Housing Demand and Expenditures: How Rising Rent Levels Affect Behavior and Costs-of-Living over Space and Time

David Albouy
University of Illinois and NBER

Gabriel Ehrlich
University of Michigan

Yingyi Liu *
University of Illinois

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*Albouy: albouy@illinois.edu; Ehrlich: gehrlich@umich.edu; Liu: liu195@illinois.edu. During work on this project, Albouy was supported by the NSF grant SES-0922340 and was a David C. Lincoln Fellow. Any mistakes are our own. We thank seminar participants at the London School of Economics, Nebraska, and West Virginia and conference participants at the AREUEA, ASSA, and SEA annual meetings, most especially Ed Olsen, for their comments and input.

Abstract

Since 1970, housing's relative price, share of expenditure, and "unaffordability" have all grown. We estimate housing demand parameters using compensated and uncompensated frameworks over space and time, testing restrictions imposed by demand theory and household mobility. The data support the hypothesis that housing demand is both income and price inelastic, and that housing demand has exhibited a secular increase over time. We estimate an ideal cost-of-living index that demonstrates how the poor are impacted disproportionately in high-rent cities, and how rising rents amplified increases in income inequality. Rising rents and inequality both help explain why housing has become more unaffordable.

Keywords: Housing demand, housing affordability, cost-of-living, inflation, non-homothetic preferences, consumer economics, income shares.

JEL Numbers: D12, E31, R21

1 Introduction

The share of Americans' budgets devoted to housing has risen considerably over the last four decades. Figure 1 illustrates this trend using several sources: The American Housing Survey (AHS) and Consumer Expenditure Survey (CEX) indicate that the share of income spent on housing rose by 7 percentage points from 1970 to 2012. This increase was even sharper for renters, while home-ownership rates were 64 percent in both years. These trends appear to support the recent claim by the Secretary of Housing and Urban Development that, "We are in the midst of the worst rental affordability crisis that this country has known" (Olick 2013).

Economically, these trends are surprising, as housing is viewed as a necessity. Thus, the share of expenditures devoted to housing should have fallen as incomes have risen over time. One possible resolution to this apparent inconsistency lies in the 35-percent increase in the price of housing (or shelter) relative to the prices of other goods, as estimated by the Bureau of Labor Statistics (BLS), and illustrated in Figure 1. If housing demand is price inelastic, the housing share will rise with its relative price.

Figure 2 graphs these ideas, using a production possibility frontier (PPF) and indifference curves for housing and non-housing goods. It seems plausible that the PPF has expanded further in the direction of non-housing goods than in housing, as many non-housing goods may be traded internationally, while housing is produced locally, and may be subject to slower technological improvements. With this expansion, households increase their consumption of non-housing goods more than housing from both income effects (illustrated by the movement from point A to point B in the figure) and substitution effects (illustrated by the movement from point B to point C). The income effect causes housing's share to fall (compare points B and D), but the rise in the relative price, determined by the slope of the PPF, causes housing's share to rise due to the limited substitution response (compare C and E).

Below, we investigate the principal features of housing demand using an intuitive framework. We demonstrate that cross-sectional data lends itself to estimating compensated (Hicksian) housing demand functions, based on how households equalize the utility households they receive from living in different locations through mobility. Because that assumption is not plausible over time, time-series data lends itself only to estimating uncompensated (Marshallian) demand. In both spatial and temporal settings, understanding housing demand is useful for measuring changes in costs-of-living over space (e.g. across cities) and time (i.e. inflation) through a price index that incorporates realistic substitution and income effects.

Unlike previous authors, we use data on non-housing prices to test restrictions imposed by demand theory, which serve as a check on the validity of our empirical methodology. Under such restrictions, we integrate a demand equation into non-homothetic utility and expenditure functions with a constant elasticity of substitution. These functions are useful to researchers interested in housing consumption behavior, or in how changes in cost-of-living affect welfare. Our measures improve on typical measures of "housing affordability" by separately accounting for income and substitution effects. The analysis also provides an unconventional examination of demand theory by using spatial variation, rather than more conventional temporal variation (e.g. Deaton 1986, Blundell et al. 1993).

Our estimates suggest that the uncompensated own-price, income, and substitution elasticities are all near two-thirds in absolute value. Time-series patterns are consistent with our cross-sectional results, but exhibit an additional secular trend towards greater housing consumption. While this shift invites further investigation, it suggests that tastes for housing may have grown over time, casting an interesting light on housing affordability problems.

We also discuss how higher housing costs have a greater impact on the poor in more expensive cities, and how rising housing costs appear to have exacerbated increases in real income inequality since 1970. Furthermore, we estimate the extent to which decreases in housing affordability measures have been increased by growing income inequality and rising rent levels, but also should have fallen because of rising average incomes, and changes in relative rent levels.[1]

[1] We also note that understanding housing demand is essential to problems involving urban form and density, the demand for local public goods, the incidence of taxes and subsidies on housing, and the response of housing prices to shifts in supply and demand.

2 Motivation and Related Literature

Mirroring our own findings, the Joint Center for Housing Studies of Harvard University (JCHS, 2013) documents that from 2000 to 2012, the median share of renters' incomes devoted to contract rent rose nearly five percentage points to 27.4 percent, and that 28 percent of renting households now spend more than half of their incomes on rent. Concerns about housing affordability are most acute when housing is a necessity and demand is price inelastic. This is particularly true for low income households, who have experienced few income gains, especially relative to the wealthiest in America's largest, most expensive cities (Baum-Snow and Pavan, 2013). Low-skilled households' inability to substitute away from expensive housing appears to account for their choosing to live in cheaper cities (Moretti 2013), while those who remain in expensive cities must earn higher wages relative to other skill groups (Black, Kolesnikova, and Taylor 2009).[2]

Households' ability to substitute between housing and non-housing goods is a key factor affecting house prices, tax incidence, and population density within and across metropolitan areas. When housing demand is price inelastic, increases in demand can lead to large local price increases in places where housing supply is price inelastic. This is important to understanding whether the recent resurgence of housing prices in some markets is sustainable or a potential signal of a new housing bubble. Recent price increases are likely be more sustainable if housing demand is inelastic. In that case, rents in high-priced markets may continue to take a larger share of income, and housing policy may need to prioritize problems in housing affordability and production over issues related to lending and credit.

Economists' interest in housing demand and expenditures has a long and distinguished history, featuring a wide range of estimates of the price and income elasticity of housing demand. Articles reviewed in Mayo (1981) find uncompensated price elasticities that range from slightly positive to less than minus one. Popular estimates in the middle include Pollinsky and Ellwood's (1979)

[2]Using grocery data, Handbury (2013) estimates a non-homothetic log-logit utility function with a constant-elasticity-of-substitution (CES) superstructure to argue that high-income households may find large cities to be more "affordable" because they contain a greater range of groceries suited to their tastes. We reinforce this conclusion by finding the large cities are more affordable for high-income households as they spend less on housing.

estimate of -0.7 and Hanushek and Quigley's (1980) estimates of -0.64 in Pittsburgh and -0.45 in Phoenix.[3] More recently, Davis and Ortalo-Magne (2009) argue that the median expenditure on housing among rentals is roughly constant across metro areas, implying a price elasticity of negative 1. Few articles estimate elastic price demand, with elasticities greater than one.[4] While some studies use non-housing price data to deflate their numbers, none actually use it to test the validity of the housing demand specification, as we do here.

The income elasticity of demand for housing, which measures households' propensity to consume more housing services as their incomes grow, also has important implications for house prices and quantities. Classical studies, such as Engel (1857) and Schwabe (1868), tended to find an income (or more precisely, an expenditure) elasticity for housing demand of less than one, which became known as "Schwabe's Law of Rent".[5] As summarized by DeLeeuw (1971), Mayo (1981) and later Harmon (1988), most studies have been consistent with Schwabe's Law, with some important exceptions. For instance, Muth (1960) estimated an income elasticity well over one. One major source of differences among studies is on how to measure income: most researchers suggest using a measure of "permanent income" – of which various varieties have been proposed – to correct for attenuation bias caused by transitory income shocks. [6]

With such disparate findings, theoretical models have taken great latitude in modeling housing demand. Many models in urban and macro-economics assume a fixed demand for housing, perfectly inelastic to price and income. This provides a simple derivation of the mono-centric city model, seen in Mills (1967), and used for urban welfare accounting in Desmet and Rossi-Hansberg (2013). Other models, such as the search and matching one of Piazzesi and Schneider

[3] There is a large literature on this topic, including Muth (1960), Reid (1962), Rosen (1985), Goodman and Kawai (1986), Goodman (1988) Ermisch et al. (1996), Goodman (2002), and Ionnides and Zabel (2003). Most estimate uncompensated price elasticities ranging from -1 to -0.3 and income elasticities from 0.4 to 1.

[4] Kau and Sirmans (1979) estimated price elasticity shifting from -2.25 to -1 from year 1876 to 1970 using historical data from Chicago. However, these are based off land-price gradients and are not robust to expected sorting behaviors or changes in commuting costs.

[5] Some confusion regarding Engel's findings stems from Wright's (1875) confused statement of the results in English; see Stigler (1954) for a discussion.

[6] For owner-occupiers, it also makes sense to include implicit rental income from home equity. See Hansen et al. (1998) and references therein for estimates less than one, Larsen (2002) for an estimate of approximately one, and Cheshire and Sheppard (1998) for an estimate greater than one, noting that the latter study estimates elasticities for housing attributes rather than for a unified bundle.

(2010), assume housing demand is responsive to price but not income, as with quasilinear preferences. Another common approach is to specify preferences as Cobb-Douglas, implying price and income elasticities of one. Examples include Eeckhout (2004), Davis and Ortalo-Magne (2011), Michaels, Rauch and Redding (2012), and Guerreiri, Hartley and Hurst (2013). While a certain level of abstraction is a necessary component of a useful and tractable economic model, we must remain aware of the limitations such assumptions place on economic analyses. In particular, they do not seem appropriate for understading changes in the income share of housing or how changes in the relative price of housing affect housing consumption or well-being.

The secular rise in housing expenditures appears to be understudied by economists. Piketty (2014) finds that the value of residential capital relative to economic output has increased substantially over the last hundred years.[7] Gyourko, Sinai, and Mayer (2013) find that the difference in housing values between the typical and highest-price locations has widened considerably over the last five decades. Davis and Heathcote (2007) present evidence of persistent real growth in land values, which accounts for an increasing share of housing costs over recent history. These findings are consistent with limited substitution possibilities between land and non-land inputs in housing production, as found in Albouy and Ehrlich (2012).[8] With inelastic substitution in both consumption and production, land values can take up an ever increasing share of the economy as housing demand rises with population growth, reviving concerns raised by Ricardo (1817) and George (1879).[9]

[7]We note that housing is a capital asset that provides a flow consumption services to its owner. This asset is a composite of land and structure, the latter of which typically depreciates over time. We follow the bulk of the literature in estimating demand for a composite housing good, but the shape of the housing demand function can have important implications for land values separately from housing values. Albouy and Ehrlich (2012) discuss the production of housing services from local land and construction inputs.

[8]Those authors, as well as Davis and Palumbo (2007), document that land values are extremely heterogeneous across time and space.

[9]This may happen if land-saving technological improvements are weak or stifled by regulation. Thus, rising demand may reverse earlier declines in land values engendered by transportation improvements.

3 Housing Demand as Prices, Income, and Amenities Vary

3.1 Household Budgets and Preferences

We use a standard static model of housing demand and embed it in a richer equilibrium framework with local household amenities, similar to the settings of Rosen (1979) and Albouy (forthcoming). The national economy contains many cities, indexed by j, which share a population of potentially mobile households. Households supply labor in their city of residence. They consume a housing good y with price p^j, and a non-housing good x with price c^j.[10] Households earn total income $m_j = I + (1-\tau)w_j$, determined by a constant unearned income, I, and which varies due to local wage levels w_j, after taxes, τ. In this static setting, household expenditure equals household income. Household preferences over the consumption good, housing, and location are modeled by a utility function $U(x, y; Q^j)$, where Q^j represents a city-specific amenity conceptualized as "quality-of-life". The indirect utility function for a household in city j is then given by $V(p^j, c^j, m^j; Q^j) = \max_{x,y}(U(x, y; Q^j)|c^j x + p^j y = (1-\tau)w^j + I)$. The expenditure function for a household in city j is likewise given by $e(p^j, c^j, u; Q^j) = \min_{x,y}(c^j x + p^j y|U(x, y; Q^j) \geq u)$.

3.2 The Housing Expenditure Share and Uncompensated Demand

In order to take the model to the data, we approximate the relationships described above around their national average values. Denote the fraction of household expenditures on housing in city j as $s_y^j \equiv (p^j y^j)/m^j$. Log-linearizing this equation produces the identity

$$\hat{s}_y^j = \hat{p}^j + \hat{y}^j - \hat{m}^j. \tag{1}$$

[10] For simplicity, the exposition of the theoretical model will refer to a system of cities and call individual geographical units as such. However, the empirical work using the Consumer Expenditure Survey data will be at the state level, and the empirical work using the Census data will also use the non-metropolitan portions of states. Therefore, the geographies considered in this model are more properly considered 'areas', with the term 'city' used for concreteness rather than precision.

A hat over a variable represents its log deviation from the (geometric) national average, i.e., $\hat{z}^j = d\ln z^j = dz^j/\bar{z}$. We take local price and income levels as parametric, so that the only behavioral variable in the share is housing consumption, y. Consumption is determined by the uncompensated (Marshallian) demand function $y^j = y(p^j, c^j, m^j; Q^j)$. Log-linearizing this function produces

$$\hat{y}^j = \epsilon_{y,p}\hat{p}^j + \epsilon_{y,c}\hat{c}^j + \epsilon_{y,m}\hat{m}^j + \epsilon_{y,Q}\hat{Q}^j. \tag{2}$$

The parameter $\epsilon_{y,p}$ is the uncompensated own-price elasticity of housing demand, $\epsilon_{y,c}$ is the uncompensated elasticity of housing demand with respect to non-housing prices (or cross-price elasticity), $\epsilon_{y,m}$ is the income elasticity, and $\epsilon_{y,Q}$ is the elasticity with respect to quality of life. Equation 2 is an identity for infinitesimal changes, and an approximation for larger changes. If housing is a normal good, then $\epsilon_{y,m} > 0$, and housing obeys the law of demand, $\epsilon_{y,p} < 0$. It is unclear whether housing is a gross substitute for non-housing goods, i.e., whether $\epsilon_{y,c} > 0$, because the cross-price elasticity will exhibit positive substitution effects and negative income effects of unknown magnitudes. Housing could also be a gross complement or substitute for non-market quality of life, i.e. $\epsilon_{y,Q} \gtrless 0$, if amenities somehow alter the marginal rate of substitution between housing and non-housing goods.[11]

We combine equations 1 and 2 to demonstrate how expenditure shares depend on behavioral responses to local attributes:

$$\hat{s}_y^j = (1+\epsilon_{y,p})\hat{p}^j + \epsilon_{y,c}\hat{c}^j + (\epsilon_{y,m} - 1)\hat{m}^j + \epsilon_{y,Q}\hat{Q}^j \tag{3}$$

Unrestricted, equation (3) is merely definitional. Rationality of preferences requires that the demand function be homogenous of degree zero in prices and income (p, c, m), so that $\epsilon_{y,p} + \epsilon_{y,c} + \epsilon_{y,m} = 0$. This restriction requires that there be "no money illusion," so that proportional increases

[11] We have not modeled how households with low tastes for housing may be inclined to seek out more amenable areas (see Black et al. 2002). Albouy and Lue (forthcoming) present evidence that household sizes, age, and marital status vary little across metropolitan areas (they vary more within), suggesting such selection issues are not of first-order importance.

in all prices and income do not lead to changes in behavior.

Adding a constant to equation 3 motivates the following regression equation:

$$\ln s_y^j = \alpha_0 + \alpha_1 \ln p^j + \alpha_2 \ln c^j + \alpha_3 \ln m^j + \alpha_4 q^j + e^j \tag{4}$$

$$= \alpha_0 + \alpha_1(\ln p^j - \ln c^j) + \alpha_3(\ln m^j - \ln c^j) + \alpha_4 q^j + e^j \tag{5}$$

Equation 5 follows 4 from imposing the homogeneity assumption as $\alpha_1 + \alpha_2 + \alpha_3 = 0$. If we demean the right-hand side variables, the regression coefficients $\alpha_0 = \ln \bar{s_y}$, $\alpha_1 = 1 + \epsilon_{y,p}$, $\alpha_2 = \epsilon_{y,c}$, and $\alpha_3 = \epsilon_{y,m} - 1$. $\bar{s_y} = e^{\alpha_0}$ is the geometric mean of expenditure shares. The own-price uncompensated elasticity is simply the coefficient on housing prices minus one, $\epsilon_{y,p} = \alpha_1 - 1$, while the income elasticity is the coefficient on income plus one, $\epsilon_{y,m} = \alpha_3 + 1$.

Quality of life cannot be observed directly but only proxied by observable amenities, q_j, meaning $\epsilon_{y,Q}$ cannot be identified in a fully cardinal sense without additional assumptions. The same holds true of other demand shifters. Consistent estimation of this equation requires that non-housing goods are properly accounted for by the index c^j, that preferences across cities are the same, that preferences can be aggregated across households, and that we have an appropriate (arguably permanent) measure of income m^j.

3.3 Compensated Demand with Household Mobility and Heterogeneity

The uncompensated demand function may be converted into a compensated (Hicksian) demand function by substituting in the expenditure function, i.e. $y^H(p, c, m; Q) = y(p, c, e(p, c, u; Q); Q)$. Alternatively, we may log-linearize the expenditure function directly, yielding

$$\hat{m}^j = \bar{s_y}\hat{p}^j + (1 - \bar{s_y})\hat{c}^j + \epsilon_{m,Q}\hat{Q}^j + \epsilon_{m,u}\hat{u}^j \tag{6}$$

where $\epsilon_{m,u}$ is the elasticity of expenditures with respect to utility, and $\epsilon_{m,Q}$ is the elasticity of expenditures with respect to quality of life.

