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Household expenditures, wages, rents

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ABSTRACT

New evidence from the 1980, 1990, and 2000 Decennial Census of Housing indicates that expenditure shares on housing are constant over time and across US metropolitan statistical areas (MSA). Consistent with this observation, we consider a model in which identical households with Cobb–Douglas preferences for housing and non-housing consumption choose a location and locations differ with respect to income earned by their residents. The model predicts that the relative price of housing of any two MSAs disproportionately reflects differences in incomes of those MSAs and is independent of housing supply in each MSA. According to the predictions of our calibrated model, the dispersion of rental prices across low- and high-wage MSAs should be larger than we observe: High-wage MSAs like San Francisco are puzzlingly inexpensive relative to low-wage MSAs like Pittsburgh.

1. Introduction

We document that renting households spend a constant fraction of income on housing expenditures in each of the top 50 US metropolitan statistical areas (MSAs) in 1980, 1990, and 2000. When household preferences are chosen to replicate this fact in equilibrium, a standard model of location choice predicts that the relative price of housing of any two MSAs disproportionately reflects differences in incomes of those MSAs and is independent of housing supply in each MSA.

When preference parameters are calibrated to match the data on housing rents and incomes, the model implies that each percentage point differential in wages across any two MSAs leads to more than a 4 percentage point differential in rental prices in those MSAs. Given data on wages in MSAs, the model predicts more dispersion in rental prices across MSAs than we observe.

In other words, without reference to amenities, differential supply constraints, heterogeneous abilities or preferences, or consumption-externality based arguments, a standard model of location choice can explain the large differences in rental prices between high-price cities like San Francisco and low-price cities like Pittsburgh. In fact, our calibrated model, designed to reproduce the constancy of expenditure shares, predicts an even greater disparity in rental prices between these two cities than we observe in the data. In our view, the relevant question for future research is: Why is San Francisco so cheap relative to Pittsburgh?

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We begin our analysis by using microeconomic data from the last three Decennial Census of Housing (DCH) surveys to document that the ratio of housing expenditures (contract rent plus utilities) to income of renting households – our estimate of the expenditure share on housing – has been remarkably constant over time and across US metropolitan areas. We use renter data to compute expenditure shares for housing because rental payments made by homeowners are never observed. Only mortgage payments for homeowners are observable, and mortgage payments can vary across households even if implicit rents on underlying housing units are identical.

In the 1980, 1990, and 2000 DCH surveys, our estimate of the expenditure share on housing by renting households displays little variation across MSAs despite significant variation in average income. The expenditure share on housing is also remarkably stable over time within each MSA, despite sometimes sizeable changes over time to real rental prices. This is our evidence supporting Cobb–Douglas preferences for consumption and housing.

In Section 3, we consider the implications of a Cobb–Douglas preference assumption for the equilibrium distribution of housing prices across MSAs. In a simple multi-location model similar to Eeckhout (2004), identical households costlessly choose their MSA in which to live and their housing and consumption. MSAs differ with respect to income that residents earn. There is a fixed stock of perfectly divisible housing units in each MSA. Given our estimate of 24 percent of income spent on housing, we show the difference in log rental prices of two MSAs must equal 4.2 ($= 1/0.24$) times the difference in log per capita income. In other words, if income growth in any MSA outpaces growth in average income across MSAs by 1 percentage point, rental prices in that MSA will outpace the average growth in rental prices by 4.2 percentage points. Thus, rental prices in an MSA will not in general increase at the same rate as income in that MSA.

The economics of this result are straightforward. Because expenditure shares are constant across locations in equilibrium, households living in high-wage MSAs spend more on both consumption and housing. Therefore they consume a greater quantity of the consumption good. The equilibrium condition that all MSAs provide the same level of utility ensures that these households consume a smaller quantity of housing. It follows that in equilibrium, the ratio of rental prices across any two MSAs must be higher than the ratio of wages in those MSAs.

The equilibrium condition that agents are indifferent across locations requires that indirect utility be identical everywhere. This requirement determines relationships between rental prices and wages in any two locations that are independent of the total quantity of housing in any location. Of course, the level of rents in every location is determined by market-clearing conditions for housing – implying that the level of housing supply in any location affects the level of rents everywhere. However, when agents have Cobb–Douglas preferences for consumption and housing, the relative price of housing in any two MSAs is completely independent of the total supply of housing in any MSA. That is, contrary to the results of Gyourko et al. (2006) and others, wages – not housing supply – determine the relative price of housing in San Francisco or any other high-priced area. This is an analytic result derived directly from the model.

In Section 4, we use year-2000 DCH data to compute constant-quality wages and rental prices for the MSAs in our sample. We then calibrate our model and compare the model-predicted rental prices for each MSA to the data. Given the observed dispersion in wages across MSAs, the model easily predicts all the dispersion in rental prices. In fact, the model predicts that rental prices in many high-wage MSAs should be higher than what we actually observe. This result also holds when we adjust wages for local consumption prices.

Finally, in Section 5, we use a dynamic version of our model to explore its predictions for the price of housing (rather than rental prices). We use the result that rental prices disproportionately reflect differences in income to examine (as an extreme example from our data) differences in house prices in San Francisco and Pittsburgh. As of the year 2000, the difference in house prices of these two MSAs seems rationalizable if incomes are expected to increase one-half percentage point per year more quickly in San Francisco than in Pittsburgh, a result well within the experience of the past 20 years.

Our finding that the share of income spent on rent is constant across places and over time has important implications for the modeling of non-housing consumption and housing. The finding provides support for the assumption of Cobb–Douglas preferences for non-housing consumption (hereafter simply "consumption") and housing. These preferences are common in many macroeconomic models with a housing or home-production sector. For example, see Davis and Heathcote (2005), Fisher (1997, 2007), Gervais (2002), Gomme et al. (2001), Greenwood et al. (1995), Iacoviello (2005), and Kiyotaki et al. (2008).

The same finding is inconsistent with the key assumption of considerable research. Several recent studies in finance and in macroeconomics try to explain the variability in stock prices and house prices by assuming that consumption and housing are more or less complementary than Cobb–Douglas in utility; see, e.g., Davis and Martin (2009), Flavin and Nakagawa (2008), Kahn (2009), Lustig and Van Nieuwerburgh (2007), and Piazzesi et al. (2007). Other studies in urban economics and local public finance (such as Moretti, 2009) assume that households demand exactly one unit of housing, regardless of wages and the local price of housing.

Work more similar to ours is Van Nieuwerburgh and Weill (2009). They calibrate a spatial equilibrium model to quantify the contribution of changes in various factors (such as wages and housing supply constraints) to observed changes in the dispersion in housing prices across US MSAs. Van Nieuwerburgh and Weill assume households have quasi-linear preferences for housing and consumption, implying that expenditure shares on housing vary.

Some models assuming Cobb–Douglas preferences for consumption and housing in utility have been able to match certain cross-sectional facts. For example, Eeckhout (2004) and Rozenfeld et al. (2009) show that a multi-city model where households have Cobb–Douglas preferences for consumption and housing can replicate key features of the size distribution of places. Lucas and Rossi-Hansberg (2002) assume Cobb–Douglas preferences in their within-city model of the allocation of land to production and residential use.

2. Evidence on expenditure shares

In this section, we study rental expenditures of households. We study renters because their expenditures on housing services – rents – are observable.

