameter	**Value**	**Source/Explanation**
λ	-0.33	Occupation output elasticity $\frac{3}{4}$ (Goos, Manning and Salomons, 2014; Lee and Shin, 2017)

Note: Standard errors in parentheses. Housing supply elasticity from Saiz (2010). See Appendix G for details.



(a) Absentee Landlords



(b) Profit Portfolio

Figure OA-12: Skill distribution across cities: Absentee Landlords vs. Profit Portfolio

	Low TFP	**Mid TFP**	**High TFP**
Absentee Landlords	6.02	147.42	1,530.91
Household Portfolio	17.98	186.07	1,495.18

Table OA-13: Equilibrium Rent Index by Local TFP: Absentee Landlords vsl Profit Portfolio

E Additional Empirical Results: Weighted Regressions

Table OA-14: IT budget per worker – 2015

	(1)	(2)	(3)	(4)	(5)	(6)
	log(IT)	log(IT)	log(IT)	log(IT)	log(IT)	log(IT)
MSA log rent index 1980	0.241***	0.140***			0.133**	0.139**
	(0.035)	(0.046)			(0.054)	(0.054)
MSA RC share 1980			0.189		0.045	0.148
			(0.376)		(0.385)	(0.378)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.0580*	0.010	0.015
				(0.0312)	(0.038)	(0.038)
MSA Offshorability 1980						-0.124
						(0.112)
Housing supply elasticity		-0.001	-0.007	-0.0060	-0.001	-0.000
		(0.006)	(0.007)	(0.0067)	(0.006)	(0.006)
Amenities	No	Yes	Yes	Yes	Yes	Yes
MSA's Industry Mix Controls	No	Yes	Yes	Yes	Yes	Yes
MSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	47.76	29.29	23.57	24.20	27.01	25.69
Adj. R^2	0.383	0.629	0.606	0.613	0.625	0.626
MSAs	217	217	217	217	217	217

Standard errors in parentheses. The dependent variable in all columns is the logarithm of the average IT budget per employee in the metro area, adjusted for plant employment interacted with three-digit SIC industry. Each observation (an MSA) is weighted by its employment in 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table OA-15: Change in routine-cognitive share, 1990-2015

	Δrout-cog					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	-0.0329**	-0.0321***			-0.0201*	-0.0193*
	(0.0157)	(0.0095)			(0.0109)	(0.0111)
MSA RC share 1980			-0.3545***		-0.3097***	-0.2936***
			(0.0883)		(0.0919)	(0.1000)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				-0.0237***	-0.0110	-0.0103
				(0.0062)	(0.0078)	(0.0078)
MSA Offshorability 1980						-0.0181
						(0.0249)
Housing supply elasticity		-0.0032**	-0.0012	-0.0023*	-0.0024*	-0.0022
		(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0014)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
CMSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	4.40	28.56	32.18	27.68	32.34	33.09
Adj. R^2	0.105	0.684	0.700	0.684	0.713	0.712
MSAs	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the share of routine cognitive occupations in the MSA's employed labor force between 1990 and 2015. Each observation (an MSA) is weighted by its employment in 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table OA-16: Wage ratios NRC-RC: 1990–2015

	$\Delta \ln\left(\frac{W_{NRC}}{W_{RC}}\right)$					
	(1)	(2)	(3)	(4)	(5)	(6)
MSA log rent index 1980	0.1248***	0.1533***			0.1383***	0.1283***
	(0.0293)	(0.0254)			(0.0304)	(0.0295)
MSA RC share 1980			0.7487***		0.6314***	0.4491*
			(0.2272)		(0.2255)	(0.2376)
MSA non-routine cognitive share 1980			0.3031**		0.1162	0.0105
			(0.1493)		(0.1883)	(0.1856)
MSA's log $\left(\frac{S}{U}\right)$ in 1980				0.0705***	-0.0029	0.0019
				(0.0228)	(0.0334)	(0.0331)
MSA Offshorability 1980						0.1893***
						(0.0678)
Housing supply elasticity		0.0003	-0.0061**	-0.0048	-0.0010	-0.0032
		(0.0031)	(0.0031)	(0.0030)	(0.0032)	(0.0032)
Amenities	No	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	Yes	Yes	Yes	Yes
CMSA Controls	No	Yes	Yes	Yes	Yes	Yes
F statistic	18.16	16.29	11.74	12.41	16.82	19.03
Adj. R^2	0.257	0.608	0.573	0.564	0.621	0.634
$MSAs$	211	211	211	211	211	211

Standard errors in parentheses. The dependent variable in all columns is the change in the log ratio of nonroutine cognitive occupation and routine cognitive occupation real average wages between 1990 and 2015. Each observation (an MSA) is weighted by its employment in 2015. MSA controls include the unemployment rate in 1980, the share of the working age population that is female, African American, and Mexican born in 1980, and a dummy for right-to-work States. Industry mix controls include the share of area's 1980 employment in agriculture and mining, construction, non-durable manufacturing, durable manufacturing, transportation and utilities, wholesale, retail, finance and real estate, business and repair services, personal services, entertainment, and professional services (public-sector share is excluded). Stars represent: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.