Substituting equation 6 into equation 3 yields a relatively complicated equation that may be simplified using the Slutsky equations. These give the relationships among the uncompensated, or Marshallian, price elasticities, and the compensated, or Hicksian, price elasticities: $\epsilon_{y,p} = \epsilon^H_{y,p} - \bar{s_y}\epsilon_{y,m}$ and $\epsilon_{y,c} = \epsilon^H_{y,c} - \bar{s_x}\epsilon_{y,m}$. Here $\epsilon^H_{y,p}$ and $\epsilon^H_{y,c}$ represent the compensated elasticities of housing demand with respect to housing prices and consumption prices, respectively.[12] Rationality requires that compensated demand functions are homogenous of degree zero in prices. This means that the own and cross-price elasticities of compensated housing demand should sum to zero, $\epsilon^H_{y,p}+\epsilon^H_{y,c} = 0$.

Combining these insights yields the following equation for differences in the expenditure share in terms of relative prices, quality of life, and utility:

$$\hat{s}^j_y = (\epsilon^H_{y,p} + 1 - \bar{s_y})(\hat{p}^j - \hat{c}^j) + (\epsilon^H_{y,u} - \epsilon_{m,u})\hat{u}^j + (\epsilon^H_{y,Q} - \epsilon_{m,Q})\hat{Q}^j \tag{7}$$

Here $\epsilon^H_{y,Q}$ is the compensated elasticity of housing demand with respect to quality of life and $\epsilon^H_{y,u}$ is a similar elasticity for income.

To handle differences in utility we impose the restriction that similarly-skilled households are equally well-off across cities. When households are sufficiently mobile, then prices and wages equilibrate so that households are indifferent across inhabited locations. In that case, utility for a particular type of household should not vary across cities. Rather, utility differences only represent inherent differences across households, such as different earnings potentials. We parameterize income in city j as $m^j = \zeta^j w^j$, where ζ^j is an index wage-earning skills, and w^j is the city-wide wage level that compensates household for living in that city.[13]

To interpret the coefficient, we posit that our utility function is money metric around national averages: $u(x, y; Q) = e(\bar{p}, \bar{c}, \tilde{u}(x, y; Q), Q)$. This added simplification allows us to write utility differences in terms of differences in the skill index $\hat{u}^j = \hat{\zeta}^j$, and impose $\epsilon_{m,u} = 1$ and $\epsilon^H_{y,u} = \epsilon_{y,m}$.

[12] The first substitution yields $\hat{s}^j_y = (1 + \epsilon_{y,p} - \bar{s_y} + \bar{s_y}\epsilon_{y,m})\hat{p}^j + [\epsilon_{y,c} - (1 - \epsilon_{y,m})(1 - \bar{s_y})]\hat{c}^j + (\epsilon_{y,Q} - (1 - \epsilon_{y,m})\epsilon_{m,Q})\hat{Q}^j - (1 - \epsilon_{y,m})\epsilon_{m,u}\hat{u}^j$. Besides the Slutsky equations we also substitute in the identities $\epsilon^H_{y,Q} = \epsilon_{y,Q} + \epsilon_{y,m}\epsilon_{m,Q}$ and $\epsilon^H_{y,u} = \epsilon_{y,m}\epsilon_{m,u}$ to get the resulting equation.

[13] When household types vary within city, the compensating wage differences will vary according to their tastes for housing, quality of life, and taxes.

Note that we implicitly impose the restriction that the skill index affects housing consumption through income, and not through differences in tastes.[14] These simplifications yield

$$\hat{s}_y^j = (\epsilon_{y,p}^H + 1 - \bar{s_y})(\hat{p}^j - \hat{c}^j) + (\epsilon_{y,m} - 1)\hat{\zeta}^j + (\epsilon_{y,Q}^H - \epsilon_{m,Q})\hat{Q}^j \tag{8}$$

Equation 8 then motivates the following empirical specification using data across cities:

$$\ln s_y^j = \beta_0 + \beta_1 \hat{p}^j + \beta_2 \hat{c}^j + \beta_3 \hat{\zeta}^j + \beta_4 q^j + e^j \tag{9}$$

$$= \beta_0 + \beta_1 (\hat{p}^j - \hat{c}^j) + \beta_3 \hat{\zeta}^j + \beta_4 q^j + e^j \tag{10}$$

where $\beta_0 = \ln \bar{s_y}, \beta_1 = \epsilon_{y,p}^H + 1 - s_y = -\beta_2$ and $\beta_3 = \epsilon_{y,m} - 1$. Similar to the uncompensated case, $\bar{s_y} = e^{\beta_0}$ and $\epsilon_{y,m} = \beta_3 + 1$, but $\epsilon_{y,p}^H = \beta_1 - 1 + e^{\beta_0}$. In practice, $\hat{\zeta}^j$ is an index estimated from the average log wages households would earn in a typical city based on their human capital and other location-invariant characteristics.

The main testable restriction here is that the coefficients on the price of housing and non-housing goods should be of opposite signs and equal magnitudes, i.e., $\beta_1 + \beta_2 = 0$. This may be seen as a joint test of both demand theory and mobility.[15] When this restriction holds we use the elasticity of substitution between housing and non-housing goods, $\sigma_D \equiv -(\hat{y}^j - \hat{x}^j)/(\hat{p}^j - \hat{c}^j) = -\epsilon_{y,p}^H/(1 - \bar{s_y})$, so that $\beta_1 = (1 - \bar{s_y})(1 - \sigma_D)$. When the elasticity of substitution is less (greater) than one, housing demand is said to be price inelastic (elastic), and the expenditure share of housing rises (falls) with the relative price of housing, p/c. One advantage of the compensated specification is that it estimates the elasticity of substitution without directly using information on income.

Quality of life amenities may affect the income share of housing if $\epsilon_{y,Q}^H \neq \epsilon_{m,Q}$, which means amenities and housing are either are net complements or substitutes. Such relations are not obvious a priori. If $0 > \epsilon_{y,Q}^H > \epsilon_{m,Q}$, compensated improvements in quality of life reduce housing

[14]If households with more skills like housing less (more) than those with fewer skills, the income elasticity estimate will be biased downwards (upwards).

[15]If mobility does not hold, then the coefficients would not be equal. Income effects in the uncompensated elasticities would likely push coefficients on both housing and non-housing prices downwards.

consumption less than other consumption. Households could spend more on their properties to enjoy a nice climate. The opposite could also be true: nice weather may make people spend time away from their houses, while cold weather could cause them to consume more housing.

3.4 Non-Homothetic Utility and Expenditure Functions for Housing

In modeling housing demand, economists almost invariably use utility functions that are homothetic or quasilinear, imposing income elasticities of one or zero. Since housing is a major consumption item, in many applications we believe it may be worth using a more general utility function that allows for non-homotheticity. We propose a non-homothetic separable family constant-elasticity-of-substitution (NH-CES) function from Sato (1977), with an adjustment for Q^j.

$$U(x, y; Q) = Q^{\frac{1}{\gamma}} \left[\frac{\delta x^{\frac{\sigma-1}{\sigma}} + \theta_1}{\theta_2 - (1-\delta) y^{\frac{\sigma-1}{\sigma}}} \right]^{\frac{\sigma}{\gamma(\sigma-1)}} \tag{11}$$

where $\theta_1 = [1 - \sigma - \gamma\delta]/(\gamma\delta)$ and $\theta_2 = [1 - \sigma - \gamma(\delta - 1)](\gamma\delta)$ This function contains three parameters: a distribution parameter δ, a substitution parameter, σ, and a non-homotheticity parameter, γ. In the limit, as $\gamma \to 0$ this function becomes a standard CES function (Arrow et al. 1961); if also $\sigma \to 1$, the function becomes Cobb-Douglas (1928). Our restricted log-linear model provides three parameters that map well to this utility function. We demonstrate in the appendix that The expenditure function and housing share are

$$e(p, c, u; Q) = \left[\frac{c^{1-\sigma}\delta^{\sigma} u^{\gamma(1-\sigma)} + p^{1-\sigma}(1-\delta)^{\sigma}}{\left(\theta_2 - \theta_1 (u^{\gamma}/Q)^{\frac{(1-\sigma)}{\sigma}}\right)^{\sigma}} \right]^{\frac{1}{1-\sigma}} \tag{12}$$

$$s_y(p, c, u; Q) = \frac{p^{1-\sigma}(1-\delta)^{\sigma}}{p^{1-\sigma}(1-\delta)^{\sigma} + c^{1-\sigma}\delta^{\sigma}(u^{\gamma}/Q)^{1-\sigma}}. \tag{13}$$

When $\gamma(1-\sigma) > 0$, households with higher utility consume less in housing, and need lower income to compensate them for rises in p. Empirically, when all of the variables are demeaned, $\beta_0 = \sigma * \ln(1-\delta) = \ln \bar{s}_y, \beta_1 = (1-\bar{s}_y)(1-\sigma), \beta_3 = -\gamma(1-\bar{s}_y)(1-\sigma)/\epsilon_{m,u}$, where $\epsilon_{m,u}$

is the elasticity of the expenditure function with respect to u. By choosing a base level of utility and prices, we may then construct a cost-of-living index, which we detail below. A money metric utility function may be expressed by choosing reference values of $p = c = 1$ and substituting (11) into (12). The parameters can be determined recursively with $\sigma = 1 - \beta_1/(1 - e^{\beta_0}), \delta = 1 - e^{\beta_0/\sigma}, \gamma = -\epsilon_{m,u}\beta_3/\beta_1$. [16]

The expenditure function may be used to construct an ideal cost-of-living index (COLI) that incorporates realistic substitution and non-homothetic consumption behaviors. If we use prices $\bar{c}$ and $\bar{p}$ as reference prices, and hold quality-of-life constant at $Q = 1$.

$$COL(p, c, u; Q = 1) = \left[\frac{\delta^\sigma u^{\gamma(1-\sigma)} c_j^{1-\sigma} + (1-\delta)^\sigma p_j^{1-\sigma}}{\delta^\sigma u^{\gamma(1-\sigma)} \bar{c}^{1-\sigma} + (1-\delta)^\sigma \bar{p}^{1-\sigma}} \right]^{\frac{1}{1-\sigma}} \tag{14}$$

The value of σ is taken from our estimates, and the distribution parameter is set as $\delta = \{1+[\bar{s_y}/(1-\bar{s_y})]^{(1/\sigma)}\}^{-1}$.This index is completed by incorporating a reference utility level. We can tie it a to a base level of housing consumption $\bar{s_y}$ by solving 13, $u^{\gamma(1-\sigma)} = [(1-\bar{s_y})(1-\delta)^\sigma \bar{p}^{1-\sigma}] \,/\, (\bar{s_y}\delta^\sigma \bar{c}^{1-\sigma})$. We consider four cases: COL_1, a fixed weight Lespeyres index, with $\sigma = \gamma = 0$; COL_2, a Cobb-Douglas index, with $\sigma = 1, \gamma = 0$; COL_3, a homothetic CES index, with $\gamma = 0$; and COL_4, a general index.

3.5 The Housing Share or "Affordability" as a Measure of Welfare

Housing experts often cite a high expenditure share on housing as an indicator that housing is unaffordable, implying that household well-being is low. As equations (8) and (13) clarify, this interpretation hinges on the shape of the housing demand function. If housing is indeed a normal good, i.e., $\epsilon_{y,m} < 1$, then high expenditure shares do indicate lower levels of well-being. If it is a luxury, a high housing share will indicate higher levels of welfare. [17]

The housing expenditure share also reflects relative price levels, which may or may not be

[16]Since the units of u and γ are not separately identified, we impose the restriction, $e(1, 1, u; 1) = 1$, to solve for u and γ simultaneously.

[17]The housing share may be complementary to realized household income, which need not be a sufficient statistic for well-being, particularly when wage levels vary across cities.

pertinent to welfare analysis. If households are mobile, then high expenditure shares stemming from high rents should reflect high relative wage levels or quality-of-life. A household living in an unsafe area with bad schools may spend little on rent, but still be vary badly off.[18] If household mobility is imperfect, then it is more appropriate to use the uncompensated framework, in which case high prices may be more likely to indicate lower welfare. Even in this case, however, price differences that reflect differing amenity levels may complicate welfare analysis. Moreover, in either case, if housing demand is unit elastic with respect to prices, prices and the expenditure share will be unrelated.

Finally, other factors that affect housing demand may influence the housing expenditure share. Most obvious are demographic factors, such as the presence of children or a cohabiting partner. Households may also vary in their demand for privacy, depending on their personal preferences or cultural backgrounds. [19] And, as mentioned earlier, amenities may affect housing demand. If housing demand is unit elastic with respect to price and income, then only these other factors would explain differences in housing expenditure shares. How such differences should be considered for welfare analysis requires a deeper framework.

4 Data

The primary data source for our cross-sectional analysis is the 2000 Decennial Census microdata samples from IPUMS; we also consider the 1980 and 1990 Census, and the combined 2007-2011 American Community Survey (ACS). Each represents 5 percent of the population.[20] These data generate metro-level indices of income, m^j, predicted income, ζ^j, the rental-price index p^j, and the

[18]A related example is commuting. In a standard urban model, workers who live far from work will spend less on housing but considerably more on commuting costs. See Albouy and Lue (forthcoming) for evidence on how differences in commuting costs can be large, and tend to be compensated by lower rents.

[19]Elderly households, particularly homeowners, may consume high amounts of housing because they have not adjusted from when their households were once larger.

[20]These metro-level indices are calculated for Primary Metropolitan Statistical Areas using 1999 Office of Management and Budget definitions. The Public-Use files are available for Public-Use Microdata Areas (PUMAs), whose borders sometimes cross that of these metro areas, and change over time. We use a geographic correlation technique which does a fairly successful job of matching or splitting PUMAs across metro areas, and attempts to preserve the geography over different cross-sectional samples.

housing share, s_y^j, as explained below. For the price of non-housing goods, we use a series from Carrillo et al. (2013), or "CEO" who construct the series from data provided by the American Chambers of Commerce Research Association (ACCRA).[21]

4.1 Rental and Housing Expenditure Shares

We focus on rental expenditures, because of the difficulties in measuring user costs of housing for owner-occupiers. With Census and AHS data, we calculate the rental share as the ratio of gross rents (including utility costs) to reported household income. We focus on the median shares to circumvent aggregation issues and mitigate measurement problems such as low-income households under-reporting income. We also use average and aggregate expenditure shares, which equal the sum of all rental payments divided by the sum of all tenant income.[22] With the CEX, we take housing expenditures as a fraction of all reported expenditures. This exercise is predicated on the belief that expenditures are a better predictor of permanent income than transitory income.

4.2 Cross-sectional Price and Wage Indices

To calculate rental and house-price indices, we run regressions of the form $\ln(P^{ij}) = \alpha_P + \beta_P X^{ij} + \delta_P^j + \epsilon_P^{ij}$, where P^{ij} is the rent or imputed rent for unit i in area j. X_P^{ij} is a vector of housing-unit characteristics, described in the appendix.[23] The coefficients δ_P^j represent area indicators, or "fixed effects" that act as our inter-area housing price indices, p^j, after differencing out the national

[21] These data begin in 1982, and so we use 1982 values for our 1980 specification.

[22] We consider two possible expenditure measures for owner-occupiers. The first is total monthly payments (or "cash-flow") related to housing, including mortgages, property taxes, and utilities. While this measure is appropriate for a static environment, it may diverge significantly from the true user-cost due to expected capital gains, mortgage terms, and net improvements relative to (unobserved) depreciation and maintenance costs. Most importantly, we do not observe income from home equity, which belongs on both the expenditure and income side of the equation. We also consider a measure of self-reported housing values relative to household income. Ideally we would be able to model the decision to rent or own, which is especially important as the composition of owners and renters may shift across time and space.

[23] We impute rents by adding utility to costs to a percentage of self-reported home values based on user costs. That percentage is either a uniform 6.2 percent, consistent with Albouy and Hanson (2014), or a measure adjusted regionally for differences in mortgage rates, state income taxes, property taxes, and price appreciation in the area for 10 years before and after the period. When the regression includes both rented and owned units, X_P^{ij} includes tenure status interacted with every characteristic.

average. Appendix table A1 presents the resulting rental and housing-cost (for all units) in 2000. Rental and housing-price indices are highly correlated, although housing prices are more dispersed. As we detail in the Appendix, all of these measures are highly correlated.

To proxy for differences in permanent income we use an index of predicted wages based on the location invariant characteristics of a city's workforce. The wage regression (also a hedonic) is of the form $\ln(W^{ij}) = \alpha_W + \beta_W X_W^{ij} + \delta_W^j + \epsilon_W^{ij}$, where W_{ij} is the hourly wage for person i in area j. X_{ij}^W is a vector of personal characteristics, described in the appendix. δ_j^W is a set of area fixed effects. Our measure of interest here, ζ^j is from the relevant moment (e.g., median or mean) of the $\hat{\beta}_{WX} X_W^{ij}$ as our predicted wage indices.[24] This wage index purges incomes of their locational component, and avoids problems with measurement error that using actual incomes may introduce, most importantly division bias.

We also consider four additional housing-price indices. The first applies the methodology of Malpezzi, Chun, and Green (1998) to the Census data. This estimates the coefficients for the housing characteristics separately for each metro area. Then, the value of the national housing stock is priced using those coefficients, so that it represents how much the "typical" American home would be priced in each metro. The second is Carillo et al.'s (CEO) housing-price index derived from the 2000 Section 8 Consumer Satisfaction Survey (CSS) for 173,000 units. Third, is a measure from the American Housing Survey. It resembles the Census, except that the list of housing characteristics is far more detailed, although the sample is much smaller. Fourth, is a measure from the CEX, which is only available by state and rough categories of metro area size.