Verbrugge (2008) and others have argued that rental payments on housing by homeowners can be proxied as a hypothetical mortgage payment computed as the product of a current mortgage rate and current house value. This procedure does not yield accurate measures of rental expenditures by homeowners because house prices reflect both current rents and expected future prices. Consider two homes in different locations but with same price. The mortgage-payment method would impute the identical rent to both houses. Now suppose that in one of the locations, house prices are expected to increase more rapidly than in the other location. The faster growth in house prices generates greater capital gains for the homeowner, reducing the user cost (i.e. rent) of the house. The mortgage-payment method would not capture this relevant difference in user cost.[2]

We construct an estimate of the expenditure share on housing by renting households using microeconomic data from the Decennial Census of Housing (DCH) files.[3] The first three columns in Table 1 list the median of the ratio of annual gross rent – rent including utilities – to total household wage and salary income for the top 50 MSAs by population in 2000, for renter households with nonzero wage and salary income and nonzero rental payments, for 1980, 1990, and 2000. These 50 MSAs account for about 46 percent of the population in 1980–2000.

The data show that the estimated expenditure share on housing is remarkably stable across MSAs and over time. In any given year, the median expenditure share on housing is nearly constant across MSAs at about 0.24 with a standard deviation of about 0.02 (last two rows).

When we use DCH data to compute expenditure shares for contract rent and utilities separately, we find an expenditure share for contract rent of 18 percent and an expenditure share for utilities of 6 percent. These estimates of expenditure shares are each about 3 percentage points higher than aggregate estimates computed using data from the National Income and Product Accounts (NIPA).[4]

There are several possible ways to reconcile these numbers, but three explanations seem compelling. First, the NIPA imputes rents to homeowners, accounting for 77 percent of NIPA contract rents in 2008. It is possible that the NIPA estimate of imputed rent is too low.[5] Second, some of the consumption reported in the NIPA may not be truly discretionary, such as expenditures on health care paid for by the government or employers. Third, we use income rather than consumption for the denominator of our measure of expenditure shares. This distinction may be important, as we discuss later.

The fourth column in Table 1 reports for each MSA the median of household wage and salary income in 2000 for renter households. The standard deviation of this measure, \$5,710, is 17 percent of the MSA-average, \$33,689. The fact that our estimates of expenditure shares are constant across MSAs is not due to lack of cross-sectional variation of income.

The last column in Table 1 reports growth of real rental prices in each MSA over 1980–2000.[6] The reported expenditure share is nearly constant over time in every MSA, despite sometimes large increases in the real relative price of rental units shown in this column. For example, the real relative price of rents in San Jose, CA more than doubled from 1980 to 2000.

The 25th and the 75th percentiles of the distribution of expenditure shares within each MSA are also stable across MSAs and over time. Table 2 shows that the average 25th and 75th MSA percentiles of the expenditure shares are 17 and 36 percent (with standard deviation of about 2 and 4 percentage points), respectively. Within each MSA, however, the expenditure share on rent is decreasing with household income.

One possibility is that rental expenditures do fall with income, and that our finding that median expenditure shares are nearly constant across 50 MSAs and three decades is a coincidence. This is not our view. We suspect the gap between consumption and income is key to explaining why expenditure shares fall with income.

Suppose that consumption is equal to permanent income, and that observed income for person i is equal to permanent income for that person, $\bar{w}_i$, times a deviation of income from permanent income, u_i, or

$$w_i = \bar{w}_i u_i. \tag{1}$$

[2] House prices and mortgage payments can also vary across locations if the location–specific risk component of housing assets varies. Campbell et al. (2009) and Ortalo-Magné and Prat (2009) suggest that these risk premiums may vary significantly across MSAs.

[3] These data are available at the Integrated Public Use Microdata Series (IPUMS) web site, http://usa.ipums.org/usa/. We exclude farm households, households living in group quarters, and households living in mobile homes, trailers, boats, tents, vans, or "other."

[4] NIPA Table 2.4.5: ratio of line 50 to line 1 (contract rent) and line 55 to line 1 (household utilities).

[5] Of course, the NIPA estimate might also be too high. Díaz and Luengo-Prado (2008) argue that a "user cost" approach provides a better estimate than a "rental equivalence" approach to estimating the cost of housing services to homeowners.

[6] Growth in real rental prices is computed as growth in nominal rental price per unit less consumer price inflation excluding housing services and utilities. Nominal rent per unit is computed in 1980 and 2000 using DCH data and a hedonic regression approach (described later). Consumer prices increased by 84 percent over the 1980–2000 period, according to data from the NIPA.

Table 1
Median ratio of rental expenditures to wage and salary income, median income, and growth in real rental prices.

MSA	Median ratio			Median HH income (2000) renters only	Real rent growth, 1980–2000
	1980	1990	2000		
Albany–Schenectady–Troy	0.21	0.23	0.23	$32,300	16.2%
Atlanta–Sandy Springs–Marietta	0.24	0.25	0.25	$36,300	25.1%
Austin–Round Rock	0.27	0.25	0.25	$36,400	42.0%
Bakersfield	0.28	0.25	0.25	$26,800	0.7%
Baltimore–Towson	0.23	0.23	0.23	$34,000	35.1%
Boston–Cambridge–Quincy	0.24	0.26	0.24	$43,000	52.1%
Buffalo–Niagara Falls	0.20	0.22	0.23	$28,800	21.1%
Charlotte–Gastonia–Concord	0.23	0.24	0.24	$37,000	27.3%
Chicago–Naperville–Joliet	0.21	0.23	0.23	$36,000	33.5%
Cincinnati–Middletown	0.21	0.22	0.20	$30,400	5.5%
Cleveland–Elyria–Mentor	0.21	0.22	0.23	$30,000	5.1%
Columbus	0.22	0.23	0.23	$33,100	38.6%
Dallas–Fort Worth–Arlington	0.24	0.24	0.24	$34,600	32.5%
Denver–Aurora	0.25	0.24	0.26	$35,000	19.5%
Detroit–Warren–Livonia	0.21	0.22	0.22	$35,000	6.8%
Fresno	0.25	0.27	0.26	$25,900	14.0%
Grand Rapids–Wyoming	0.19	0.24	0.21	$31,000	16.9%
Greensboro–High Point	0.24	0.23	0.22	$33,000	23.7%
Houston–Sugar Land–Baytown	0.23	0.22	0.23	$32,000	7.2%
Indianapolis–Carmel	0.21	0.23	0.23	$34,000	8.6%
Jacksonville	0.27	0.24	0.25	$31,000	3.5%
Kansas City	0.21	0.22	0.22	$35,700	21.4%
Las Vegas–Paradise	0.29	0.27	0.27	$35,000	20.1%
Los Angeles–Long Beach–Santa Ana	0.25	0.29	0.27	$33,000	37.2%
Louisville–Jefferson County	0.22	0.23	0.21	$32,000	4.2%
Miami–Fort Lauderdale–Pompano Beach	0.27	0.29	0.29	$28,000	24.3%
Milwaukee–Waukesha–West Allis	0.20	0.23	0.22	$32,000	12.2%
Minneapolis–St. Paul–Bloomington	0.24	0.25	0.23	$35,500	19.3%
Nashville–Davidson–Murfreesboro–Franklin	0.23	0.24	0.24	$33,000	22.9%
New Orleans–Metairie–Kenner	0.24	0.25	0.24	$25,000	24.6%
New York–Northern New Jersey–Long Island	0.22	0.24	0.24	$39,600	38.2%
Orlando–Kissimmee	0.26	0.27	0.27	$32,950	41.1%
Philadelphia–Camden–Wilmington	0.22	0.24	0.23	$37,000	33.2%
Phoenix–Mesa–Scottsdale	0.28	0.26	0.26	$32,000	9.5%
Pittsburgh	0.21	0.21	0.22	$30,000	10.1%
Portland–Vancouver–Beaverton	0.27	0.24	0.25	$36,000	19.1%
Riverside–San Bernardino–Ontario	0.26	0.28	0.27	$32,000	17.9%
Sacramento–Arden-Arcade–Roseville	0.25	0.28	0.26	$33,000	38.9%
St. Louis	0.22	0.23	0.22	$30,000	4.4%
Salt Lake City	0.24	0.23	0.27	$30,900	22.5%
San Antonio	0.22	0.24	0.24	$30,000	13.5%
San Diego–Carlsbad–San Marcos	0.29	0.30	0.28	$34,000	38.4%
San Francisco–Oakland–Fremont	0.26	0.28	0.25	$46,900	70.7%
San Jose–Sunnyvale–Santa Clara	0.24	0.26	0.25	$58,500	110.0%
Seattle–Tacoma–Bellevue	0.25	0.25	0.26	$38,200	33.7%
Syracuse	0.24	0.24	0.24	$27,000	16.7%
Tampa–St. Petersburg–Clearwater	0.26	0.25	0.25	$31,400	23.0%
Tucson	0.26	0.29	0.26	$24,600	−2.7%
Tulsa	0.23	0.22	0.23	$31,000	1.8%
Washington–Arlington–Alexandria	0.23	0.26	0.24	$44,600	46.7%
Average	0.24	0.25	0.24	$33,689	24.2%
Standard deviation	0.02	0.02	0.02	$5710	19.4%

We assume that the median of u_i is 1. This would occur if the natural log of u_i is normally distributed with mean 0 and some variance σ^2. If each person spends a constant fraction α of permanent income on rent, the observed expenditure share is a random variable with a distribution of

$$\frac{x_i}{w_i} = \left(\frac{x_i}{\bar{w}_i}\right)\left(\frac{\bar{w}_i}{w_i}\right) = \alpha\left(\frac{1}{u_i}\right). \tag{2}$$

An unbiased estimate of α is the median of Eq. (2), as the median value of u_i is equal to 1, by assumption. As long as the distribution of u_i is similar across MSAs, the distribution of our estimated expenditure shares will also be similar

Table 2
25th and 75th percentiles of ratio of rental expenditures to wage and salary income.

MSA	1980		1990		2000	
	25th	75th	25th	75th	25th	75th
Albany–Schenectady–Troy	0.15	0.33	0.16	0.33	0.15	0.35
Atlanta–Sandy Springs–Marietta	0.17	0.35	0.19	0.38	0.17	0.37
Austin–Round Rock	0.19	0.44	0.18	0.37	0.18	0.40
Bakersfield	0.17	0.36	0.17	0.41	0.16	0.40
Baltimore–Towson	0.16	0.34	0.16	0.35	0.16	0.35
Boston–Cambridge–Quincy	0.17	0.35	0.18	0.40	0.16	0.37
Buffalo–Niagara Falls	0.14	0.29	0.15	0.33	0.16	0.37
Charlotte–Gastonia–Concord	0.17	0.37	0.17	0.34	0.17	0.35
Chicago–Naperville–Joliet	0.14	0.31	0.16	0.34	0.16	0.36
Cincinnati–Middletown	0.15	0.29	0.15	0.33	0.14	0.31
Cleveland–Elyria–Mentor	0.15	0.32	0.15	0.32	0.16	0.36
Columbus	0.16	0.31	0.16	0.33	0.16	0.34
Dallas–Fort Worth–Arlington	0.17	0.33	0.18	0.35	0.17	0.34
Denver–Aurora	0.18	0.37	0.18	0.35	0.18	0.39
Detroit–Warren–Livonia	0.15	0.31	0.16	0.35	0.14	0.33
Fresno	0.16	0.39	0.19	0.44	0.18	0.40
Grand Rapids–Wyoming	0.14	0.32	0.17	0.35	0.15	0.33
Greensboro–High Point	0.16	0.36	0.17	0.35	0.15	0.32
Houston–Sugar Land–Baytown	0.16	0.34	0.16	0.32	0.16	0.34
Indianapolis–Carmel	0.15	0.32	0.16	0.32	0.15	0.34
Jacksonville	0.18	0.39	0.18	0.35	0.18	0.37
Kansas City	0.15	0.33	0.16	0.33	0.16	0.32
Las Vegas–Paradise	0.20	0.47	0.19	0.38	0.17	0.41
Los Angeles–Long Beach–Santa Ana	0.17	0.39	0.20	0.45	0.18	0.44
Louisville–Jefferson County	0.14	0.32	0.16	0.36	0.15	0.31
Miami–Fort Lauderdale–Pompano Beach	0.19	0.43	0.20	0.45	0.19	0.45
Milwaukee–Waukesha–West Allis	0.15	0.30	0.17	0.35	0.15	0.34
Minneapolis–St. Paul–Bloomington	0.17	0.34	0.18	0.37	0.17	0.34
Nashville–Davidson–Murfreesboro–Franklin	0.16	0.33	0.17	0.34	0.17	0.35
New Orleans–Metairie–Kenner	0.16	0.38	0.17	0.41	0.17	0.40
New York–Northern New Jersey–Long Island	0.15	0.33	0.16	0.37	0.15	0.38
Orlando–Kissimmee	0.18	0.37	0.19	0.39	0.19	0.42
Philadelphia–Camden–Wilmington	0.16	0.34	0.18	0.36	0.16	0.35
Phoenix–Mesa–Scottsdale	0.20	0.45	0.19	0.40	0.18	0.39
Pittsburgh	0.15	0.31	0.14	0.33	0.15	0.37
Portland–Vancouver–Beaverton	0.18	0.41	0.17	0.34	0.18	0.38
Riverside–San Bernardino–Ontario	0.18	0.41	0.20	0.42	0.18	0.43
Sacramento–Arden-Arcade–Roseville	0.17	0.37	0.20	0.41	0.17	0.39
St. Louis	0.16	0.35	0.16	0.33	0.16	0.35
Salt Lake City	0.17	0.40	0.17	0.34	0.17	0.39
San Antonio	0.16	0.34	0.18	0.35	0.17	0.36
San Diego–Carlsbad–San Marcos	0.20	0.45	0.21	0.46	0.19	0.44
San Francisco–Oakland–Fremont	0.18	0.39	0.19	0.41	0.17	0.39
San Jose–Sunnyvale–Santa Clara	0.18	0.36	0.20	0.39	0.18	0.39
Seattle–Tacoma–Bellevue	0.18	0.36	0.18	0.36	0.18	0.39
Syracuse	0.16	0.37	0.17	0.35	0.16	0.38
Tampa–St. Petersburg–Clearwater	0.18	0.41	0.19	0.37	0.18	0.37
Tucson	0.19	0.40	0.20	0.42	0.19	0.44
Tulsa	0.18	0.36	0.15	0.34	0.16	0.35
Washington–Arlington–Alexandria	0.16	0.33	0.19	0.36	0.17	0.35
Average	0.17	0.36	0.17	0.37	0.17	0.37
Standard deviation	0.02	0.04	0.02	0.04	0.01	0.03

across MSAs. This may be the reason the interquartile range of the expenditure share is stable across MSAs and over time.[7]

If deviations of (w_i/x_i) from average do reflect differences in current income from permanent income, u_i should reflect life-cycle income profiles: u_i should rise with age until somewhere around age 55, and then decline. To test this, we compute deviations of $\log(w_i/x_i)$ from its average – these deviations are exactly equal to $\log(u_i)$ – and then regress the deviations on age of the primary wage earner of the household (binned into 5-year intervals). The coefficients from these

[7] An alternative explanation for the data in Table 2 is that there may be within-MSA variation in tastes for housing. Families with children might choose to devote more to housing than childless families. As long as the distribution of preferences for housing does not vary across MSAs, the analysis of this section holds.