4.3 Time-Series Data

The time series price index for shelter from the BLS is based on observed rents, and rents imputed for owned units using a rental-equivalence approach based (primarily) on a re-weighting procedure. It is a chain-weighted index, accounting for gradual changes in the geographic distribution

[24]Thus, raw wage differences across cities are the product of differences due to the area itself – compensating wage differentials for costs-of-living and amenities – and the local skills of the workforce, summarized by the wage index. Additional specifications use the average predicted values from the wage regressions.

of occupied houses. The BEA measure of housing expenditures is from the Personal Consumption Expenditures (PCE) series, and imputes rental-equivalent measures for owner-occupied units. From the CEX we take measures of average rental expenditures relative to all expenditures, rather than to income, as it is closer to the ideal presented in the static model. With both datasets, we include series with owner-occupiers.

4.4 Potential Biases

Variation in non-housing prices are potentially important as they vary positively with housing prices. This covariance arises because the workers who provide local services must purchase local housing, and help bid up the price of land. We model this covariance with

$$\hat{c}^j = \rho \hat{p}^j + v^j \tag{15}$$

where $\rho > 0$ and v^j is white noise. Substituting this projection into equation 8, together with the elasticity of substitution, gives

$$\hat{s}_y^j = (1 - \bar{s_y})(1 - \sigma_D)(1 - \rho)\hat{p}^j + (\epsilon_{y,m} - 1)\hat{\zeta}^j + (\epsilon_{y,Q}^H - \epsilon_{m,Q})\hat{Q}^j \tag{16}$$

We may write the estimated elasticity of substitution as a function of the parameters $\hat{\sigma}_D = 1 - \beta_1/[(1 - e^{\beta_0})(1 - \rho)]$ The higher is ρ, the more ignoring non-housing prices will bias $\hat{\beta}_1$ towards zero and $\hat{\sigma}_D$ towards one.[25]

If housing is indeed a necessity, omitting worker skill levels should bias the estimated price elasticity to be smaller (larger in absolute value), as higher skilled individuals tend to locate in areas with higher rents (Moretti 2013). Skilled households have a smaller housing share, their sorting behavior could make demand appear overly elastic.

[25] Technically, Davis and Ortalo-Magne's (2011) data support an elasticity of substitution of 0.85. However, their index of rental costs differs from ours by controlling for commuting costs, and thus exaggerating the actual price differences faced by households (e.g. that suburban dwellers in the New York suburbs face Manhattan prices), biasing their results towards one. Their study also suffers from the other potential biases we correct for.

Another potential bias stems from using renters. Suppose that the probability of renting rises with rent levels, so that only the poor rent in cheap cities, while the affluent rent in expensive cities. If housing is a necessity, and our controls for utility are incomplete, this selection bias will make our estimated elasticity more negative. We may attempt to deal with this problem by controlling for the home-ownership rate.

Finally, there is the issue of household sorting on unobserved taste for housing. Households that care more for housing will prefer to locate in areas where housing is less expensive. This selection effect would also make the expenditure-rent gradient more negative, as those who wish to consume the least amount of housing locate in the most expensive areas.

5 Empirical Results

5.1 Cross-sectional Estimates across Metro Areas

Figures 4A and 4B illustrate the inter-metropolitan relationship between median expenditure shares and relative rental or housing prices using the Census data: 4A is for renters only, while 4B is for renters and owners. Accordingly, the former uses a price-index for rental units, while the latter uses a price index for all housing units. The regression line has a slope equal to $\beta_1 = -\beta_2$ in the empirical regression (10), with $\beta_3 = \beta_4 = 0$ imposed. In both cases, the relationship is positive and statistically significant, indicating that housing demand is price-inelastic. The regression line in figure 3B has a steeper slope and a tighter fit.

Table 1 presents estimates using the full compensated model from (10), starting with the median expenditure share for renters in columns 1-4. Column 1 displays the results of a simple regression of the median housing expenditure share on the log rental price index. The geometric mean of the median expenditure share across areas is 21.7 percent, while the implied price elasticity of housing demand is -0.81, statistically different from minus one. Following the discussion in section 4.4, the coefficient on the housing-price index increases when the non-housing price index and the predicted wage index are included in column 2. The implied price elasticity of demand is -0.68, while the implied income elasticity of demand is 0.62. The coefficients on the two price indices have opposite and roughly equal magnitudes, so that the regression does not reject the rationality restriction of demand theory; the p-value on the test that the coefficients on the two price indices sum to zero is 0.64. The failure to reject this restriction motivates restricting the coefficients to sum to zero in column 3, which is our preferred specification. The price and income elasticities do not change much from column 2, while the implied elasticity of substitution between housing and other goods is 0.69, significantly less than one. These results are unaffected by controlling for the local rate of homeownership in column 4. This evidence supports Schwabe's Law that housing is a necessity, and is inconsistent with housing demand being unit-elastic or perfectly inelastic with respect to income or price.

Column 5 includes the expenditures of homeowners, as opposed to renters, while column 6 includes both. In these specifications, the homogeneity restriction fails and the expenditure share is lower on average. The expenditure share also rises more strongly with prices, as already seen in figure 4B. The estimates suggest lower income and price elasticities. However, we view these results with caution in light of the problems with using out-of-pocket expenses for home-owners.

Column 7 presents such results using the aggregate expenditure share, which weights households in proportion to their expenditures.[26] This specification produces estimates that are similar to those in column 3, but with slightly more elastic housing demand with respect to price and income. The estimates satisfy the rationality restriction.

Finally, column 8 presents results using within metropolitan variation in housing prices at the PUMA level. These numbers suggest slightly more price-elastic housing demand, consistent with the higher degree of household sorting by tastes we would expect to see within metro areas. Unsurprisingly, the demand function no longer satisfies the test for demand homogeneity when PUMA-level house prices are considered. The greater potential for household sorting across PUMAs, rather than MSAs, leads us to focus on the MSA as our principal unit of analysis.

Table 2 considers how estimates vary using different years or data sets, maintaining our pre-

[26]This specification also uses the average rather than median of the predicted wage index across MSAs.

ferred specification from column 3 of table 1. The first three columns use similar Census datasets from 1980, 1990, and 2010 (technically 2007-11). As seen in figure 1, the mean expenditure share shows an especially pronounced uptick from 2000 to 2010. Nevertheless, the price elasticities are roughly stable from 1980 to 2010 at approximately -0.75. The income elasticities are closer to 0.9 in 1980 and 2010. In those cases, the fit of the model, seen in the adjusted coefficient of variation, is notably poorer.

Column 4 introduces a rental price index for the year 2000 in the style of Malpezzi, Chun, and Green (1998). The results are almost indistinguishable from our baseline results. Column 5 uses the 2000 CEO rental-price index. The results imply slightly more price-elastic demand, although attenuation bias may play a role here.[27] Column 6 uses price indices from the AHS. These numbers suggest a somewhat higher expenditure share, a greater price elasticity, and a lower income elasticity. Finally, column 7 presents numbers using the CEX data. The expenditure share on housing is substantially higher here.

Table 3 presents specifications corresponding to equation 4, which feature a more traditional raw measure of household income. Column 1 shows results from an unrestricted regression of the log median expenditure share on the housing and non-housing price indices and the household income index. The three coefficients sum to -0.05, a number that is insignificantly different than zero, passing the homogeneity restriction with a p-value of 0.47. Unsurprisingly, the results are similar in the restricted regression displayed in column 2. The uncompensated price elasticity is -0.41 and the income elasticity is 0.33. However, in contrast to the compensated regressions in tables 1 and 2, measurement error in the household income measure used in table 3 will likely lead to division bias, causing the coefficient to be too low and underestimating the income elasticity.

Column 3 table 3 uses a compensated demand framework but controls for two natural amenities, distance to the coast and the average slope of the land within an MSA. The housing expenditure share is not statistically related to the former, but is positively related to the average slope of the land. This novel result appears justified: housing on hillier terrain has better views and is more

[27] The results are more similar if we use the CEO price index to instrument the Census prices.

easily seen. Households may choose to spend more on their houses to take advantage of the better views, or to impress their neighbors.[28] One limitation of including these amenities, however is that it causes the homogeneity restriction to fail, and so we leave this issue for further research. Column 4 controls for the same amenities in an uncompensated framework. The resulting parameter estimates are similar to those in column 2, while the relationship between the housing expenditure share and the amenities is similar to to the relationship in column 3.

5.2 Household Demand for Housing over Time

Table 4 estimates an uncompensated housing demand using the time series data presented in table 1. In all of the cases we use purely nominal values of prices and income. However, we include separately the log CPI-U for shelter and the log CPI-U for all items less shelter, thereby remaining agnostic about the proper deflator, which should be revealed by the behavior we observe.

In the bottom panel, we provide a decomposition to explain the growing share of income spent on housing discussed in the introduction. Rearranging (7) and replacing Q and j with t, we have

$$\hat{s}_y^t = (1 - \bar{s_y} + \epsilon_{y,p}^H)(\hat{p}^t - \hat{c}^t) + (\epsilon_{y,m} - 1)[(\hat{m}^t - \hat{c}^t) - \bar{s_y}(\hat{p}^t - \hat{c}^t)] + \alpha_t t + e_t \tag{17}$$

The first component represents the change in the income effect due to the pure compensated price effect. This effect is positive when the relative price of housing increases if $\sigma < 1$, as $1-s_y+\epsilon_{y,p}^H) = (1 - s_y)(1 - \sigma)$. The second component is the income effect, making the proper adjustment for changes in relative prices, from a parallel rise in the budget set. The third component is due to the time trend, which could represent a change in household preferences. Indeed, number of people in a household has fallen from 3.2 to 2.5 since 1970. Another possibility could be increasing complementarity of housing with local amenities as households have shifted locations. The time trend may also reflect limitations in the data and its ability to identify low-frequency responses in housing consumption from shifting prices and income.

[28] This finding is complementary to that in Albouy and Ehrlich (2012) that housing is more expensive to construct in hilly terrain.

The first column applies to owners and renters using the BEA numbers, using nominal GDP per household as the income measure. As required by demand theory, the three coefficients add up to a number not significantly different from zero. In the restricted model, the implied uncompensated own-price elasticity is -0.68, which is not significantly different from the preferred regression in Table 1. The income elasticity is slightly smaller at 0.55. Its estimate may be confounded by income's collinear time trend, which is statistically significant. It suggests a secular trend towards greater housing consumption independent of price and income movements.

In the BEA numbers, the overall increase in the housing share over the sample period was 8 percent (just under 2 percentage points). According to these estimates, the increase in the relative price of housing raised the income share devoted to it by 7 percent, while rising incomes reduced it by 12 percent. The positive time trend over-predicts the change at 15 percent, raising questions.

Columns 2 and 3 use average expenditure shares from the CES for renters, and for renters and owners combined, using measures of average income. These estimates are less precise, although the point estimates suggest elasticities closer to one, especially when owners are included. Consequently, the decomposition suggests that changes in the expenditure share on housing were raised somewhat by the rising price of housing, but even more by by the time trend, which ultimately explains little. In interpreting this trend, one should bear in mind reporting issues in the CEX with households reporting fewer and fewer of their non-housing expenditures (citation?).

In column 4 and 5, we examine the median income shares from the AHS for renters and renters and owners. These estimates are less precise, and suggest that demand is fairly elastic in prices and less elastic in income. The decomposition reveals that the rather large increase in housing expenditures for renters is due somewhat to increases in prices, and also to *falling* median incomes. When home-owners are included, the income effect is again negative as median incomes as a whole rose. Nevertheless, much of the change is explained by the secular time trend.

The point estimates over time are similar to the ones over space, albeit on average slightly more elastic with respect to prices and less with respect to incomes. Statistical tests would not reject that the underlying parameters are the same. If we apply the cross-sectional parameters, we would find (positive) relative-price effects further from zero and (negative) income effects closer to zero. This would explain more of the observed change, and reduce the change attributed to the time trend. The cause of the time trend may be due to measurement problems, as it does differ considerably across data sets. Yet even the lowest estimate of this trend, from the BEA, is substantial. The trend could reflect a growing taste for housing, possibly from a greater value placed on personal privacy. Decreases in the size of households or changes in their composition, might also explain this trend.

6 Putting the Parameter Estimates into Use

6.1 Utility and Expenditure Functions

The estimates from the previous sections are sufficient to identify the utility and expenditure outlined in section 3.4. To illustrate what may be a realistic example, we take inspiration from column 3 of table 1, and use slightly rounded rational numbers for the parameters, setting $\sigma = 2/3, \delta = 5/6, \gamma = 4/9$. Substituting in these parameter values into equations (11) and (12) yields non-homothetic separable CES utility and expenditure functions ready for quantitative analysis:

$$U(x, y; 1) = \left(\frac{33 - 4y^{-1/2}}{20x^{-1/2} - 3}\right)^{9/2}, e(p, c, u; 1) = \frac{16}{9}\left[\frac{7^{2/3}c^{1/3}u^{4/27} + p^{1/3}}{(11 + u^{2/9})^{2/3}}\right]^3 \tag{18}$$

In the utility function, the units of x and y are as median income shares, with baseline values at $x = 0.78$ and $y = 0.22$. Thus, a value of $y = 1$ would correspond to housing consumption $1/0.22 = 4.54$ times that of a median renter. These functions could be applied immediately in a number of models in urban, macro, or public economics involving the housing sector.

6.2 Cost-of-Living Indices over Space and Time

We use our estimates of σ and s_y to calculate the four different cost-of-living indices derived above. Figures 4A and 4B plot these four cost-of-living indices against the relative price of housing (p^j/c^j), with 4B adjusting for a base level of income that is one half the median represented in 4A.

To underscore the relevance of these measures, the relative rents in 2009 were 1.4 times higher than in 1970; the same as the average difference between New York and St. Louis in 2000. In San Francisco rents were 1.7 times and Oklahoma City in 2007.

In 4A, we see how the fixed housing demand measure overstates differences in cost-of-living by ignoring households' ability to substitute between housing and other goods according to their relative prices, while the Cobb-Douglas preference measure understates these differences by assuming that substitution is easier than it is. Our evidence implies the value $\sigma = 2/3$ more accurately reflects substitution possibilities. For example, when housing rents are double the national average (i.e. $p^j/c^j = 2$), the fixed demand measure overstates the true cost-of-living differential by 3.3 percentage points, while the Cobb-Douglas measure understates it by 1.4 percentage points.

In figure 4B, we see how the non-homothetic CES cost-of-living index has a much greater slope than the one that fails to account for housing being a necessity. For poorer households, the other COL indices understate the burden of living in expensive areas, and overstate it in poorer areas. In other words, the correct index accounts for how high-rent cities are especially expensive for the poor.

Of course, the regular CES function could be adapted to poorer households simply by changing its distribuiton parameter δ. The advantages of the non-homothetic CES function is that it offers a continuous mapping of cost-of-living for any level of well-being, based on income at some reference city at a given point in time.

6.3 Deflating Income Changes and Inequality

Using the ideal price index may be used to deflate changes in income over time has different effects along the income distribution. As housing is a necessity, the welfare of poorer households is reduced more by increases in the price of housing. Substitution effects, not generally well accounted for, reduce the welfare reduction for all groups. In Table 5 we compare the nominal changes at the 10, 50, and 90th percentile of the household income distribution, and deflate the changes using the ideal index, and a comparable fixed-price index.

The ideal index reduces the gain at the 10th percentile, implying that real incomes there increased by 11 percent, much like at the 50th percentile. At the 90th percentile, the impact of inflation is overstated substantially by the fixed-price index, as it ignores both income and substitution effects. The resulting adjustment suggests that relative housing-price inflation has aggravated increases in real-income inequality: the 90-10 differential under the ideal cost-of-living adjustment is 4.4 percent higher than with a uniform, fixed-bundle index.

6.4 Changes in Housing Affordability, 1980 to 2010

In the housing affordability literature, households paying over 50 percent of income in rent are said to face "extreme" burdens while those paying 30 percent are said to face "moderate" burdens. Table 7 shows that since 1980, the percentage of households facing extreme burdens rose from 20 to 28 percent, while the share with moderate burdens rose from 39 to 53 percent.

To explain this decline in affordability, we consider four separate trends in the economy over the past 30 years. First is the increase in income inequality. Renters tend to have lower incomes than homeowners, so their lagging incomes may account for the decrease in affordability. To assess this effect, we construct a counterfactual income distribution that assigns each household the income it would have earned if all incomes had increased proportionally between 1980 and 2010.[29] We denote household i's counterfactual income $\tilde{m}_i$. We multiply $\ln(\tilde{m}_i/m_i)$ by the income effect $\epsilon_{y,m} - 1$ to determine household i's counterfactual log income share devoted to housing, $\hat{s}_i^1 = (\epsilon_{y,m} - 1)\ln(\tilde{m}_i/m_i)$. Because counterfactual incomes are higher than actual incomes at the bottom of the income distribution, this method will lead to decreases in the housing unaffordability measure if $\epsilon_{y,m} < 1$.

Second, we consider changes in the national average rent level, which the BLS estimates increased 15 percent from 1980 to 2010. We calculate what affordability would have been if all rents were 15 percent lower in 2010 using the uncompensated price elasticity of housing demand to ac-

[29]Formally, we calculate household incomes at each percentile, $k = 1, ..., 100$ for years $t = 1980, 2010$, m_t^k, as well as mean incomes, $\bar{m}_t$. Based on each household's observed income m_i, the counterfactual income is $\tilde{m}_i = m_i[(\bar{m}_{2010}/\bar{m}_{1980})/(m_{2010}^k/m_{1980}^k)]$.

count for the behavioral response through the formula: $\hat{s}_i^2 = (\epsilon_{y,p} + 1)\ln(\bar{p}_{1980}/\bar{p}_{2010})$. This effect shows that a decline in rents to 1980 levels would reduce measures of unaffordability provided that $\epsilon_{y,p} > -1$.

Third, we consider changes in relative rents, to account for their potential effects on different income groups. Accounting for increasing rental dispersion will address increases in unaffordability if rent increases in particular areas created affordability burdens for a disproportionate number of households. We assume that households are mobile in their responses to relative price increases, and thus calculate the compensated response $\hat{s}_i^3 = (\epsilon_{y,p}^H + 1 - \bar{s_y})[\ln(p_{1980}^j/p_{2010}^j) - \ln(\bar{p}_{1980}/\bar{p}_{2010})]$.[30]

Fourth, we consider changes in average real incomes from 1980 to 2010. We calculate the income effect on housing demand as the change in average income after accounting for the change in non-housing prices times the income effect, $\epsilon_{y,m} - 1$.[31]

The results in Table 6 account for these factors' contributions to the 13.7 and 8.7 percentage point increase in households facing moderate burdens and extreme affordability burdens. Widening income inequality accounts for 3.6 and 1.6 point increases, respectively, as renters' gains in nominal income were slower than homeowners'. Increases in overall rental prices account for further 2.8 and 1.7 percentage point increases. Changes in relative rent levels actually improved affordability by a small amount, an effect consistent with Moretti's (2013) finding that changes in relative rents disproportionately reduced real wages at the upper end of the income distribution. Finally, changes in average real incomes also produced moderate increases in housing affordability.

Our novel accounting still leaves a substantial fraction of the decrease in housing affordability unexplained. One possibility is that under-reporting of household incomes in the Census numbers has increased over time. Another is that there has been a secular increase in the taste for housing, consistent with the results in section 5.2. An increase in households' taste for housing relative to other goods would increase standard measures of unaffordability without having clear implications on household well-being.

[30] We use the current population distribution to calculate relative price changes.

[31] The change in housing prices has already been accounted for in the first counterfactual scenario.

7 Conclusion

The temporal and spatial relationships between housing prices and expenditure shares suggest that uncompensated housing demand is both price and income inelastic. Most of our estimates of uncompensated elasticities are close to two-thirds in absolute value, meaning that unit elasticities are better approximations than zero elasticities. However, both extremes have difficulty explaining the variation we observe in housing consumption across metro areas and over time. Taste-based sorting across space would bias our estimates towards finding greater price elasticity, although sorting across metro areas is limited and would likely produce estimates inconsistent with the demand restrictions we imposed using non-housing prices. Sorting over time is impossible, of course, although the temporal analysis uncovers a secular rise in housing consumption that may be due either to systematic measurement error or shifts in household preferences, as households themselves have changed.

With these estimates, we offer a plausible ideal cost-of-living index that improves on traditional CPI-style indices, which may overstate inflation or differences in costs-of-living over space, or misrepresent them for the poor. Indeed, we find that expensive cities are even more expensive for the poor, thereby exacerbating affordability problems. The estimated non-homothethic CES utility function should be useful for realistic and tractable economic modeling across fields, particularly in urban, public, trade, macro, and real-estate economics.[32]

The recent affordability crisis among renters appears to stem partially from rising rents and stagnant (or declining) real incomes among those who rent. While Moretti (2013) is correct that relative increases in across space have reduced real income inequality, increases in average rent over time have exacerbated inequality as poorer households devote more of their budgets to housing. Nevertheless, rising rents only partly explain the growing income share of housing, underscoring the need for further investigation into the secular rise in housing consumption that we uncover.

[32] Our elasticity of substitution estimates are consistent with the assumptions made by Albouy and Stuart (2014) and Rappaport (2008a), although they do not consider non-homotheticity.

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TABLE 1: COMPENSATED DEMAND FUNCTIONS - 2000 CENSUS DATA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Log Median Rental Share	Log Median Rental Share	Log Median Rental Share	Log Median Rental Share	Log Median Housing Share	Log Median Housing Share	Log Aggregate Housing Share	Log Median Rental Share
Regression Results:								
Rental/Housing Price Index	0.187	0.238	0.244	0.248	0.500	0.477	0.208	0.191
	(0.020)	(0.021)	(0.020)	(0.017)	(0.020)	(0.012)	(0.024)	(0.013)
Non-Housing Price Index		-0.199	-0.244	-0.248	-0.500	-0.477	-0.208	-0.191
		(0.095)	(0.020)	(0.017)	(0.020)	(0.012)	(0.024)	(0.013)
Predicted Wage Index		-0.379	-0.373	-0.378	-0.308	-0.409	-0.184	-0.441
		(0.095)	(0.095)	(0.102)	(0.091)	(0.063)	(0.088)	(0.025)
Homeownership				0.017				
				(0.120)				
Constant	-1.529	-1.529	-1.529	-1.529	-1.842	-1.753	-1.680	-1.535
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.001)
Sample Size	380	380	380	380	380	380	380	2071
Adjusted R-squared	0.423	0.474	0.475	0.473	0.869	0.854	0.411	-0.017
Constrained Regression	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Unconstrained Sum of Housing and Non-Housing Price Index Coefficients		0.039	0.039	0.040	0.441	0.351	0.024	0.291
		(0.084)	(0.084)	(0.080)	(0.089)	(0.091)	(0.092)	(0.104)
P-value of Test of Homogeneity of Demand		0.643	0.643	0.618	0.000	0.000	0.792	0.005
Sample	Renters Only	Renters Only	Renters Only	Renters Only	Owners Only	Renters and Owners	Renters Only	Renters Only
Unit of Observation	MSA	MSA	MSA	MSA	MSA	MSA	MSA	PUMA
Implied Demand Parameters:								
Geometric Mean Expenditure Share	0.217	0.217	0.217	0.217	0.159	0.173	0.186	0.215
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Uncompensated Own Price Elasticity of Housing Demand	-0.813	-0.680	-0.675	-0.670	-0.451	-0.452	-0.757	-0.714
	(0.020)	(0.032)	(0.032)	(0.041)	(0.030)	(0.015)	(0.029)	(0.017)
Income Elasticity of Housing Demand	1.000	0.621	0.627	0.622	0.692	0.591	0.816	0.559
	Restricted	(0.095)	(0.095)	(0.102)	(0.091)	(0.063)	(0.088)	(0.025)
Elasticity of Substitution Between Housing and Consumption Goods			0.689	0.684	0.406	0.423	0.744	0.757
			(0.025)	(0.032)	(0.023)	(0.014)	(0.029)	(0.016)
Distribution Parameter			0.891	0.893	0.989	0.984	0.895	0.868
			(0.008)	(0.011)	(0.003)	(0.002)	(0.009)	(0.006)
Non-homotheticity Parameter			1.529	1.524	0.617	0.858	0.881	2.313
			(0.375)	(0.366)	(0.169)	(0.135)	(0.439)	(0.115)

TABLE 2: COMPENSATED DEMAND FUNCTIONS - ADDITIONAL YEARS, DATASETS, AND PRICE INDICES

Dataset/Price Index:	Census 1980	Census 1990	ACS 2007-11	Alt Housing Price Index	CEO Housing Price Index	AHS Housing Price Index	CEX Housing Price Index
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	Log Median Rental Share						
Regression Results:							
Rental/Housing Price Index	0.174	0.218	0.229	0.235	0.193	0.136	0.261
	(0.052)	(0.024)	(0.027)	(0.020)	(0.037)	(0.068)	(0.054)
Predicted Wage Index	-0.114	-0.259	-0.058	-0.363	-0.351	-0.580	0.159
	(0.139)	(0.123)	(0.035)	(0.099)	(0.135)	(0.232)	(0.178)
Constant	-1.552	-1.508	-1.310	-1.529	-1.529	-1.366	-1.038
	(0.009)	(0.006)	(0.005)	(0.005)	(0.006)	(0.010)	(0.008)
Sample Size	302	379	369	380	380	109	163
Adjusted R-squared	0.158	0.498	0.294	0.443	0.276	0.044	0.122
Constrained Regression	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unconstrained Sum of Housing and Non-Housing Price Index Coefficients	-0.225	-0.194	-0.051	0.052	0.205	0.109	0.467
	(0.306)	(0.154)	(0.078)	(0.087)	(0.127)	(0.221)	(0.189)
P-value of Test of Homogeneity of Demand	0.462	0.209	0.514	0.553	0.107	0.622	0.015
Implied Demand Parameters:							
Geometric Mean Expenditure Share	0.212	0.221	0.270	0.217	0.217	0.255	0.354
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
Uncompensated Own Price Elasticity of Housing Demand	-0.801	-0.724	-0.756	-0.686	-0.731	-0.716	-0.795
	(0.074)	(0.047)	(0.031)	(0.034)	(0.057)	(0.098)	(0.083)
Income Elasticity of Housing Demand	0.886	0.741	0.942	0.637	0.649	0.420	1.159
	(0.139)	(0.123)	(0.035)	(0.099)	(0.135)	(0.232)	(0.178)
Elasticity of Substitution Between Housing and Consumption Goods	0.779	0.719	0.687	0.700	0.753	0.817	0.595
	(0.067)	(0.031)	(0.037)	(0.026)	(0.048)	(0.091)	(0.083)
Distribution Parameter	0.864	0.877	0.852	0.887	0.869	0.812	0.825
	(0.022)	(0.010)	(0.015)	(0.009)	(0.016)	(0.035)	(0.043)
Non-homotheticity Parameter	0.652	1.185	0.254	1.544	1.816	4.257	-0.607
	(0.693)	(0.490)	(0.152)	(0.400)	(0.624)	(2.478)	(0.692)

All specifications use the Hicksian model, with renters only imposing homogeneity of demand. They correspond to specification (3) in Table 1.

TABLE 3: UNCOMPENSATED AND AMENITY DEMAND FUNCTIONS - 2000 CENSUS DATA

	Marshallian Demand	Marshallian Demand	Hicksian Demand	Marshallian Demand
	(1)	(2)	(3)	(4)
Dependent Variable:	Log Median Rental Share			
Regression Results:				
Housing Price Index	0.600	0.591	0.257	0.580
	(0.039)	(0.041)	(0.018)	(0.044)
Non-Housing Price Index	0.024	0.081	-0.257	-0.580
	(0.085)	(0.025)	(0.018)	(0.044)
Household Income Index	-0.674	-0.673	-0.423	-0.642
	(0.059)	(0.060)	(0.092)	(0.061)
Inverse Distance to Coast			-0.106	-0.044
			(0.082)	(0.064)
Average Slope of Land			0.012	0.004
			(0.002)	(0.001)
Constant	-1.529	-1.529	-1.530	-1.530
	(0.003)	(0.003)	(0.004)	(0.003)
Sample Size	380	380	376	376
Adjusted R-squared	0.811	0.811	0.553	0.819
Constrained Regression	No	Yes	Yes	Yes
Unconstrained Sum of Housing Price, Non-Housing Price, and Household Income Coefficients	-0.050	-0.050	-0.023	-0.086
	(0.069)	(0.069)	(0.092)	(0.084)
P-value of Test of Homogeneity of Demand	0.472	0.472	0.801	0.309
Implied Demand Parameters:				
Geometric Mean Expenditure Share	0.217	0.217	0.217	0.217
	(0.001)	(0.001)	(0.001)	(0.001)
Uncompensated Own Price Elasticity of Housing Demand	-0.400	-0.409	-0.651	-0.420
	(0.039)	(0.041)	(0.029)	(0.044)
Income Elasticity of Housing Demand	0.326	0.327	0.577	0.358
	(0.059)	(0.060)	(0.092)	(0.061)
Elasticity of Substitution Between Housing and Consumption Goods		0.431	0.672	0.437
		(0.037)	(0.023)	(0.040)

All specifications include renters only. Robust standard errors in parentheses. Test of homogeneity of demand is that the coefficients on both price indices and income sum to zero.

TABLE 4: PRICES, INCOMES, AND HOUSING EXPENDITURE SHARES - TIME SERIES DATA

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Log Aggregate Housing Share	Log Average Renter Share	Log Average Housing Share	Log Median Renter Share	Log Median Housing Share	Log Median Housing Share
Data Source:	BEA	CEX	CEX	AHS	AHS	Census
Unrestricted Regression Results:						
Log CPI-U: Shelter	0.313	0.253	-0.036	0.398	-0.163	1.019
	(0.082)	(0.294)	(0.237)	(0.484)	(0.316)	(0.337)
Log CPI-U: All Items Less Shelter	0.138	-0.055	0.142	0.105	1.022	0.802
	(0.099)	(0.253)	(0.210)	(0.608)	(0.370)	(0.779)
Log Household Income Measure	-0.449	-0.238	-0.044	-0.562	-0.758	-1.352
	(0.085)	(0.129)	(0.091)	(0.166)	(0.224)	(0.488)
Linear Time Trend (Per Decade)	0.004	0.009	0.005	0.007	0.008	-0.011
	(0.002)	(0.004)	(0.002)	(0.005)	(0.004)	(0.015)
Constant	-1.718	-1.232	-1.381	-1.283	-1.605	-1.427
	(0.003)	(0.004)	(0.003)	(0.010)	(0.009)	(0.009)
P-value of Test of Homogeneity of Demand	0.948	0.782	0.343	0.815	0.534	0.331
Restricted Regression Results:						
Log CPI-U: Shelter minus Log CPI-U: All Items Less Shelter	0.318	0.249	0.152	0.262	0.103	0.862
	(0.071)	(0.281)	(0.080)	(0.197)	(0.182)	(0.340)
Log Average Household Income minus Log CPI-U: All Items Less Shelter	-0.453	-0.234	-0.132	-0.522	-0.889	-0.954
	(0.054)	(0.122)	(0.031)	(0.127)	(0.203)	(0.324)
Linear Time Trend (Per Decade)	0.004	0.008	0.007	0.006	0.010	0.004
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Constant	-1.718	-1.232	-1.381	-1.283	-1.605	-1.427
	(0.003)	(0.004)	(0.003)	(0.010)	(0.009)	(0.012)
Sample size (years)	42	28	29	21	23	11
Implied Demand Parameters from Restricted Regressions:						
Geometric Mean Expenditure Share	0.179	0.292	0.251	0.277	0.201	0.24
	(0.000)	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)
Uncompensated Own-Price Elasticity of Housing Demand	-0.682	-0.751	-0.848	-0.738	-0.897	-0.138
	(0.071)	(0.281)	(0.080)	(0.197)	(0.182)	(0.340)
Income Elasticity of Housing Demand	0.547	0.766	0.868	0.478	0.111	0.046
	(0.054)	(0.122)	(0.031)	(0.127)	(0.203)	(0.324)
Decomposition of Long-run Change in Expenditure Share on Housing:						
Total Change in Log Share	0.080	0.263	0.271	0.341	0.356	0.306
Change Attributable to Time Trend	0.150	0.286	0.281	0.231	0.396	0.128
	(0.041)	(0.044)	(0.020)	(0.069)	(0.056)	(0.054)
Change Attributable to Compensated Relative Price Effect	0.065	0.052	0.031	0.034	-0.021	0.183
	(0.020)	(0.073)	(0.020)	(0.051)	(0.044)	(0.077)
Change Attributable to Income Effect	-0.140	-0.018	-0.028	0.032	-0.019	0.049
	(0.017)	(0.010)	(0.007)	(0.008)	(0.004)	(0.016)
Residual	0.006	-0.057	-0.013	0.043	-0.001	-0.054
	(0.013)	(0.033)	(0.012)	(0.027)	(0.036)	(0.048)
Simulated Decomposition of Long-run Change in Expenditure Share on Housing:						
Total Change in Log Share	0.080	0.263	0.271	0.341	0.356	0.306
Change Attributable to Time Trend	0.150	0.286	0.281	0.231	0.396	0.128
Change Attributable to Compensated Relative Price Effect	0.065	0.068	0.062	0.068	0.066	0.068
Change Attributable to Income Effect	-0.103	-0.034	-0.077	0.016	-0.005	0.016
Residual	-0.031	-0.058	0.005	0.026	-0.102	0.094

Homogeneity of demand requires that the coefficients on log CPI-U for shelter, log CPI-U for all items less shelter, and log real household income sum to zero. The restricted regressions impose this constraint. Newey-West standard errors reported in parentheses. For non-BEA series, a moving average with weight of 0.5 for the year after and the year before is used.

TABLE 5: INCOME CHANGES IDEALLY DEFLATED

Household Position	Income Ratio 2009/1970	Ideal Deflator	Ideal Deflated Income	Deflated Fixed Bundle	Ideal Correction to Fixed
10th Percentile	6.103	5.480	1.114	1.121	-0.008
50th Percentile	6.002	5.404	1.111	1.103	0.008
90th Percentile	7.869	5.310	1.482	1.446	0.036

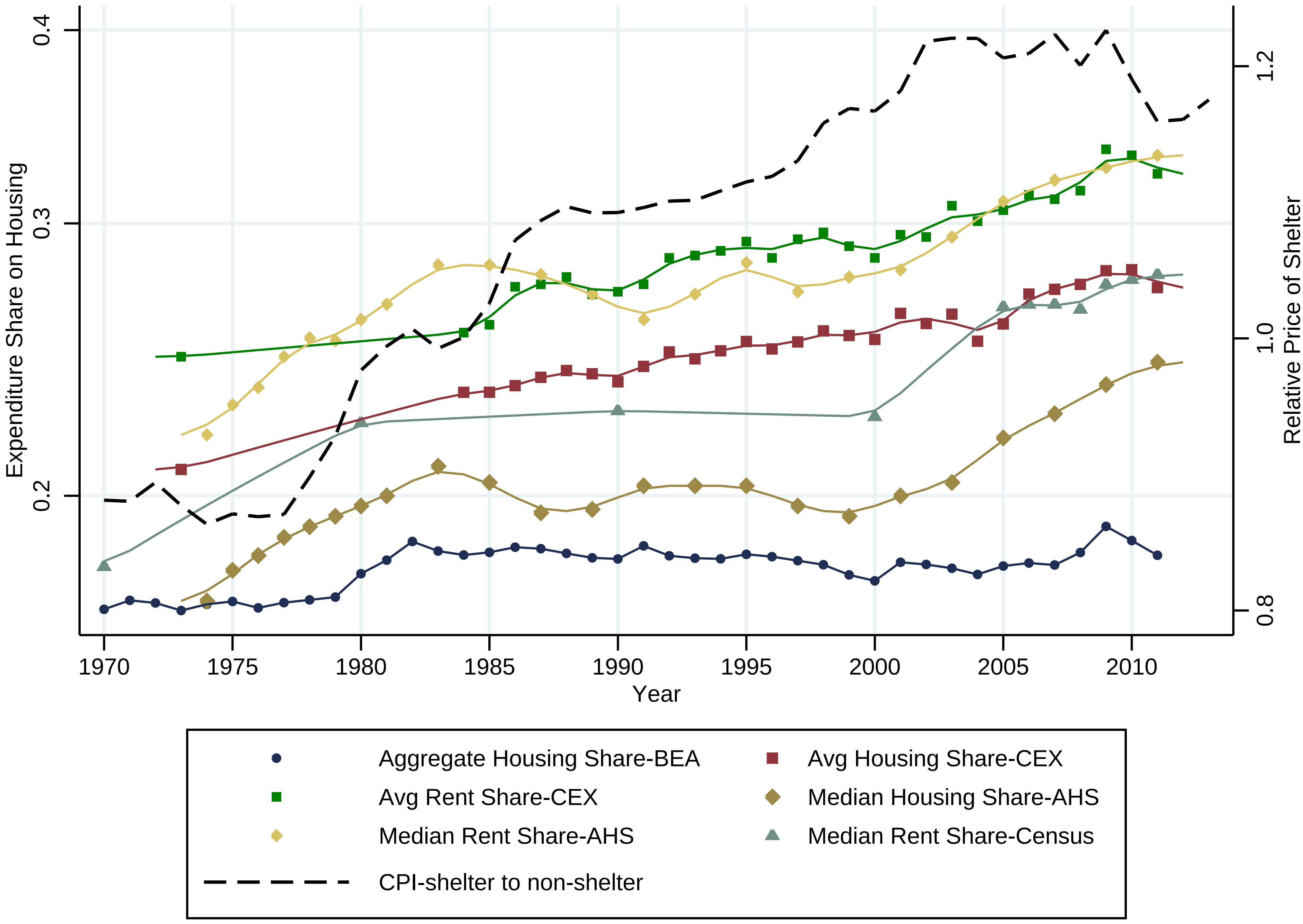
Income ratio in nominal terms. Ideal deflator uses estimated COL_4 index. Fixed-bundle deflator uses COL_1 index. Ideal correction takes difference.