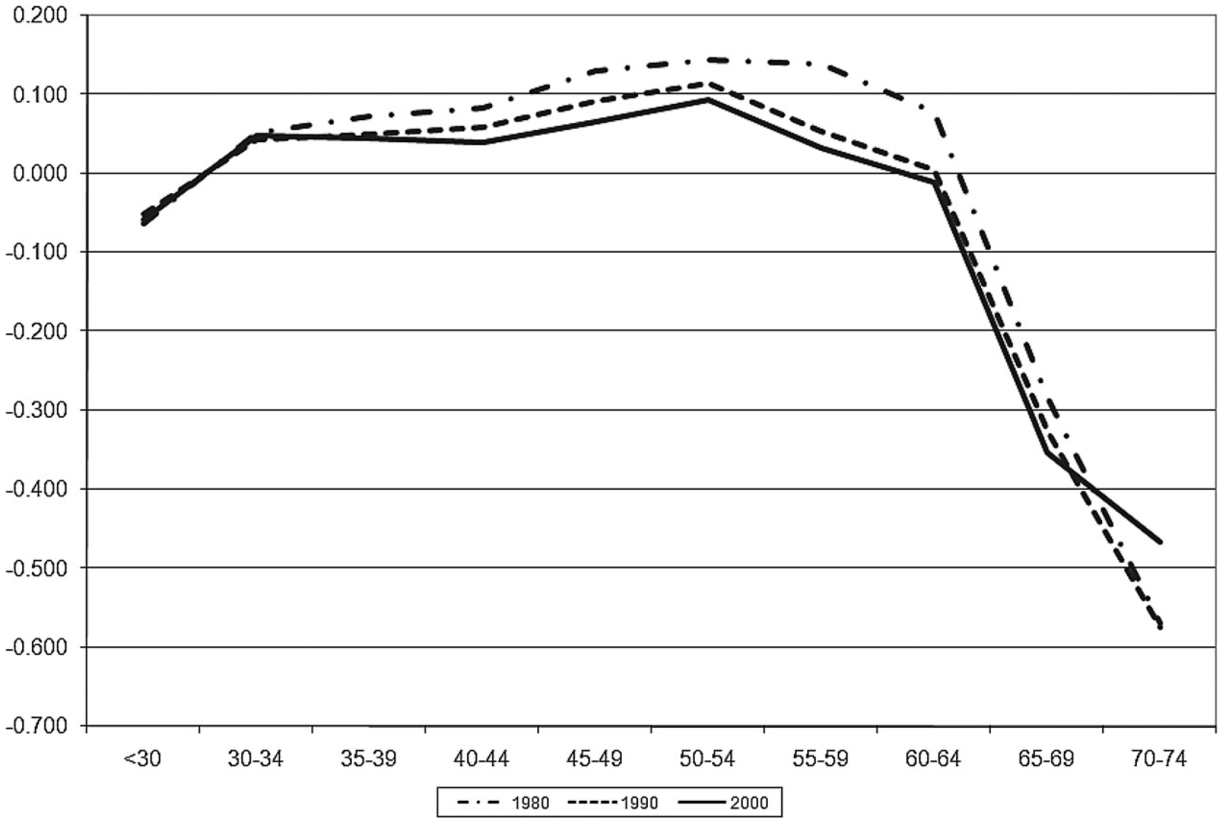

Fig. 1. Average deviation of log ratio of income to housing expenditures by age, decennial census of housing 1980–2000.

regressions for all three DCH years are shown in Fig. 1. The coefficients on each age segment are broadly comparable across years, and the coefficients behave as expected.[8]

In a final check on the independence of expenditures on housing from permanent income, we study panel data from the Consumer Expenditure Survey (CEX), made available for download by Aguiar and Hurst (2009).[9] For households headed by wage earners between the ages of 25 and 55, we run a regression using quarterly CEX data from 1982q1 through 2003q2 of log rental expenditures – including owner-equivalent rent for homeowners – on instrumented log total outlays with controls for date, age, cohort, marital status, household size, and number of children.[10] The coefficient on total non-durable expenditures from this regression is 0.986 with a standard error of 0.009. Depending on the instruments, the control variables, whether or not we use total outlays or total non-durable expenditures as the regressor, and the age range of the CEX sample, we obtain coefficients on spending in the range of $[0.90, 1.10]$. Our point is not to argue that the CEX data suggest 1.0 is the exact estimate, but that they suggest the income elasticity of rental expenditures is at or near 1.0.[11]

When we combine the evidence from the CEX with the evidence from the 1980, 1990, and 2000 DCH that, at the median, renters spend roughly a constant fraction of their income on rent regardless of location or rental prices, we conclude that shares of expenditures on rents are independent of time, location, rental price, and income. The evidence suggests that households have Cobb–Douglas preferences for consumption and housing services, an assumption we adopt in our equilibrium model of location choice.

3. Model with constant expenditure shares

Eeckhout (2004) uses a multi-city environment assuming households have Cobb–Douglas preferences over consumption and housing to study the size distribution of places. We use a similar framework, but focus on the cross-sectional distribution of housing rents.

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[8] This evidence is in line with the findings of Fernandez-Villaverde and Krueger (2007).

[9] Erik Hurst suggested this approach, and kindly provided both data and Stata programs (any errors are our own). The CEX data are available at the web site: http://www.markaguiar.com/aguiarhurst/lifecycle/datapage.html.

[10] The instruments are log nominal income, nominal income squared and cubed, and education dummies. We instrument total expenditures because (a) rent is a component of total expenditures, implying a correlation of the two variables if rent is measured with error, and (b) both rent and total expenditures are determined jointly.

[11] This point is also made by Piazzesi et al. (2007).

3.1. Environment

We consider an economy with N MSAs indexed by $i = 1, \ldots, N$. The economy is populated by a measure 1 of identical agents. The decision problem of agents in this economy is static, so we suppress time subscripts.[12] Any agent who lives in MSA i produces w_i units of non-housing consumption goods. There are H_i units of divisible housing in MSA i owned by a measure zero of agents who behave competitively in the rental housing market.

Agents choose where to live, how many non-housing goods to consume, and how much housing to rent. Given a set of housing rental prices for each MSA, $\{r_i\}_{i=1,N}$, agents choose the MSA i, non-housing consumption c, and housing h that solve the problem:

$$\max_{i,c,h} c^{1-\alpha} h^{\alpha}, \tag{3}$$

$$\text{subject to } c + r_i h \leqslant w_i, \tag{4}$$

with $0 < \alpha < 1$.

Note from the budget constraint that the price of consumption everywhere is equal to 1.0.[13] All agents who choose the same MSA i choose the same levels of non-housing consumption and housing:

$$c_i = (1-\alpha) w_i \tag{5}$$

and

$$h_i = \alpha w_i / r_i. \tag{6}$$

An *allocation* is fully characterized by the set of non-housing consumption and housing chosen by agents in each MSA, $\{c_i, h_i\}_{i=1,N}$ and the measures of agents living in each MSA, $\{n_i\}_{i=1,N}$. An *equilibrium* in this economy is a set of rental prices $\{r_i\}_{i=1,N}$, and an allocation such that: (1) Agents maximize their utility, taking rental prices as given; (2) In every MSA occupied, the housing market clears; i.e., $n_i h_i = H_i$ if $n_i > 0$; (3) No household wants to move, i.e., all agents derive the same utility whatever MSA they choose.