TABLE 6: UNDERSTANDING INCREASES IN HOUSING AFFORDABILITY BURDENS, 1980-2010

	Share with Moderate Burden (1)	Share with Extreme Burden (2)
Renter Households in 2010	0.528	0.283
Counterfactuals for 2010 (exercises applied cumulatively)		
1. Undoing Increases in Income Inequality	0.496	0.267
2. Undoing Increase in Average Rents	0.468	0.250
3. Undoing Changes in Relative Rents	0.474	0.253
4. Undoing Increase in Average Income	0.494	0.265
Renter Households in 1980	0.391	0.196

Notes: moderate burden is defined as an expenditure share on housing in excess of 30%; extreme burden is defined as expenditure share in excess of 50%. Counterfactual 1 assumes no increase in income inequality 1980-2010. Counterfactual 2 additionally assumes no increase in national rents 1980-2010. Counterfactual 3 additionally assumes no increases in dispersion of rents across metropolitan areas 1980-2010. Counterfactual 4 additionally assumes no change in average incomes 1980-2010.

Figure 1: Expenditure Share on Housing 1970-2013



Note: For non-BEA series, a moving average with weight of 0.5 for the year after and the year before is shown in the curve.

Figure 2: Housing Consumption with Production Possibility Expansions

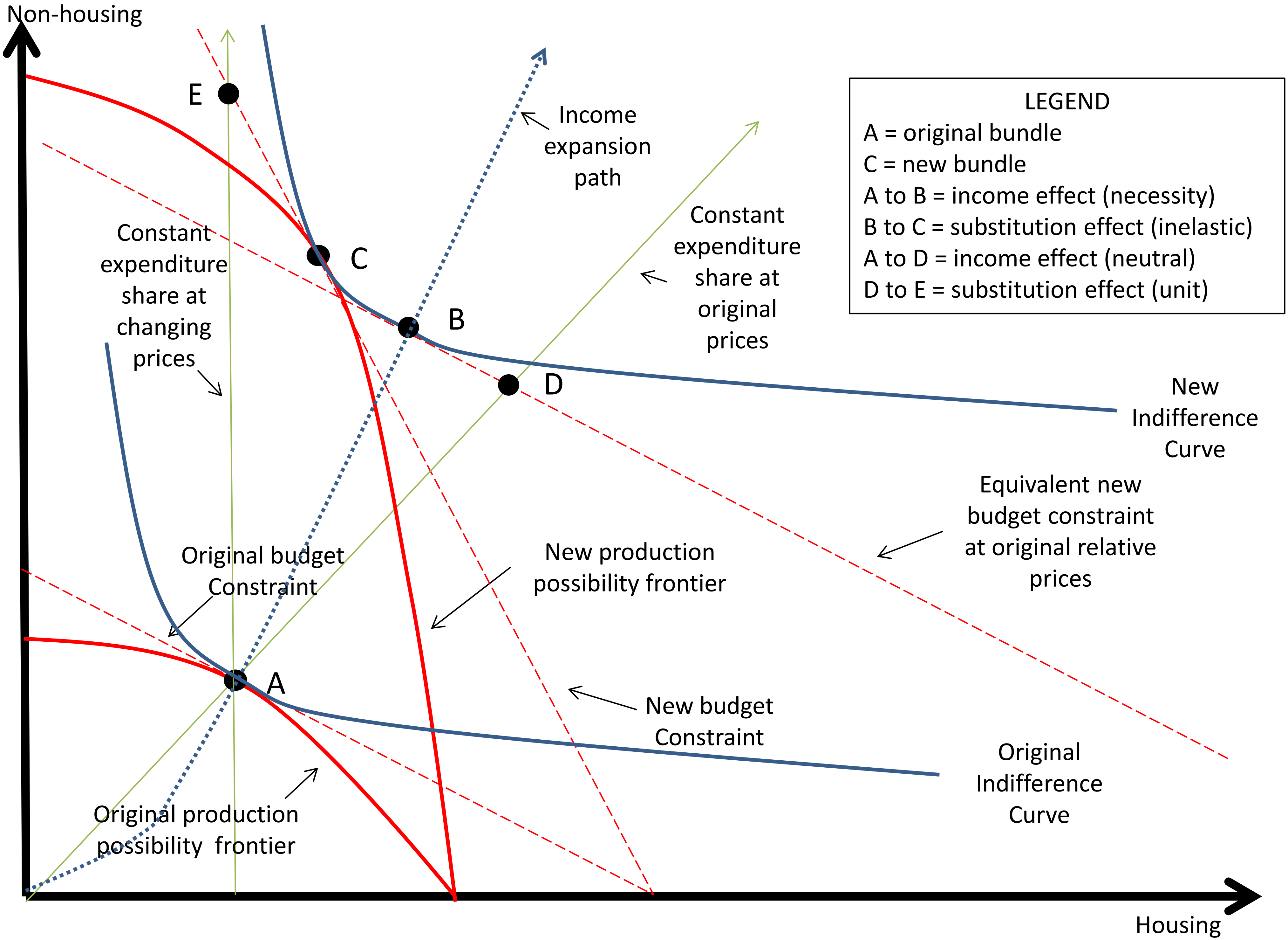


Figure 3A: Non-Housing Price Index vs. Housing Price Index, 2000

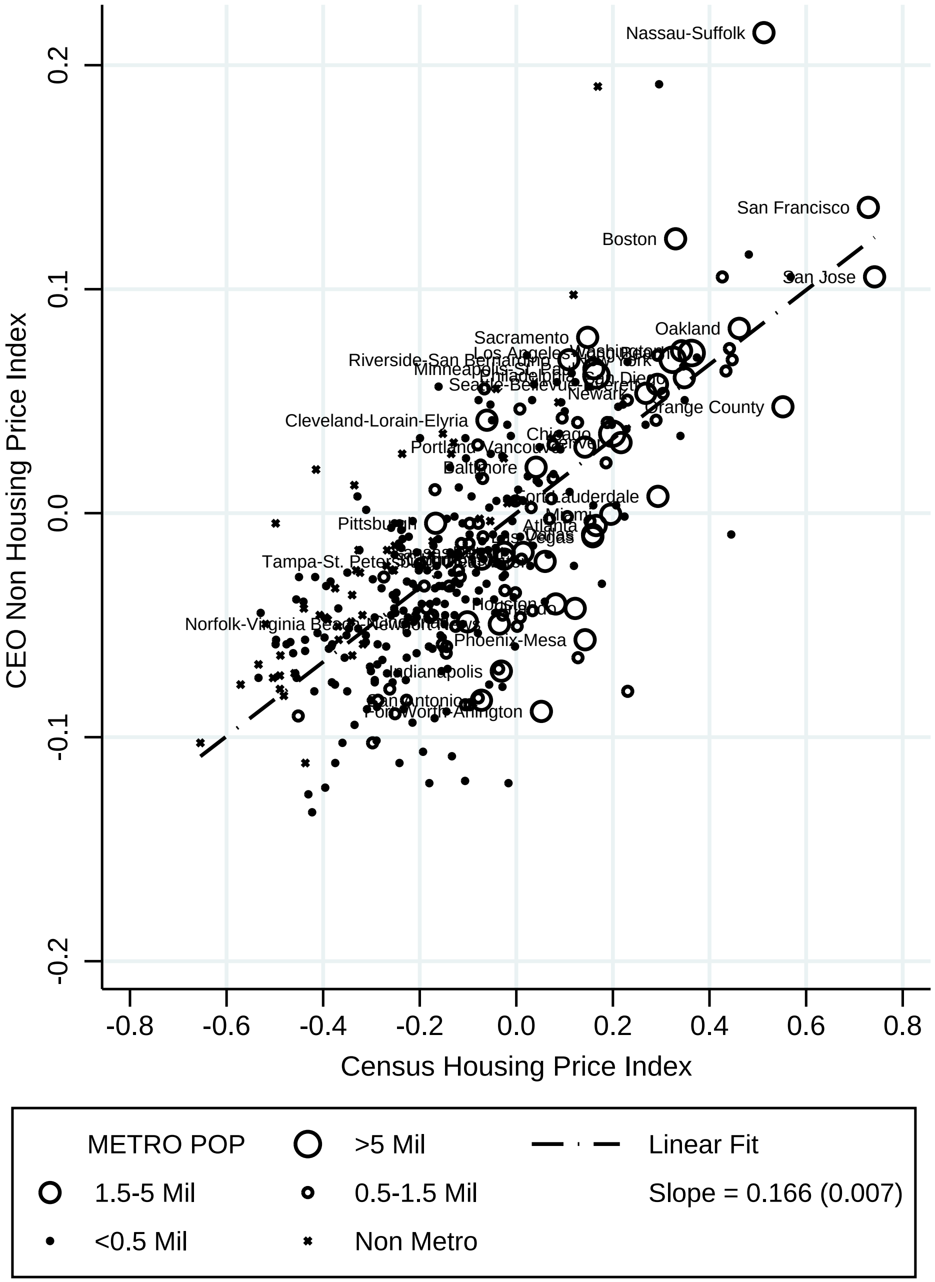
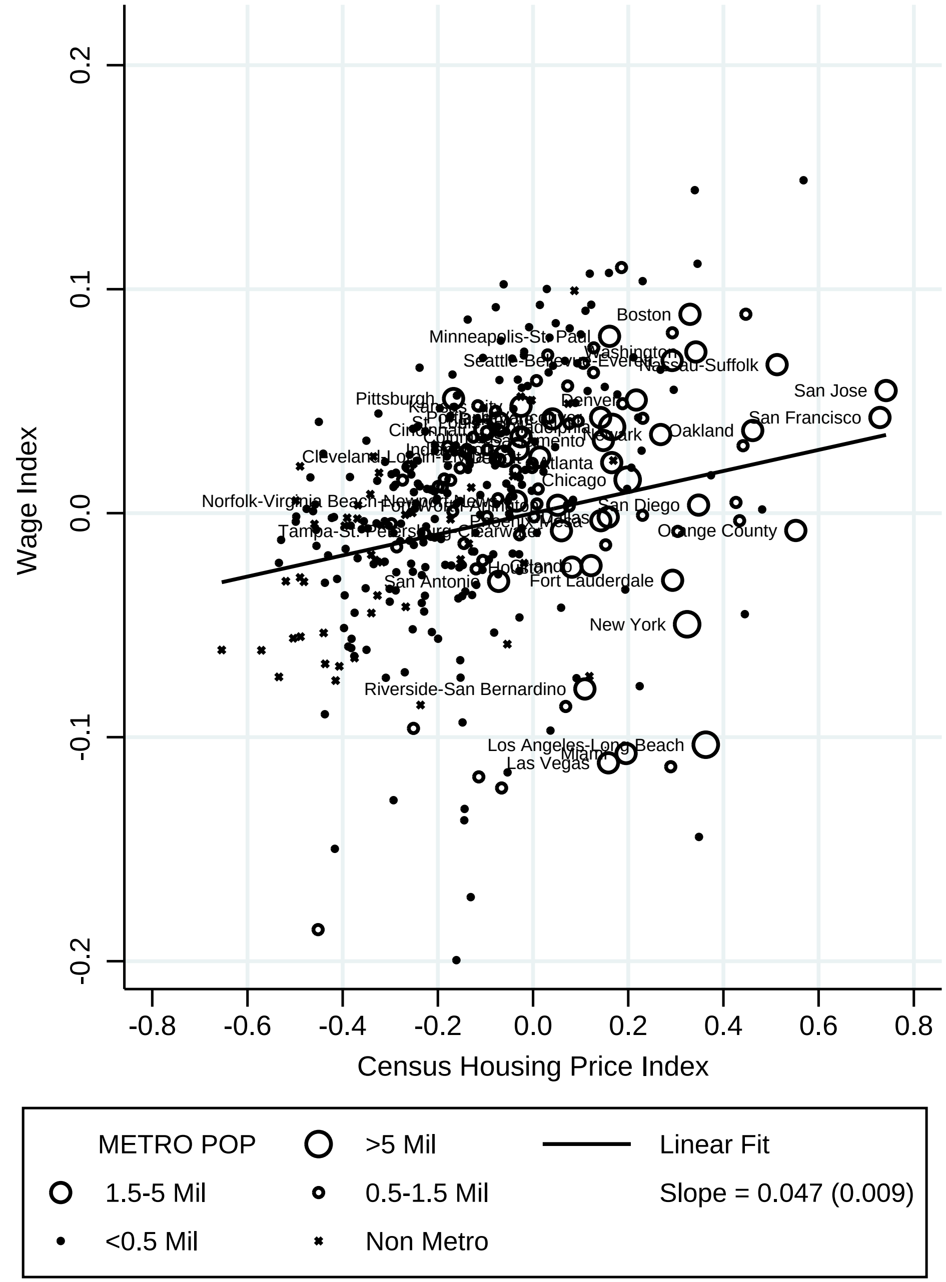


Figure 3B: Wage Index vs. Housing Price Index, 2000



Data Source: Non-housing price index is from CEO prices panel, housing price index is from Census

Figure 4A: Median Share of Income Spent on Rent
and the Relative Price of Housing, Renters Only 2000

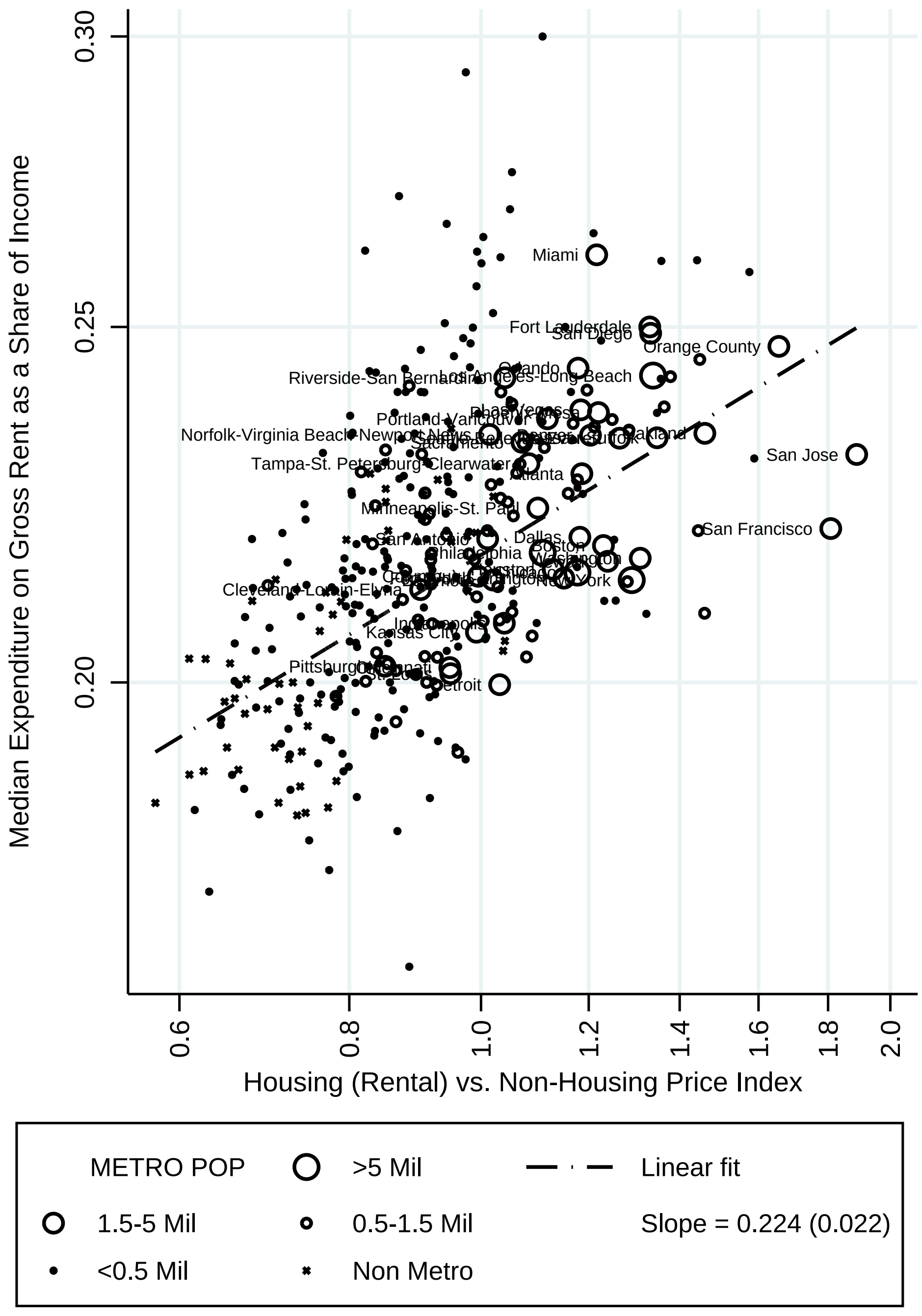


Figure 4B: Median Share of Income Spent on Housing
and the Relative Price of Housing, All Households 2000

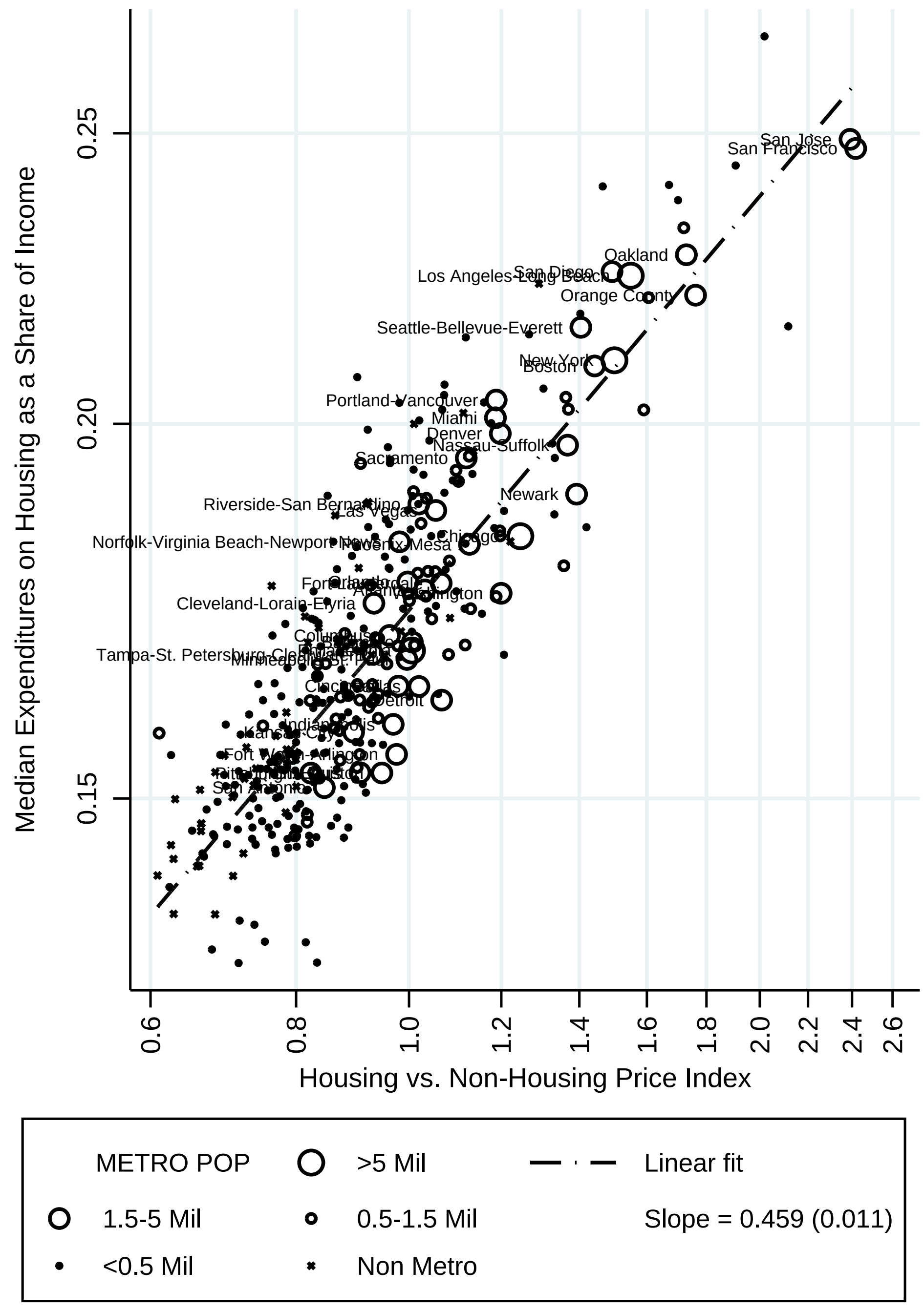


Figure 5A: Comparison of Cost-of-living Indices at median household income

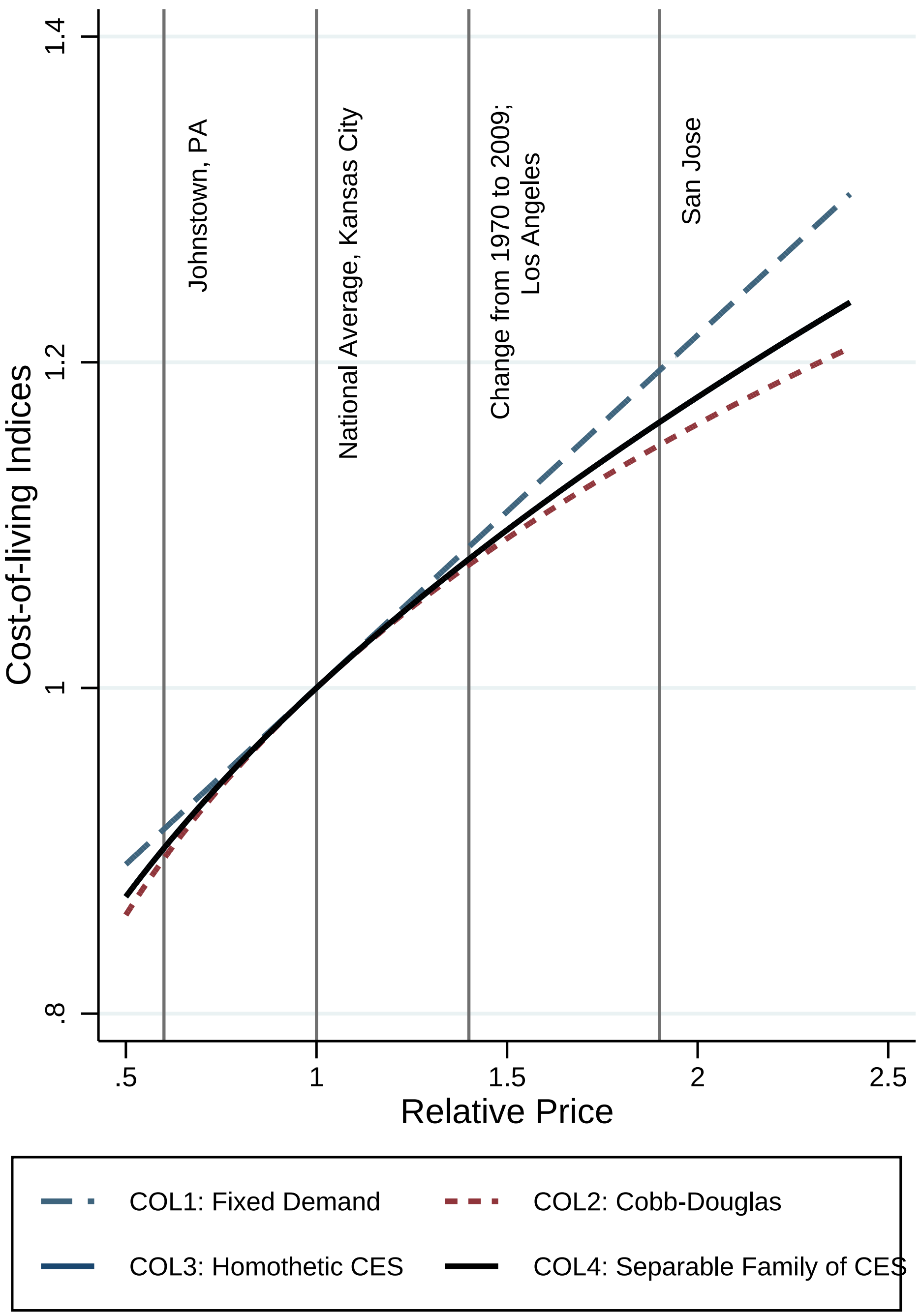
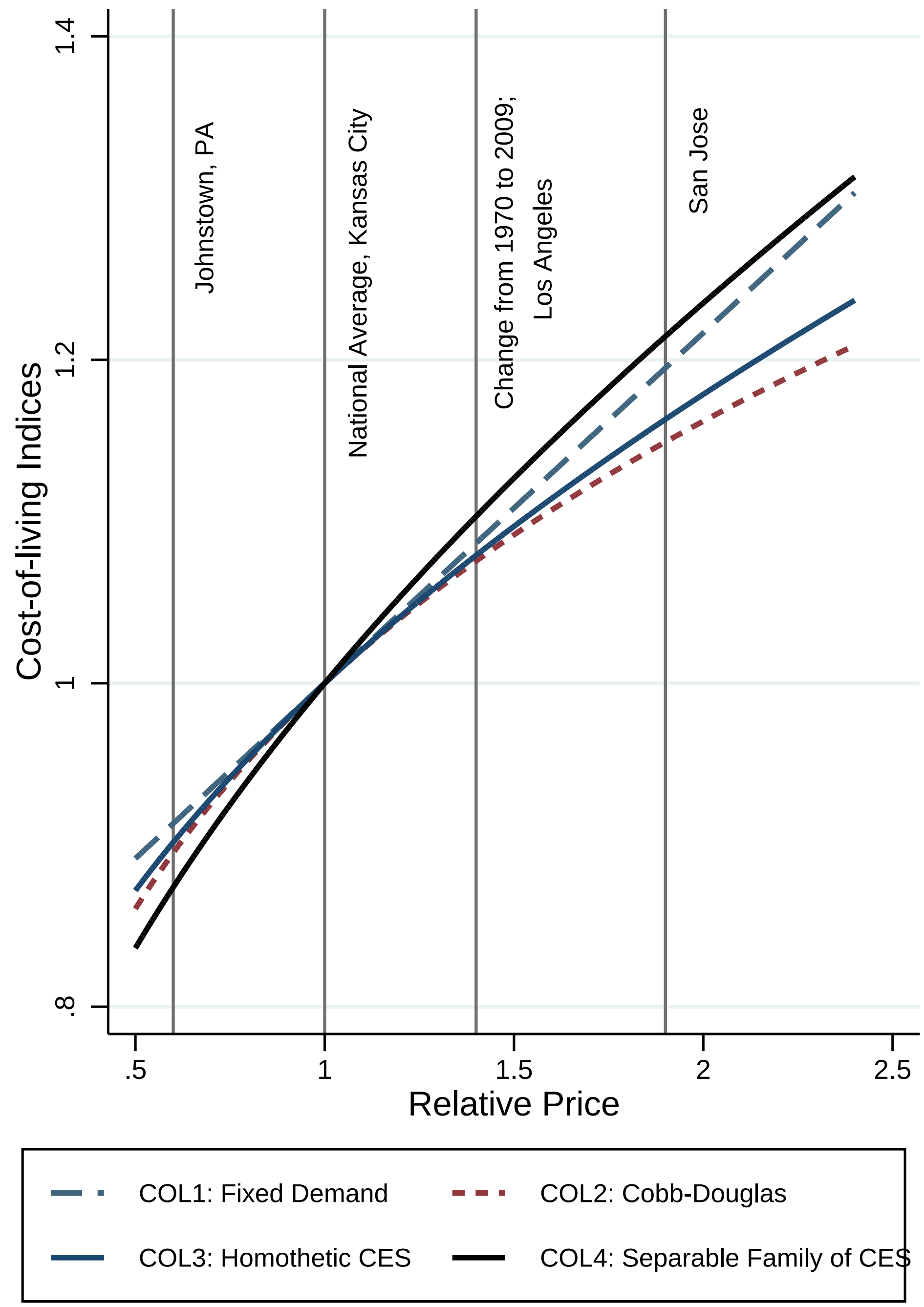


Figure 5B: Comparison of Cost-of-living Indices at one half of median household income



Appendix

A Separable Family of CES

A.1 Formulation and Parameters

We use the simple "separable family" of CES utility function from Sato (1977), who writes it as

$$U = \left(\frac{\delta_1 x^\rho + \theta_1}{\delta_2 y^\rho + \theta_2}\right)^{\frac{\alpha}{\rho}}$$

where $\theta_i = -(\alpha - \delta_i)\,\rho - \delta_i$ is composed of more elementary parameters. These are the distribution parameter, $\delta = \delta_1 = 1 + \delta_2$, the substitution parameter, $\sigma = 1/(1-\rho) =$, and the non-homotheticity parameter, $\gamma = 1/\alpha$. Using these parameters, we may rewrite the utility function as

$$U = \left[\frac{\delta x^\rho + \theta_1}{(\delta - 1)y^\rho + \theta_2}\right]^{\frac{1}{\gamma\rho}} = \left[\frac{\gamma\sigma\delta x^{\frac{\sigma-1}{\sigma}} + 1 - \gamma\delta - \sigma}{\gamma\sigma(\delta-1)y^{\frac{\sigma-1}{\sigma}} + 1 - \gamma(\delta-1) - \sigma}\right]^{\frac{\sigma}{\gamma(\sigma-1)}}$$

A.2 Marginal rate of substitution

Taking the ratio of partial derivatives, the marginal rate of substitution between the housing and non-housing goods is then

$$MRS_{x,y} = \frac{\delta}{1-\delta}\left(\frac{x}{y}\right)^{\rho-1}\left(\frac{\delta x^\rho + \theta_1}{(\delta-1)y^\rho + \theta_2}\right)^{-1} = \frac{\delta}{1-\delta}\left(\frac{x}{y}\right)^{-\frac{1}{\sigma}} u^{\frac{\gamma(1-\sigma)}{\sigma}}$$

At the household's optimal consumption bundle, $c/p = MRS_{x,y}$, implying:

$$\frac{c}{p} = \frac{\delta}{1-\delta}\left(\frac{x}{y}\right)^{-\frac{1}{\sigma}} u^{\frac{\gamma(1-\sigma)}{\sigma}} \Rightarrow \frac{x}{y} = \left[\frac{c}{p}\cdot\frac{1-\delta}{\delta}u^{-\frac{\gamma(1-\sigma)}{\sigma}}\right]^{-\sigma} = \left(\frac{c}{p}\right)^{-\sigma}\left(\frac{1-\delta}{\delta}\right)^{-\sigma} u^{\gamma(1-\sigma)}$$

A.3 Expenditure Share on Housing

To solve for the expenditure share on housing, note that $d\ln y/d\ln x = dy/dx(x/y) = cx/py = s_x/s_y$. Then the ratio of the expenditure share spent on x to the share spent on y is:

$$\frac{s_x}{s_y} = \frac{\mathrm{d}\ln y}{\mathrm{d}\ln x} = \frac{\delta}{1-\delta}\left(\frac{x}{y}\right)^{1-\frac{1}{\sigma}} u^{\frac{\gamma(1-\sigma)}{\sigma}} = \left(\frac{\delta}{1-\delta}\right)^{\sigma}\left(\frac{c}{p}\right)^{1-\sigma} u^{\gamma(1-\sigma)}$$

Then to solve for the housing expenditure share s_y, add one and invert:

$$\frac{1}{s_y} = \frac{cx}{py} + 1 = \frac{c^{1-\sigma}\delta^{\sigma}u^{\gamma(1-\sigma)} + p^{1-\sigma}(1-\delta)^{\sigma}}{(1-\delta)^{\sigma}p^{1-\sigma}}$$
$$\Rightarrow s_y = \frac{(1-\delta)^{\sigma}p^{1-\sigma}}{\delta^{\sigma}c^{1-\sigma}u^{\gamma(1-\sigma)} + (1-\delta)^{\sigma}p^{1-\sigma}}.$$

Taking logarithms, we obtain an only partly linear equation

$$\ln s_y = \sigma\ln(1-\delta) + (1-\sigma)\ln(p) - \ln[\delta^{\sigma}c^{1-\sigma}u^{\gamma(1-\sigma)} + (1-\delta)^{\sigma}p^{1-\sigma}] \tag{A.1}$$

To complete the log-linearization, we take the total derivative to get the approximation:

$$\widehat{s_y} = (1-\sigma)\hat{p} - \frac{(1-\sigma)\delta^{\sigma}c^{1-\sigma}u^{\gamma(1-\sigma)}\widehat{c} + \gamma(1-\sigma)\delta^{\sigma}c^{1-\sigma}u^{\gamma(1-\sigma)}\widehat{u} + (1-\sigma)(1-\delta)^{\sigma}p^{1-\sigma}\widehat{p}}{\delta^{\sigma}c^{1-\sigma}u^{\gamma(1-\sigma)} + (1-\delta)^{\sigma}p^{1-\sigma}}$$
$$= (1-s_y)(1-\sigma)\widehat{p} - (1-s_y)(1-\sigma)\widehat{c} - \gamma(1-s_y)(1-\sigma)\widehat{u}$$

Relating the above equation to the regression equation 10 gives $\beta_0 = \sigma\ln(1-\delta) = \ln\bar{s}_y, \beta_1 = (1-\bar{s}_y)(1-\sigma), \beta_3 = -\gamma(1-\bar{s}_y)(1-\sigma)$. The parameters can thus be expressed recursively as $\sigma = 1 - \beta_1/(1-e^{\beta_0}), \delta = 1 - e^{\beta_0/\sigma}$, and $\gamma = -\beta_3/\beta_1$.