We examine only sets of parameters such that all MSAs are occupied in equilibrium. Rearranging the market clearing conditions and summing over all MSAs yields:

$$\sum_{i=1}^{N} n_i = \sum_{i=1}^{N} H_i / h_i = 1. \tag{7}$$

The condition that agents are indifferent between living in MSAs i and j means:

$$\left[(1-\alpha) w_i\right]^{1-\alpha} [h_i]^{\alpha} = \left[(1-\alpha) w_j\right]^{1-\alpha} [h_j]^{\alpha} \tag{8}$$

where we replace non-housing consumption using the solution to the agents' utility maximization problem. Rearranging, we obtain:

$$\frac{h_i}{h_j} = \left(\frac{w_i}{w_j}\right)^{\frac{\alpha-1}{\alpha}}. \tag{9}$$

Combining this equation with Eq. (7) yields the equilibrium quantity of housing per agent in each MSA:

$$h_i = \frac{\left(\sum_{k=1}^{N} H_k w_k^{\frac{1-\alpha}{\alpha}}\right)}{w_i^{\frac{1-\alpha}{\alpha}}}. \tag{10}$$

Plugging this equation into the solution to the agent's optimal housing choice yields the equilibrium rental prices:

$$r_i = \frac{\alpha w_i^{\frac{1}{\alpha}}}{\left(\sum_{k=1}^{N} H_k w_k^{\frac{1-\alpha}{\alpha}}\right)}. \tag{11}$$

From this we obtain equilibrium measures of households for each MSA:

$$n_i = \frac{H_i w_i^{\frac{1-\alpha}{\alpha}}}{\left(\sum_{k=1}^{N} H_k w_k^{\frac{1-\alpha}{\alpha}}\right)}. \tag{12}$$

[12] We consider dynamic implications of the model in Section 5.

[13] We relax this assumption later.

3.2. Predictions

The model predicts that the optimal expenditure share on housing is constant at α in every MSA. Eqs. (11) and (12) can be combined to show that at the aggregate level, the model produces a constant ratio of rental expenditures to income:

$$\frac{\sum_i r_i H_i}{\sum_i n_i w_i} = \alpha. \tag{13}$$

The model predicts that the ratio of average rental price per unit to aggregate per-capita income is independent of the dispersion of income across MSAs. Rather, the ratio of average rental price per unit to aggregate per capita income is equal to the expenditure share on housing divided by the average quantity of housing consumed per household:

$$\frac{\left(\frac{\sum_i r_i H_i}{\sum_i H_i}\right)}{\left(\frac{\sum_i n_i w_i}{\sum_i n_i}\right)} = \alpha\left(\sum_i H_i\right)^{-1}. \tag{14}$$

The model predicts that the ratio of rental prices between any two MSAs i and j depends disproportionately on the ratio of their incomes. Working with Eq. (11), it is easy to show that

$$\frac{r_i}{r_j} = \left(\frac{w_i}{w_j}\right)^{\frac{1}{\alpha}}. \tag{15}$$

The intuition behind this result is straightforward. In equilibrium, to ensure that agents are indifferent to living in any two MSAs i and j, it must be that:

$$c_i^{1-\alpha} h_i^{\alpha} = c_j^{1-\alpha} h_j^{\alpha}. \tag{16}$$

Now, suppose that residents of city i earn more than residents in city j. This implies from Eq. (5) that c_i is higher than c_j. If $c_i > c_j$, then $h_i < h_j$ for Eq. (16) to hold. Since consumption and housing are complements in utility, rental prices must be relatively high in the high-income MSA.

Eq. (15) also implies that the supply of housing in MSA i or j does not affect the relative rental price of housing, r_i/r_j. Thus, according to the model, San Francisco is not expensive compared to, say, Pittsburgh, because of supply restrictions enacted in San Francisco or growth policies in Pittsburgh. Of course, the supply of housing in MSA i, H_i, determines the rental price of housing r_i through the term $(\sum_{k=1}^{N} H_k w_k^{\frac{\alpha}{1-\alpha}})$ in Eq. (11), just as the supply of housing does in any other MSA. The model predicts that changes in the supply of housing in any MSA affect the price level of housing in every MSA. With Cobb–Douglas preferences, however, the relative price of housing in any two MSAs is independent of the level of supply in any MSA.

4. Model fit

After taking logs of Eq. (15), and recognizing that Eq. (15) holds for any k, we link rental prices and wages in MSA i to the average across a set of N MSAs:

$$\log(r_i) - \frac{1}{N}\sum_{k=1}^{N}\log(r_k) = \frac{1}{\alpha}\left[\log(w_i) - \frac{1}{N}\sum_{k=1}^{N}\log(w_k)\right]. \tag{17}$$

We define $\bar{r}$ and $\bar{w}$ such that

$$\bar{r} = \exp\left(\frac{1}{N}\sum_{k=1}^{N}\log(r_k)\right), \tag{18}$$

$$\bar{w} = \exp\left(\frac{1}{N}\sum_{k=1}^{N}\log(w_k)\right) \tag{19}$$

and construct predicted rental values for each MSA, $\hat{r}_i$, as

$$\hat{r}_i = \bar{r}\left(\frac{w_i}{\bar{w}}\right)^{\frac{1}{\alpha}}. \tag{20}$$

We set $\alpha = 0.24$ and use Eq. (20) to ask if the model can explain the observed dispersion in rental prices across MSAs, given the observed dispersion in wages across MSAs. We provide results for the year 2000, but results for 1980 and 1990 are similar.

To proceed, we need to compute a standardized measure of income, w_i, appropriate for each MSA. That is, we want to remove variation in median MSA income reported in Table 1 that arises from variations in average levels of human capital and average numbers of workers in households across MSAs. To do this, we turn to microeconomic data from the 2000 DCH. On an MSA-by-MSA basis, we run a Mincer-style regression of the log of reported wage and salary income for any one who worked at least 40 weeks in the past year on a constant and a set of human capital variables. These variables include sex, age in 5-year brackets, and categorical variables for educational attainment (none or missing, less than high school degree, high school degree, some college, college degree or higher). On average, these regressions capture 32 percent of the variation in log wages within each MSA.

By regressing wages on age and education variables, we control for the variation in within-MSA wages that is attributable to differences in human capital. We use wage and salary income, rather than a broader measure that includes transfer or capital income, to focus on income-earning potential that is location–specific. We consider only income of those working 40 weeks or more in the past year to abstract from differences in average wages across MSAs that are attributable to differences in the number of part-time workers.

To compute a standardized wage that holds age and human capital constant across locations, we multiply the estimated regression coefficients in each MSA by the fraction of workers for the entire US that is appropriate for each dummy variable in the regression. Then we multiply by 1.53 to compute average household income in an MSA; this is the average number of full-time workers in each household, for all households that include at least one full time worker.

We estimate constant-quality rental prices r_i consistently across MSAs similarly. On an MSA-by-MSA basis, we regress the level of gross rents paid by renting households on available characteristics of the housing unit and the method and time of commute (home to work) of the highest income earner in the household. For housing unit characteristics, we include categorical variables for number of rooms, number of bedrooms, year the unit was built, and total number of units in the building in which the unit is located, and from these categorical variables we generate a full set of dummy variables. For the method of commute of the household's highest income earner, we subdivide responses into three dummy variables: private automobile, public transportation, or walk/bicycle. For commute time, we use the recorded response.[14] On average, these rent regressions capture 25 percent of the variation in reported rental expenditures within each MSA.

Using the regression coefficients for each MSA, we predict the level of rent, by MSA, for a four-room two-bedroom unit located in a 5–9-family building, where the primary wage earner commutes 15 minutes by private auto. The building is assumed to have been built between 1960 and 1969. These are the median values for our sample of renting households in the US.

Our estimates of standardized wages and rental prices, w_i and r_i, for the year 2000 are listed in the first two columns of Table 3, in descending order by standardized wages.[15] Rental prices are high in high-wage places; the correlation of rental prices and wages in this table is 0.80. The third and fourth columns of the table show predicted rental prices based on Eq. (20), $\hat{r}_i$, and the difference between the observed and the predicted rental rate, denoted e_i.

Table 3 shows that, given the distribution of wages across MSAs, the simple frictionless model can easily generate the observed distribution of rental prices. In fact, the model overpredicts the dispersion of rental prices. The standard deviation of predicted rental prices, \$293, is higher than the observed standard deviation, \$145. The correlation of e_i and w_i is -0.92, implying the calibrated model predicts that rental prices are not high enough in high-wage places and too high in low-wage places. Fig. 2 plots the predicted relationship between wages and rents as the solid line alongside plusses marking the wage and rent data shown in Table 3. Fig. 2 shows that the model underpredicts rental prices in relatively low wage places like Pittsburgh (the solid circle marked as "PT") and overpredicts rental prices in relatively high wage places such as San Francisco ("SF").