A.4 Hicksian Demand and Expenditure Functions

The Hicksian, or compensated, demands for the housing and non-housing goods associated with this utility function can be derived as:

$$y = \frac{p^{-\sigma}(1-\delta)^{\sigma}}{[c^{1-\sigma}\delta^{\sigma}u^{\gamma(1-\sigma)} + p^{1-\sigma}(1-\delta)^{\sigma}]^{\frac{\sigma}{\sigma-1}}}\left[\frac{1-\gamma(\delta-1)-\sigma}{\gamma\sigma} - \frac{1-\gamma\delta-\sigma}{\gamma\sigma}u^{\frac{\gamma}{\sigma}(1-\sigma)}\right]^{\frac{\sigma}{\sigma-1}}$$

$$x = \frac{c^{-\sigma}\delta^{\sigma}u^{\gamma(1-\sigma)}}{[c^{1-\sigma}\delta^{\sigma}u^{\gamma(1-\sigma)} + p^{1-\sigma}(1-\delta)^{\sigma}]^{\frac{\sigma}{\sigma-1}}}\left[\frac{1-\gamma(\delta-1)-\sigma}{\gamma\sigma} - \frac{1-\gamma\delta-\sigma}{\gamma\sigma}u^{\frac{\gamma}{\sigma}(1-\sigma)}\right]^{\frac{\sigma}{\sigma-1}}$$

.

The associated expenditure function is:

$$e(p,c,u;1) = \left\{\frac{c^{1-\sigma}\delta^{\sigma}u^{\gamma(1-\sigma)} + p^{1-\sigma}(1-\delta)^{\sigma}}{\left[\frac{1}{\gamma\sigma}\left(\gamma + (1-\sigma-\gamma\delta)(1-u^{\frac{\gamma(1-\sigma)}{\sigma}})\right)\right]^{\sigma}}\right\}^{\frac{1}{1-\sigma}}. \tag{A.2}$$

B Data

We define cities at the Metropolitan Statistical Area (MSA) level using the 1999 Office of Management and Budget definitions of consolidated MSAs (e.g., San Francisco is combined with Oakland

and San Jose), of which there are 276. We use United States Census data from the 2000 Integrated Public-Use Microdata Series (IPUMS), from Ruggles et al. (2004), to calculate wage and housing price differentials.

B.1 Wage Differentials

The wage differentials are calculated for workers ages 25 to 55 who report working at least 30 hours a week, 26 weeks a year. The MSA assigned to a worker is determined by their place of residence, rather than their place of work. The wage differential of an MSA is calculated by regressing log hourly wages on a rich set of covariates and a set of indicators for which MSA a worker lives in. The wage differentials are taken to be the coefficients on these MSA indicators, renormalized to have a national average value of zero. The covariates consist of:

- 12 indicators of educational attainment;
- a quartic in potential experience, and potential experience interacted with years of education;
- 9 indicators of industry at the one-digit level (1950 classification);
- 9 indicators of employment at the one-digit level (1950 classification);
- 4 indicators of marital status (married, divorced, widowed, separated);
- an indicator for veteran status, and veteran status interacted with age;
- 5 indicators of minority status (Black, Hispanic, Asian, Native American, and other);
- an indicator of immigrant status, years since immigration, and immigrant status interacted with black, Hispanic, Asian, and other;
- 2 indicators for English proficiency (none or poor).

All covariates are interacted with gender.

This regression is run using census-person weights.

B.2 Housing Rent and Price Indices

The housing rent and price differentials are calculated using the logarithm of rents, whether they are reported gross rents or imputed rents derived from housing values. The differential housing price of an MSA is calculated in a manner similar to the wage differential, except using a regression of the actual or imputed rent on a set of covariates at the unit level and a set of MSA indicators. The covariates for the adjusted differentials are:

- 9 indicators of building size;
- 9 indicators for the number of rooms, 5 indicators for the number of bedrooms, number of rooms interacted with number of bedrooms;
- 2 indicators for lot size;

- 7 indicators for when the building was built;
- 2 indicators for complete plumbing and kitchen facilities;
- 8 indicators for home heating fuel;
- an indicator for commercial use;
- an indicator for condominium status (owned units only).

We first run a regression of housing values on housing characteristics and MSA indicator variables weighting by census-housing weights. The housing-price index are taken from the MSA indicator variables in this regression, renormalized to have a national average of zero.

B.2.1 Alternative Census Housing Price Index

The Alternative Census Housing Price Index are estimated from the 2000 united States Census 5% data from the Integrated Public-Use Microdata Series (IPUMS), following Malpezzi, Chun and Green (1998). The housing price differentials are calculated using the logarithm of rents, whether they are reported gross rents or imputed rents derived from housing values. We first fit separate regressions for each MSA, regressing the log yearly rents on a set of MSA dummies and a number of covariates at the unit level. We then use the predicted price from each regression in each location to get the normalized price index. The covariates for the adjusted differential are:

- 9 indicators of building size;
- 9 indicators for the number of rooms, 5 indicators for the number of bedrooms, number of rooms interacted with number of bedrooms;
- 2 indicators for lot size;
- 7 indicators for when the building was built;
- 2 indicators for complete plumbing and kitchen facilities;
- 8 indicators for home heating fuel;
- an indicator for commercial use;
- an indicator for condominium status (owned units only).

We first run a hedonic regression for each MSA, using housing characteristics alone. Second, we calculate predicted housing prices in each MSA from each regression, and calculate the MSA-level means. Third, we obtain the normalized housing price index for each MSA by using the predicted values of housing minus the national average.

B.2.2 AHS Housing Price Index

The AHS Housing Price Index is constructed from 2001 American Housing Survey data similarly to the Census housing price indices. The AHS index is calculated using the logarithm of reported gross rents, restricted to renter-occupied units only. The AHS uses 1980-design PMSA codes, while the 2000 Census uses 2000-design PMSA codes. To facilitate comparison between the two, we match the geographical areas in the AHS with PMSA definitions consistent with the 2000 Census.

We regress the log yearly rents on a set of MSA dummies and a number of covariates at the unit level. The covariates for the adjusted differential are:

- 3 indicators of building size;
- 9 indicators for the number of rooms, 5 indicators for the number of bedrooms, number of rooms interacted with number of bedrooms;
- 5 indicators for the number of bathrooms;
- 1 indicators for lot size;
- 11 indicators for when the building was built;
- 2 indicators for complete plumbing and kitchen facilities;
- 8 indicators for home heating fuel;
- an indicator for commercial use;
- an indicator for condominium status (owned units only).

We run a regression of housing values on housing characteristics and MSA indicator variables with AHS-housing weights. The index is taken from the estimated coefficients on the MSA indicator variables, re-normalized to have a national average of zero.

B.2.3 CEX Housing Price Index

The CEX Housing Price Index is computed from 2000 Consumer Expenditure Survey. The housing price differentials are calculated using the logarithm of rents, whether they are reported gross rents or imputed rents derived from housing values. We regress the log yearly rents on a set of geographical area dummies and a number of covariates at the unit level. The geographical area is defined based on state, population size, and whether it is in a metro area. In order to compare with the other price indices, we match CEX geographical units with Census PMSAs by state, population, and metropolitan area status. The matching process is not perfect, since a state may have two MSAs with indistinguishable populations, preventing us from differentiating them.

The covariates for the adjusted differentials are:

- 9 indicators of building size;
- 9 indicators of building structure;

- 9 indicators for the number of rooms, 5 indicators for the number of bedrooms, number of rooms interacted with number of bedrooms;
- 5 indicators for the number of bathrooms;
- 7 indicators for when the building was built;
- 2 indicators for complete plumbing and kitchen facilities;
- 4 indicators for home heating fuel;
- an indicator for commercial use;
- an indicator for condominium status (owned units only).

We first run a regression of housing values on housing characteristics and geographical area indicator variables weighting by CEX-housing weights. The housing-price index is taken from the coefficients on the geographical area indicator variables in this regression, renormalized to have a national average of zero.

B.2.4 CEO Prices Panel Housing Price Index

We use the Carrillo, Early, Olsen (2013) Prices Index Panel for all areas in the United States in the year 2000. CEO's source of housing data is HUD's 2000 Section 8 Customer Satisfaction Survey (CSS). They produce a geographic housing price index for 2000 by estimating a hedonic regression. They regress the logarithm of gross rents on observed characteristics of the rental units and their neighborhoods, other determinants that reflect unobserved characteristics that affect market rents, and a set of geographic area dummies for metropolitan areas and the non-metropolitan areas of each state.

B.3 Housing Expenditure Share

B.3.1 Census Housing Expenditure Share

The Census housing expenditure share is calculated from the 2000 United States 5% data from the Integrated Public-Use Microdata Series (IPUMS). The housing expenditure share is calculated as the ratio of housing expenditure to household income. For renters, we use gross rent as housing expenditure, while for owners, we use imputed rents derived from housing values plus utility fees. The cross-MSA mean of the MSA-level median rental share is 0.217 and the mean of the MSA-level meadian housing share for both renters and owners is 0.173.

B.3.2 AHS Rental Share

The AHS rental share is computed from the 2001 American Housing Survey microdata. We exclude MSAs with very few observations (e.g. less than 10 renters) and areas with suppressed MSA names. The AHS housing expenditure share is defined as the ratio of monthly housing cost to household income. The mean of the MSA-level median rental share is 0.257 with a standard deviation of 0.0289 over 109 MSAs.

B.3.3 CEX Rental Share

The CEX rental share is derived from 2000 Consumer Expenditure Survey microdata. The CEX rental share is computed as the ratio of expenditure on rents to total expenditure. We define geographies in the CEX as discussed in section B.2.3. The cross-MSA mean of the MSA-level median rental share is 0.354 with a standard deviation of 0.003 over 163 MSAs.

Figure A: Alternative vs. Census Housing Price Index

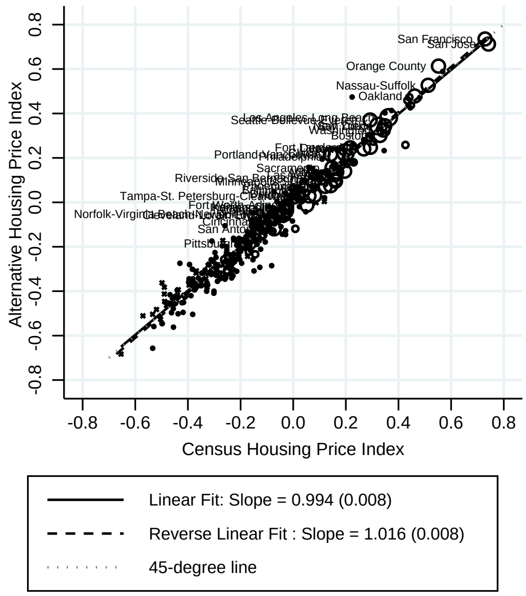


Figure B: CEO vs. Census Housing Price Index

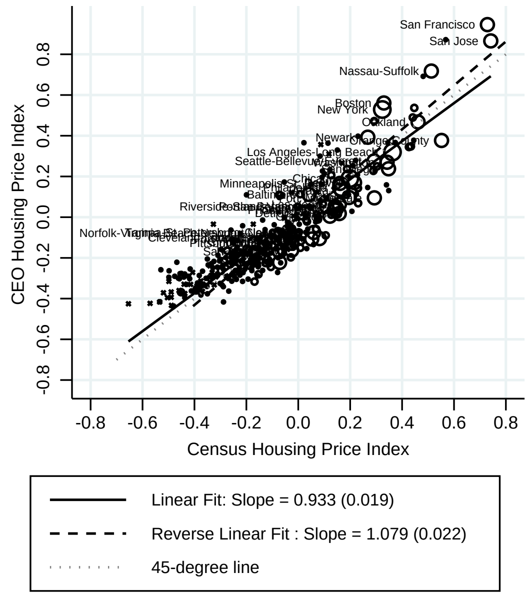


Figure C: AHS vs. Census Housing Price Index

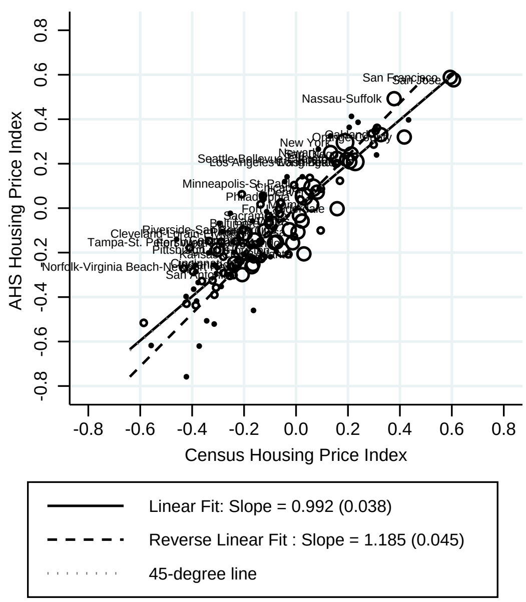
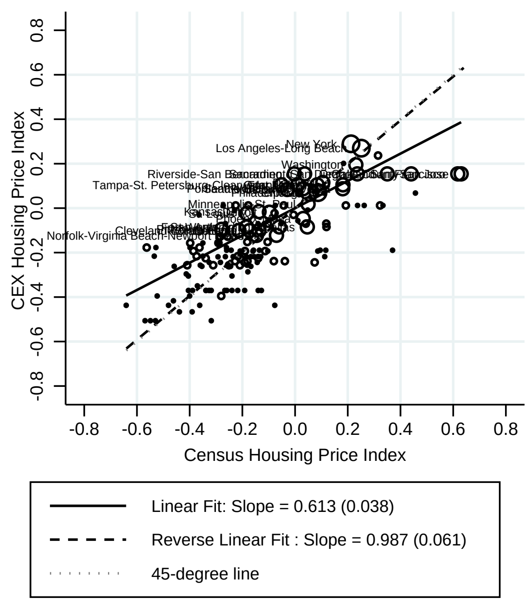


Figure D: CEX vs. Census Housing Price Index



Data Source: 2000 Census, 1997-2003 CEX, 1997-2003 AHS, renters only

TABLE A1: INTER-METROPOLITAN INDICES, YEAR 2000

MSA Name	MSA Population	Relative Price of Housing Index	Median Expenditure Share on Housing		Housing Price Index		Non-Housing Price Index	Predicted Wage Index	
			Renters Only	Renters & Owners	Rentals Only	Rentals & Owned		Renters Only	Renters & Owners
San Jose, CA	1,688,089	1.90	0.23	0.25	0.74	0.98	0.11	0.10	0.08
Stamford, CT	354,363	1.59	0.23	0.22	0.57	0.85	0.11	0.11	0.18
Santa Barbara-Santa Maria-Lompoc, CA	400,661	1.58	0.27	0.25	0.45	0.63	-0.01	0.01	-0.02
San Francisco-Oakland, CA	4,645,830	1.54	0.23	0.23	0.57	0.75	0.14	0.09	0.05
Ventura, CA	754,070	1.45	0.25	0.22	0.44	0.54	0.06	0.01	0.02
Santa Cruz, CA	258,576	1.45	0.27	0.27	0.48	0.81	0.12	0.04	0.03
Salinas-Seaside-Monterey, CA	281,166	1.41	0.24	0.24	0.40	0.62	0.05	-0.06	-0.10
Los Angeles-Long Beach, CA	12,400,000	1.39	0.25	0.22	0.40	0.53	0.07	-0.06	-0.07
Austin, TX	1,167,216	1.39	0.25	0.18	0.25	0.12	-0.08	0.05	0.06
Honolulu, HI	876,066	1.38	0.25	0.23	0.43	0.65	0.11	0.09	0.01
Danbury, CT	184,523	1.38	0.22	0.19	0.39	0.46	0.07	0.01	0.14
Santa Rosa, CA	459,235	1.36	0.24	0.24	0.38	0.58	0.07	0.04	0.03
San Diego, CA	2,807,873	1.34	0.25	0.23	0.35	0.46	0.06	0.02	0.01
Fort Lauderdale-Hollywood, FL	1,624,272	1.33	0.26	0.18	0.30	0.08	0.01	-0.03	-0.03
Washington, DC-MD-VA	4,733,359	1.33	0.22	0.18	0.36	0.27	0.07	0.07	0.08
New York, NY-NJ	17,200,000	1.32	0.22	0.20	0.34	0.47	0.07	0.01	0.00
Seattle-Everett, WA	2,332,682	1.27	0.24	0.22	0.30	0.40	0.06	0.07	0.07
Trenton, NJ	350,093	1.26	0.21	0.17	0.27	0.23	0.04	0.02	0.06
Naples, FL	249,728	1.25	0.22	0.19	0.23	0.29	0.00	-0.10	-0.06
Monmouth-Ocean, NJ	1,128,173	1.25	0.24	0.18	0.30	0.25	0.07	0.02	0.08
Ann Arbor, MI	479,754	1.24	0.24	0.18	0.24	0.21	0.02	0.12	0.13
Phoenix, AZ	3,070,331	1.23	0.24	0.18	0.15	0.08	-0.06	-0.01	0.00
Yolo, CA	170,044	1.23	0.27	0.21	0.21	0.27	0.00	0.04	0.03
Manchester, NH	107,037	1.23	0.22	0.18	0.17	0.12	-0.03	0.02	-0.03
Denver-Boulder, CO	2,198,801	1.22	0.24	0.20	0.23	0.22	0.03	0.03	0.05
Miami, FL	2,221,632	1.22	0.27	0.20	0.20	0.17	0.00	-0.11	-0.12
Colorado Springs, CO	515,629	1.22	0.24	0.19	0.13	0.03	-0.06	0.06	0.07
San Luis Obispo-Atascadero-Paso Robles, CA	246,312	1.21	0.28	0.24	0.23	0.42	0.04	0.04	0.04
Las Vegas, NV	1,375,174	1.21	0.24	0.19	0.18	0.07	-0.01	-0.08	-0.12
Newburgh-Middletown, NY	343,591	1.21	0.22	0.17	0.23	0.13	0.04	-0.02	0.01
Boston, MA	3,951,557	1.20	0.22	0.21	0.31	0.46	0.12	0.09	0.09
West Palm Beach-Boca Raton, FL	1,133,519	1.20	0.25	0.18	0.23	0.09	0.05	-0.04	0.00
Nashua, NH	116,182	1.20	0.22	0.16	0.25	0.15	0.07	0.07	0.07
Atlanta, GA	3,987,990	1.19	0.23	0.18	0.17	0.03	-0.01	-0.01	0.02
Orlando, FL	1,652,742	1.18	0.25	0.18	0.12	-0.05	-0.04	-0.01	-0.03
Dutchess County, NY	277,140	1.18	0.23	0.17	0.21	0.15	0.05	0.04	0.06
Madison, WI	429,839	1.17	0.24	0.19	0.16	0.12	0.00	0.11	0.11
Sarasota, FL	587,565	1.17	0.24	0.18	0.15	0.08	0.00	-0.02	-0.01
Reno, NV	339,936	1.17	0.25	0.20	0.20	0.20	0.04	-0.03	-0.03
Bridgeport-Milford, CT	343,379	1.17	0.24	0.20	0.20	0.36	0.05	-0.08	0.03
Chicago, IL	8,804,453	1.16	0.22	0.18	0.19	0.24	0.04	0.00	0.02
Fort Collins, CO	235,532	1.16	0.26	0.20	0.13	0.12	-0.02	0.09	0.12