We perform two sensitivity analyses to ensure that this last result is a robust feature of the data. In the first, we eliminate homeowners from our regressions and computations of MSA-average wages, so that MSA-specific calculations of r_i and w_i are from exactly the same samples of renting households. In the second, we include only households where (a) the primary respondent in the household has moved to a different metropolitan area within the past 5 years and (b) the previous metropolitan area of residence is directly identifiable. Although our estimates of w_i change in the first analysis, and w_i and r_i both change in the second analysis, in both analyses the correlation of e_i and w_i is approximately -0.90.

One question that arises is whether a small change in the fraction spent on rent more closely aligns predicted rental rates with observed rental rates. It is possible to show that potentially reasonable changes to α are not sufficient to drive the correlation of e_i and w_i to zero. For example, at $\alpha = 0.35$, the correlation of e_i and w_i is -0.65. When $\alpha = 0.52$, the correlation falls to zero. Thus, our finding that w_i and e_i are negatively correlated seems robust, because in economic terms expenditure shares of 50 percent are far from the 24 percent we estimate.

There are a few reasons the model may overpredict dispersion in rental prices. To start, we may be overestimating the dispersion in constant-quality wage rates and underestimating the dispersion in constant-quality rental rates. In the case of wages, even after controlling for observables in our wage regressions, workers in high wage places like San Francisco may be

[14] We create a separate dummy variable for households with a recorded commute of zero minutes.

[15] The standardized wage estimates are very close to estimates of median household income by MSA for all households, owner and renter, in 2000 (not reported). The w_i reported in Table 3 are systematically higher, but have a correlation of 0.90 with the median household-level wage and salary income for renters reported in Table 1.

Table 3
2000 wages (w_i), observed rents (r_i), predicted rents ($\hat{r}_i$), and error ($e_i = r_i - \hat{r}_i$), 2000.

MSA	w_i	r_i	$\hat{r}_i$	e_i
San Jose–Sunnyvale–Santa Clara	$72,187	$1264	$1999	−$735
San Francisco–Oakland–Fremont	$64,782	$1029	$1274	−$244
New York–Northern New Jersey–Long Island	$63,893	$794	$1202	−$408
Washington–Arlington–Alexandria	$62,894	$827	$1126	−$299
Boston–Cambridge–Quincy	$61,500	$880	$1026	−$145
Chicago–Naperville–Joliet	$60,853	$728	$981	−$254
Detroit–Warren–Livonia	$60,782	$679	$977	−$298
Philadelphia–Camden–Wilmington	$58,957	$749	$860	−$111
Dallas–Fort Worth–Arlington	$58,914	$611	$858	−$246
Seattle–Tacoma–Bellevue	$58,254	$785	$818	−$33
Los Angeles–Long Beach–Santa Ana	$58,187	$869	$814	$54
Atlanta–Sandy Springs–Marietta	$57,993	$657	$803	−$146
Houston–Sugar Land–Baytown	$57,553	$605	$778	−$173
Baltimore–Towson	$57,501	$696	$775	−$79
Minneapolis–St. Paul–Bloomington	$57,490	$656	$774	−$118
Denver–Aurora	$57,278	$634	$763	−$129
Charlotte–Gastonia–Concord	$57,070	$623	$751	−$128
Austin–Round Rock	$56,322	$670	$711	−$41
Sacramento–Arden-Arcade–Roseville	$55,663	$612	$677	−$65
Cincinnati–Middletown	$55,488	$518	$668	−$150
Phoenix–Mesa–Scottsdale	$55,331	$624	$660	−$36
Las Vegas–Paradise	$55,041	$638	$646	−$7
Indianapolis–Carmel	$54,785	$563	$633	−$71
Kansas City	$54,753	$631	$632	−$1
San Diego–Carlsbad–San Marcos	$54,630	$753	$626	$127
Portland–Vancouver–Beaverton	$54,555	$616	$622	−$6
Cleveland–Elyria–Mentor	$54,352	$546	$613	−$67
Riverside–San Bernardino–Ontario	$54,003	$593	$597	−$4
Milwaukee–Waukesha–West Allis	$53,933	$624	$593	$31
Columbus	$53,657	$605	$581	$24
Louisville–Jefferson County	$53,474	$446	$573	−$127
Grand Rapids–Wyoming	$53,153	$504	$558	−$54
St. Louis	$52,952	$549	$550	$0
Salt Lake City	$52,322	$581	$523	$58
Jacksonville	$52,245	$557	$520	$37
Nashville–Davidson–Murfreesboro–Franklin	$52,219	$534	$519	$15
Tampa–St. Petersburg–Clearwater	$51,746	$623	$499	$123
Greensboro–High Point	$51,560	$508	$492	$16
Bakersfield	$51,449	$450	$488	−$37
Tulsa	$50,990	$505	$470	$35
Albany–Schenectady–Troy	$50,946	$644	$468	$176
Orlando–Kissimmee	$50,139	$635	$438	$197
Miami–Fort Lauderdale–Pompano Beach	$49,392	$720	$411	$309
San Antonio	$48,734	$557	$389	$168
Syracuse	$48,675	$557	$387	$170
Pittsburgh	$48,167	$536	$370	$165
Buffalo–Niagara Falls	$48,152	$592	$370	$222
Fresno	$48,003	$512	$365	$147
New Orleans–Metairie–Kenner	$48,000	$570	$365	$204
Tucson	$45,914	$512	$303	$209
Average	$54,937	$644	$678	−$34
Standard deviation	$5045	$145	$293	$184

of higher unobservable skill than workers in low wage places like Pittsburgh. In the case of rents, the hedonics used in the rent regressions to uncover constant-quality rental prices may be too crude, and our measure of rental price per unit might reflect expenditures instead of prices. In this case, to the extent that quantities of housing consumed are low in high-wage places and high in low-wage places (as theory predicts), we would expect our measured dispersion of rental price per unit to be biased downward.

An alternative explanation is that some fraction of non-housing consumption may be produced locally. If the prices of locally produced consumption goods are correlated with wages, then real wages after accounting for variation in consumption prices are likely to be less dispersed than nominal wages. If wages are less dispersed, predicted rental prices will also be less dispersed, holding α constant.

Data on local consumption prices in 2000 by MSA are available from the 2000 American Chamber of Commerce Researchers Association (ACCRA) Cost of Living Index, as published by the Council for Community and Economic Research. ACCRA participants collect price-level data on 53 items not related to housing or utilities, grouped in four broad categories:

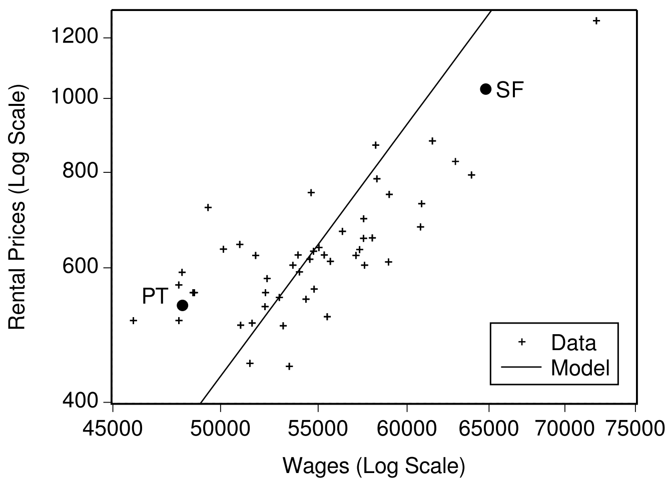

Fig. 2. Plot of wage and rental price data in Table 3.

Grocery (26 questions), Transportation (2), Health Care (5), and Miscellaneous (20). The questions range from the price of a box of corn flakes (Grocery) to the average price per game of bowling on Saturday between 6 and 10 pm (Miscellaneous).[16] For each category, ACCRA constructs a local price level based on the sample of prices of individual items, and sets the average price level across sampled MSAs for each category at 100. ACCRA also reports expenditure shares for each category in 2000: Grocery (0.16), Transportation (0.10), Health Care (0.05), and Miscellaneous (0.33).[17]

To incorporate local prices in our model, and be consistent with the construction of the ACCRA data, we assume that households have Cobb–Douglas preferences over a bundle of S consumption goods and housing. That is, utility in city i is assumed to be of the form

$$\left(\prod_{s=1}^{S} c_{i,s}^{\beta_s}\right) h_i^{\alpha}, \tag{21}$$

and households are subject to the budget constraint

$$\sum_{s=1}^{S} p_{i,s} c_{i,s} + r_i h_i \leqslant w_i, \tag{22}$$

where we assume that $\sum_{s=1}^{S} \beta_s + \alpha = 1$. With Cobb–Douglas preferences, households optimally choose constant expenditure shares on the bundle of all consumption items and housing, $p_{i,s} c_{i,s} = \beta_s w_i$ and $r_i h_i = \alpha w_i$.

In equilibrium the relation among rental prices, wages, and consumption prices in any two MSAs i and j is:

$$\left(\frac{r_i}{r_j}\right) = \left(\frac{\tilde{w}_i}{\tilde{w}_j}\right)^{\frac{1}{\alpha}}, \tag{23}$$

where

$$\tilde{w}_k = \frac{w_k}{\prod_{s=1}^{S} p_{k,s}^{\beta_s}}. \tag{24}$$

After adjusting nominal wages for consumption prices, as in Eq. (24), we predict rental prices using an equation similar to (20), replacing w_k with $\tilde{w}_k$ and appropriately redefining $\bar{r}_i$ and $\bar{w}_i$.

We compute $\prod_{s=1}^{S} p_{i,s}^{\beta_s}$ for 48 of our 50 MSAs, eliminating Buffalo, NY, and Bakersfield, CA.[18] We match the ACCRA metropolitan division codes to the relevant MSAs.[19] We assume households consume a basket of $S = 4$ consumption items

[16] The complete list of questions is available at http://www.coli.org/SurveyForms/PricingSurveyForm.pdf.

[17] For the year 2000, the ACCRA expenditure share on utilities is 8 percent and the expenditure share on housing (owned or rented) is 28 percent.

[18] ACCRA does not provide consumption price data for Buffalo, NY and for Bakersfield, CA. ACCRA also does not provide consumption price data for San Jose, but we set consumption prices in San Jose equal to prices in San Francisco.

[19] For about 10 of the larger MSAs, the ACCRA survey covers only a subset of metropolitan divisions within the MSA. We suspect this distinction is probably not of quantitative importance, except perhaps for the New York MSA, where we find the level of consumption prices is about 11 percent higher than the next-most pricey MSA, San Francisco. In the New York MSA, the only included metropolitan division (of four in total) is the New York–White Plains–Wayne Division.

Table 4
2000 wages (w_i), consumption prices ($p_i = \prod_{s=1}^{S} p_{i,s}^{\beta_s}$), adjusted wages ($\tilde{w}_i$), observed rents ($r_i$), predicted rents based on adjusted wages ($\tilde{r}_i$), and error ($\tilde{e}_i = r_i - \tilde{r}_i$).

MSA	w_i	p_i	$\tilde{w}_i$	r_i	$\tilde{r}_i$	$\tilde{e}_i$
San Jose–Sunnyvale–Santa Clara	$72,187	1.13	$64,035	$1264	$1195	$69
San Francisco–Oakland–Fremont	$64,782	1.13	$57,466	$1029	$762	$268
New York–Northern New Jersey–Long Island	$63,893	1.24	$51,624	$794	$487	$307
Washington–Arlington–Alexandria	$62,894	1.05	$60,013	$827	$912	−$85
Boston–Cambridge–Quincy	$61,500	1.07	$57,252	$880	$750	$130
Chicago–Naperville–Joliet	$60,853	1.02	$59,609	$728	$887	−$159
Detroit–Warren–Livonia	$60,782	0.99	$61,627	$679	$1019	−$340
Philadelphia–Camden–Wilmington	$58,957	1.03	$57,167	$749	$745	$4
Dallas–Fort Worth–Arlington	$58,914	0.98	$60,282	$611	$930	−$318
Seattle–Tacoma–Bellevue	$58,254	1.02	$57,055	$785	$739	$46
Los Angeles–Long Beach–Santa Ana	$58,187	1.03	$56,394	$869	$704	$164
Atlanta–Sandy Springs–Marietta	$57,993	0.97	$59,581	$657	$885	−$228
Houston–Sugar Land–Baytown	$57,553	0.95	$60,806	$605	$964	−$359
Baltimore–Towson	$57,501	0.94	$61,003	$696	$977	−$281
Minneapolis–St. Paul–Bloomington	$57,490	1.03	$55,914	$656	$679	−$23
Denver–Aurora	$57,278	1.01	$56,969	$634	$734	−$101
Charlotte–Gastonia–Concord	$57,070	0.97	$58,931	$623	$846	−$222
Austin–Round Rock	$56,322	0.93	$60,823	$670	$965	−$294
Sacramento–Arden-Arcade–Roseville	$55,663	1.07	$52,164	$612	$509	$103
Cincinnati–Middletown	$55,488	0.96	$57,992	$518	$791	−$273
Phoenix–Mesa–Scottsdale	$55,331	0.98	$56,350	$624	$702	−$78
Las Vegas–Paradise	$55,041	1.03	$53,262	$638	$555	$84
Indianapolis–Carmel	$54,785	0.95	$57,826	$563	$782	−$219
Kansas City	$54,753	0.98	$55,617	$631	$664	−$34
San Diego–Carlsbad–San Marcos	$54,630	1.06	$51,741	$753	$492	$261
Portland–Vancouver–Beaverton	$54,555	1.02	$53,528	$616	$567	$50
Cleveland–Elyria–Mentor	$54,352	1.01	$53,653	$546	$572	−$26
Riverside–San Bernardino–Ontario	$54,003	1.06	$51,102	$593	$467	$126
Milwaukee–Waukesha–West Allis	$53,933	0.95	$56,540	$624	$712	−$88
Columbus	$53,657	0.96	$56,114	$605	$690	−$84
Louisville–Jefferson County	$53,474	0.96	$55,546	$446	$661	−$215
Grand Rapids–Wyoming	$53,153	1.02	$52,304	$504	$514	−$10
St. Louis	$52,952	0.97	$54,789	$549	$624	−$75
Salt Lake City	$52,322	1.01	$51,907	$581	$498	$83
Jacksonville	$52,245	0.95	$54,707	$557	$620	−$63
Nashville–Davidson–Murfreesboro–Franklin	$52,219	0.94	$55,841	$534	$676	−$142
Tampa–St. Petersburg–Clearwater	$51,746	0.97	$53,359	$623	$559	$64
Greensboro–High Point	$51,560	0.94	$54,755	$508	$623	−$115
Bakersfield	$51,449					
Tulsa	$50,990	0.94	$54,113	$505	$593	−$88
Albany–Schenectady–Troy	$50,946	0.97	$52,440	$644	$520	$124
Orlando–Kissimmee	$50,139	0.97	$51,726	$635	$491	$144
Miami–Fort Lauderdale–Pompano Beach	$49,392	1.02	$48,227	$720	$367	$353
San Antonio	$48,734	0.91	$53,584	$557	$569	−$12
Syracuse	$48,675	0.99	$49,267	$557	$401	$156
Pittsburgh	$48,167	0.99	$48,441	$536	$374	$162
Buffalo–Niagara Falls	$48,152					
Fresno	$48,003	1.02	$46,888	$512	$326	$186
New Orleans–Metairie–Kenner	$48,000	0.97	$49,649	$570	$414	$156
Tucson	$45,914	0.96	$48,036	$512	$361	$151
Average	$54,937	1.00	$55,167	$649	$664	−$15
Standard deviation	$5045	0.06	$3983	$145	$197	$179

– groceries, transportation, health care, and miscellaneous – and proportionately rescale the four ACCRA expenditure shares so that the sum $\sum_{s=1}^{4} \beta_s = 0.76$, which yields a 24 percent expenditure share on housing including utilities.

For the MSAs in our sample, Table 4 shows nominal wages, w_i; our estimate of consumption prices, $p_i = \prod_{s=1}^{S} p_{i,s}^{\beta_s}$ (after a rescaling to set the average of p_i across MSAs equal to 1.0); wages after adjusting for prices as in Eq. (24), $\tilde{w}_i$; actual rental prices, r_i; and predicted rental prices after wages have been adjusted for consumption prices, $\tilde{r}_i$. Entries appear in descending order of nominal wages.

The correlation of nominal wages and consumption price levels (p_i) is high, 0.60. After adjusting incomes for variation in consumer price levels, the standard deviation of predicted rental prices falls from $293 to $197, closer to the standard deviation in the data of $145. Yet, rental prices are still too high in places that offer relatively low wages after accounting for consumption prices. At $\alpha = 0.24$, the correlation of the gap between actual and predicted rental prices, $\tilde{e}_i$, and adjusted income, $\tilde{w}_i$, shown in Table 4 is -0.72; and, the value of α required to set this correlation to zero is 0.71.[20]

We are aware we can more accurately predict rental prices, given the distribution of wages, if we are willing to redefine household utility. Ignoring variation in local consumption prices, suppose utility in city i is defined as $z_i c_i^{1-\alpha} h_i^{\alpha}$. In equilibrium, indifference across MSAs requires

$$\frac{r_i}{r_j} = \left(\frac{z_i w_i}{z_j w_j}\right)^{\frac{1}{\alpha}}. \tag{25}$$

Whatever z_i is, assuming $\alpha = 0.24$, the results of Tables 3 and 4 show it must be negatively correlated with wages. It could perhaps be a quality of life variable, as in Albouy (2009), Kahn (1995), or Rappaport (2008). It also could be related to congestion externalities linked to density. Without z_i, however, a simple model of location choice that reproduces the observation that housing expenditure shares are constant across locations predicts that rental prices in the highest-wage MSAs are higher than currently observed.

5. Extension: House prices

Given that households are assumed to have no savings, they solve the static problem defined above each period. For a dynamic extension of the baseline model, we index rents and wages by time. The ratio of rental prices in any two MSAs at time t is

$$\frac{r_{i,t}}{r_{j,t}} = \left[\frac{w_{i,t}}{w_{j,t}}\right]^{\frac{1}{\alpha}}. \tag{26}$$

Suppose now that wages in MSA i increase at rate $1 + g_i$ and wages in MSA j increase at rate $1 + g_j$, where g_j does not have to equal g_i. This implies:

$$\frac{r_{i,t+1}}{r_{j,t+1}} = \left[\frac{w_{i,t}(1+g_i)}{w_{j,t}(1+g_j)}\right]^{\frac{1}{\alpha}} = \left(\frac{r_{i,t}}{r_{j,t}}\right)\left(\frac{1+g_i}{1+g_j}\right)^{\frac{1}{\alpha}}. \tag{27}$$

Denote the growth rate of rents in MSA i as γ_i and the growth rate of rents in MSA j as γ_j. Then Eq. (27) implies

$$\frac{1+\gamma_i}{1+\gamma_j} = \left(\frac{1+g_i}{1+g_j}\right)^{\frac{1}{\alpha}}. \tag{28}$$

In words, for each percentage point that income in i outpaces income in j, rental prices in i outpace rental prices in j by approximately $1/\alpha$ percentage points. Assuming $\alpha = 0.24$, each percentage point differential in wage growth translates to a 4.2 percentage point differential in rental price growth.

The intuition that small differences in income can lead to much greater differences in rental prices might help explain why the ratio of house prices to incomes varies widely across the country. According to data from the 2000 DCH, the ratio of house value to income was roughly 5.2 in San Francisco and 2.5 in Pittsburgh in 2000. A more traditional metric of valuation studied in real estate finance is the ratio of housing rents to house prices, the "rent-price" ratio. Campbell et al. (2009) document that the rent-price ratio for owner-occupied housing was 3.2% in San Francisco in 2000 and 5.2% for Pittsburgh.

According to the classic dividend discounting model, the rent-price ratio is simply a required return less an expected rate of growth. Suppose the required return on housing is the same in both areas.[21] Then, the available data suggest that in 2000 the expected growth rate of rents was 2.0 ($= 5.2 - 3.2$) percentage points per year higher in San Francisco than in Pittsburgh. Eq. (28) tells us that each percentage point differential in income growth leads to a 4.2 percent differential in rental growth. Thus, income growth need be only 0.5 percent per year faster in San Francisco than in Pittsburgh to generate a 2 percentage point per year differential in rental growth.

We do not know whether this was a reasonable expectation, but it is well within recent historical experience. According to data from the 1980 and 2000 DCH, over the 1980–2000 period median household wage and salary income for all households in San Francisco increased 1.3 percentage points per year more rapidly than the median wage and salary income of households in Pittsburgh.[22]

[20] At the suggestion of a referee, we experimented with subtracting utilities costs from rental prices in Tables 3 and 4. This had the potential to increase the dispersion of measured rents because, across MSAs, average utilities expenditures and rental prices are negatively correlated. However, the negative correlation is not pronounced enough to affect any of our main results, especially if we recalibrate α to 0.18, the appropriate value reflecting the expenditure share of rent exclusive of utilities payments.

[21] Of course, housing in San Francisco may be more or less risky and thus require a higher or lower return than in Pittsburgh.

[22] The median household wage and salary income for renters in San Francisco increased 2.2 percentage points per year more rapidly than the median wage and salary income for renters in Pittsburgh.

6. Conclusions

We use microeconomic data from the 1980, 1990, and 2000 Decennial Census of Housing to document that the ratio of rental expenditures to income is remarkably constant across MSAs and over time. We study the equilibrium properties for housing rents of a simple model consistent with this observation. We show that, given the distribution of wages across MSAs, a calibrated version of the model can easily account for the observed distribution of rental prices across MSAs. In fact, the model predicts that rental prices in many high-wage MSAs should be higher than what we observe.

A distinctive feature of our general spatial equilibrium model, relative to many papers in the urban economics and local public finance literatures, is our use of Cobb–Douglas preferences. This assumption yields a constant housing expenditure share in equilibrium, consistent with the evidence we uncover. The same assumption has been used to explain the distribution of population across places (Eeckhout, 2004 and Rozenfeld et al., 2009) and to study the internal structure of cities (Lucas, 2001 and Lucas and Rossi-Hansberg, 2002).

Our multi-location model predicts that, in the aggregate, the ratio of rental prices per unit to per capita income is constant, as long as the aggregate stock of housing per capita is also constant. This is a common result of macroeconomic models when households have Cobb–Douglas utility. We show that this result does not hold at the MSA level; instead, rental prices disproportionately reflect income differentials.

We conclude that the common intuition that local house price indexes should rise at the same rate as local per capita income is incorrect whenever income growth differs across MSAs.

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