TABLE A1: INTER-METROPOLITAN INDICES, YEAR 2000

MSA Name	MSA Population	Relative Price of Housing Index	Median Expenditure Share on Housing		Housing Price Index		Non-Housing Price Index	Predicted Wage Index	
			Renters Only	Renters & Owners	Rentals Only	Rentals & Owned		Renters Only	Renters & Owners
Dalls-Fort Worth, TX	5,043,876	1.16	0.22	0.16	0.14	-0.02	-0.01	0.00	0.01
Non-metropolitan CT	1,350,818	1.14	0.21	0.17	0.17	0.17	0.03	0.04	0.07
Portland, OR-WA	1,789,019	1.13	0.24	0.21	0.15	0.21	0.03	0.03	0.05
Houston, TX	4,413,414	1.13	0.22	0.15	0.08	-0.10	-0.04	-0.04	-0.02
New Haven-West Haven, CT	358,125	1.12	0.23	0.19	0.16	0.20	0.04	0.01	0.04
Minneapolis-St. Paul, MN-WI	2,856,295	1.12	0.23	0.17	0.18	0.07	0.06	0.05	0.08
Raleigh-Durham, NC	1,182,869	1.11	0.24	0.18	0.11	0.05	0.00	0.02	0.07
Philadelphia, PA-NJ	5,082,137	1.11	0.22	0.17	0.17	0.07	0.06	0.02	0.03
Anchorage, AK	259,063	1.11	0.24	0.17	0.30	0.20	0.19	0.07	0.05
Bryan-College Station, TX	153,194	1.11	0.35	0.21	-0.01	-0.12	-0.12	0.03	0.04
Santa Fe, NM	148,785	1.11	0.24	0.20	0.11	0.29	0.01	0.11	0.10
Fort Myers-Cape Coral, FL	440,333	1.10	0.24	0.17	0.06	-0.03	-0.04	-0.04	-0.05
Charlottesville, VA	160,421	1.09	0.24	0.19	0.07	0.00	-0.02	0.04	0.06
Tampa-St. Petersburg, FL	2,386,781	1.09	0.23	0.17	0.06	-0.09	-0.02	0.00	-0.01
Milwaukee, WI	1,499,015	1.08	0.21	0.17	0.04	0.04	-0.04	0.02	0.04
Wilmington, DE-NJ-MD	499,454	1.08	0.21	0.17	0.12	0.07	0.04	0.01	0.05
Rochester, NY	1,030,303	1.08	0.24	0.15	0.08	-0.09	0.01	0.02	0.06
Stockton, CA	562,377	1.08	0.23	0.19	0.07	0.11	0.00	-0.11	-0.08
Non-metropolitanNH	1,011,597	1.08	0.22	0.17	0.08	0.04	0.01	0.07	0.07
Hartford, CT	708,743	1.07	0.21	0.17	0.11	0.16	0.04	-0.02	0.03
Sacramento, CA	1,632,863	1.07	0.24	0.20	0.15	0.19	0.08	0.03	0.03
Daytona Beach, FL	445,477	1.07	0.25	0.17	-0.01	-0.17	-0.08	0.01	-0.03
Atlantic City, NJ	359,167	1.07	0.25	0.19	0.09	0.10	0.03	-0.13	-0.08
Flagstaff, AZ-UT	117,109	1.07	0.25	0.19	0.01	0.03	-0.06	0.06	0.01
Tacoma, WA	706,103	1.06	0.23	0.19	0.08	0.11	0.02	0.02	0.00
Olympia, WA	210,011	1.06	0.24	0.19	0.08	0.08	0.02	0.05	0.08
Jacksonville, FL	1,101,766	1.06	0.23	0.16	0.01	-0.11	-0.05	0.02	0.00
Iowa City, IA	108,518	1.06	0.30	0.18	0.03	-0.01	-0.02	0.09	0.09
Tucson, AZ	843,732	1.06	0.25	0.19	0.00	-0.03	-0.05	-0.01	0.00
State College, PA	134,971	1.05	0.29	0.19	0.04	-0.06	-0.01	0.14	0.07
Barnstable-Yarmouth, MA	144,360	1.05	0.25	0.21	0.11	0.28	0.06	0.04	0.05
Salt Lake City-Ogden, UT	1,331,833	1.05	0.23	0.19	0.08	0.04	0.03	0.02	0.04
Albany-Schenectady-Troy, NY	796,100	1.05	0.22	0.16	0.05	-0.04	0.00	0.06	0.07
Riverside-San Bernardino-Ontario, CA	3,253,263	1.04	0.25	0.19	0.11	0.09	0.07	-0.06	-0.07
Indianapolis, IN	1,603,021	1.04	0.21	0.16	-0.03	-0.10	-0.07	0.00	0.02
Charleston-North Charleston, SC	454,054	1.04	0.24	0.18	-0.01	-0.01	-0.05	0.00	-0.01
Albuquerque, NM	712,937	1.04	0.25	0.19	0.00	0.00	-0.04	0.03	0.02
Omaha, NE-IA	584,099	1.04	0.21	0.16	-0.05	-0.16	-0.08	0.03	0.05
Detroit, MI	4,430,477	1.04	0.20	0.16	0.02	0.05	-0.02	-0.02	0.02
Nashville-Davidson, TN	1,234,004	1.04	0.23	0.18	-0.03	-0.05	-0.07	0.01	0.01
Bellingham, WA	169,001	1.04	0.27	0.22	0.05	0.12	0.01	0.04	0.02
Melbourne-Titusville-Cocoa, FL	479,298	1.03	0.23	0.16	0.00	-0.17	-0.04	0.06	0.04

TABLE A1: INTER-METROPOLITAN INDICES, YEAR 2000

MSA Name	MSA Population	Relative Price of Housing Index	Median Expenditure Share on Housing		Housing Price Index		Non-Housing Price Index	Predicted Wage Index	
			Renters Only	Renters & Owners	Rentals Only	Rentals & Owned		Renters Only	Renters & Owners
Charlotte-Gastonia, NC	1,499,677	1.03	0.21	0.17	0.01	-0.04	-0.02	-0.02	0.00
Non-metropolitan RI	258,023	1.03	0.22	0.19	0.08	0.21	0.05	0.08	0.11
Bremerton, WA	234,652	1.03	0.23	0.19	0.04	0.11	0.01	0.09	0.08
Brockton, MA	258,188	1.03	0.22	0.19	0.09	0.18	0.06	-0.02	0.00
Baltimore, MD	2,513,661	1.03	0.22	0.17	0.05	0.03	0.02	0.02	0.03
Lafayette-West Lafayette, IN	181,493	1.02	0.27	0.18	-0.05	-0.12	-0.08	0.05	0.01
Non-metropolitan HI	335,651	1.02	0.23	0.22	0.12	0.35	0.10	-0.01	-0.09
Des Moines, IA	375,685	1.02	0.21	0.16	0.00	-0.07	-0.02	0.04	0.05
Lancaster, PA	464,550	1.02	0.21	0.17	0.01	-0.03	-0.01	-0.04	-0.01
Portland, ME	241,693	1.02	0.22	0.18	0.05	0.07	0.03	0.07	0.07
Norfolk-Virginia Beach-Portsmouth, VA-NC	1,553,838	1.02	0.24	0.18	-0.03	-0.07	-0.05	0.00	0.00
San Antonio, TX	1,551,396	1.02	0.22	0.15	-0.07	-0.25	-0.08	0.00	-0.04
Killeen-Temple, TX	313,151	1.01	0.22	0.17	-0.10	-0.25	-0.12	0.05	-0.03
Memphis, TN-AR-MS	998,698	1.01	0.23	0.17	-0.07	-0.16	-0.09	-0.04	-0.03
Richmond, VA	995,112	1.01	0.23	0.17	-0.02	-0.10	-0.03	0.01	0.03
Rochester, MN	122,319	1.01	0.21	0.15	0.02	-0.14	0.01	0.02	0.07
Kenosha, WI	148,260	1.01	0.21	0.16	0.03	0.02	0.02	0.01	0.03
Chico, CA	202,375	1.01	0.28	0.21	-0.02	0.03	-0.03	0.02	0.00
Columbus, OH	1,443,293	1.00	0.22	0.17	-0.02	-0.06	-0.02	0.02	0.03
Kansas City, MO-KS	1,682,053	1.00	0.21	0.16	-0.01	-0.12	-0.02	0.02	0.05
Gainesville, FL	219,795	1.00	0.30	0.19	-0.04	-0.16	-0.04	0.07	0.07
Galveston-Texas City, TX	249,853	1.00	0.22	0.15	-0.03	-0.15	-0.03	0.02	0.02
Provo-Orem, UT	367,035	1.00	0.24	0.21	-0.01	-0.02	0.00	0.04	0.08
Fort Pierce, FL	323,090	1.00	0.25	0.16	-0.03	-0.12	-0.02	-0.07	-0.04
Allentown-Bethlehem, PA-NJ	641,637	1.00	0.21	0.16	0.00	-0.04	0.01	-0.01	0.01
Eugene-Springfield, OR	324,317	0.99	0.27	0.21	0.01	0.08	0.01	0.04	0.04
Redding, CA	162,160	0.99	0.26	0.20	-0.04	0.00	-0.04	0.01	0.01
Columbia, SC	544,165	0.99	0.22	0.16	-0.09	-0.15	-0.09	0.01	0.02
Medford, OR	179,811	0.99	0.26	0.21	-0.02	0.06	-0.01	0.03	0.03
Non-metropolitan VT	608,387	0.99	0.23	0.18	-0.02	-0.06	0.00	0.06	0.05
Lansing-East Lansing, MI	445,925	0.98	0.23	0.16	-0.03	-0.12	-0.01	0.03	0.05
Wilmington, NC	233,637	0.98	0.25	0.20	-0.04	0.00	-0.02	0.00	0.00
Modesto, CA	450,865	0.98	0.22	0.18	0.04	0.05	0.06	-0.08	-0.09
Non-metropolitan AK	367,124	0.98	0.21	0.18	0.17	0.11	0.19	0.08	0.02
South Bend, IN	266,264	0.98	0.21	0.15	-0.13	-0.24	-0.11	-0.02	0.01
Bloomington, IN	122,388	0.98	0.32	0.21	-0.02	-0.08	0.01	0.05	0.07
Non-metropolitan CO	924,086	0.98	0.23	0.20	0.03	0.13	0.06	0.05	0.06
Lexington-Fayette, KY	258,129	0.98	0.24	0.17	-0.06	-0.11	-0.03	0.03	0.05
Richland-Kennewick-Pasco, WA	191,186	0.97	0.21	0.16	-0.04	-0.11	-0.02	-0.07	0.00
Non-metropolitan CA	1,249,739	0.97	0.24	0.20	-0.03	0.13	0.00	-0.04	-0.05
Worcester, MA	282,673	0.97	0.21	0.18	0.02	0.10	0.05	0.02	0.04
Savannah, GA	232,087	0.97	0.24	0.18	-0.06	-0.08	-0.03	-0.02	-0.02

TABLE A1: INTER-METROPOLITAN INDICES, YEAR 2000

MSA Name	MSA Population	Relative Price of Housing Index	Median Expenditure Share on Housing		Housing Price Index		Non-Housing Price Index	Predicted Wage Index	
			Renters Only	Renters & Owners	Rentals Only	Rentals & Owned		Renters Only	Renters & Owners
Reading, PA	368,284	0.96	0.21	0.16	-0.05	-0.11	-0.01	-0.02	-0.02
Racine, WI	185,041	0.96	0.21	0.16	-0.06	-0.07	-0.02	0.02	0.04
Green Bay, WI	227,296	0.96	0.19	0.16	-0.07	-0.07	-0.03	-0.01	0.03
Myrtle Beach, SC	195,205	0.96	0.22	0.17	-0.08	-0.13	-0.04	-0.04	-0.05
Non-metropolitan NV	285,196	0.96	0.22	0.17	-0.04	-0.04	0.00	0.02	-0.02
Champaign-Urbana-Rantoul, IL	181,422	0.96	0.27	0.17	-0.01	-0.12	0.03	0.08	0.06
Cincinnati, OH-KY-IN	1,473,012	0.96	0.21	0.16	-0.09	-0.06	-0.05	0.00	0.03
Lincoln, NE	246,945	0.96	0.23	0.17	-0.06	-0.15	-0.02	0.04	0.06
Boise City, ID	430,161	0.96	0.24	0.17	-0.04	-0.11	0.01	0.02	0.05
St. Louis, MO-IL	2,602,448	0.95	0.21	0.15	-0.07	-0.11	-0.02	0.02	0.03
Springfield, IL	112,222	0.95	0.20	0.15	-0.14	-0.21	-0.09	0.04	0.05
Corpus Christi, TX	261,023	0.95	0.22	0.15	-0.10	-0.24	-0.05	0.02	-0.01
Salem, OR	282,595	0.95	0.23	0.19	-0.03	0.03	0.03	-0.03	-0.02
Yuma, AZ	160,196	0.95	0.23	0.17	-0.14	-0.18	-0.09	-0.05	-0.12
Non-metropolitan MA	569,691	0.95	0.21	0.18	-0.03	0.11	0.02	0.04	0.06
Punta Gorda, FL	141,080	0.95	0.23	0.16	-0.07	-0.15	-0.02	0.00	-0.03
Hamilton-Middletown, OH	334,518	0.95	0.21	0.16	-0.07	-0.08	-0.01	0.03	0.05
Syracuse, NY	731,789	0.95	0.23	0.15	-0.07	-0.21	-0.01	0.01	0.03
Tallahassee, FL	286,063	0.94	0.30	0.18	-0.02	-0.10	0.04	0.07	0.06
Fort Walton Beach, FL	171,551	0.94	0.23	0.17	-0.05	-0.14	0.00	0.09	0.04
Jackson, MS	438,789	0.94	0.23	0.16	-0.18	-0.26	-0.12	-0.03	0.00
Athens, GA	153,445	0.94	0.27	0.19	-0.11	-0.16	-0.05	-0.03	0.00
Tulsa, OK	694,760	0.94	0.22	0.15	-0.12	-0.22	-0.06	0.00	0.04
Sioux Falls, SD	124,076	0.94	0.21	0.16	-0.10	-0.18	-0.03	-0.02	-0.01
Cedar Rapids, IA	188,914	0.94	0.21	0.15	-0.10	-0.13	-0.04	0.05	0.06
Elkhart, IN	182,252	0.93	0.20	0.15	-0.14	-0.20	-0.07	-0.04	-0.05
Harrisburg, PA	629,304	0.93	0.21	0.16	-0.08	-0.08	0.00	0.03	0.01
Wichita, KS	543,518	0.93	0.20	0.15	-0.12	-0.25	-0.05	0.02	0.04
Fitchburg-Leominster, MA	141,969	0.93	0.20	0.17	-0.05	0.02	0.03	-0.03	0.00
Tyler, TX	174,917	0.92	0.22	0.15	-0.13	-0.25	-0.05	-0.02	-0.02
Greensboro--Winston-Salem--High Point, NC	1,252,554	0.92	0.21	0.16	-0.14	-0.14	-0.06	-0.05	-0.02
Amarillo, TX	215,463	0.92	0.22	0.15	-0.15	-0.27	-0.07	-0.02	-0.02
Akron, OH	692,912	0.92	0.22	0.17	-0.09	-0.08	-0.01	0.01	0.03
Springfield-Chicopee-Holyoke, MA-CT	594,643	0.92	0.22	0.18	-0.07	0.02	0.02	0.01	0.02
Appleton-Oshkosh, WI	357,928	0.92	0.19	0.15	-0.12	-0.14	-0.03	0.04	0.05
Buffalo, NY	1,175,089	0.92	0.23	0.16	-0.11	-0.16	-0.03	0.02	0.04
York, PA	383,994	0.92	0.20	0.16	-0.09	-0.12	-0.01	0.00	0.00
Fayetteville-Springdale, AR	309,915	0.92	0.22	0.17	-0.19	-0.22	-0.11	0.01	-0.02
Panama City, FL	146,122	0.92	0.23	0.17	-0.12	-0.17	-0.04	0.00	-0.02
New Orleans, LA	1,246,651	0.92	0.23	0.18	-0.11	-0.09	-0.03	-0.04	-0.04
Glens Falls, NY	123,609	0.91	0.23	0.17	-0.05	-0.17	0.04	0.00	0.00
Greeley, CO	178,872	0.91	0.24	0.20	-0.07	-0.02	0.02	-0.03	0.01

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			Renters Only	Renters & Owners	Rentals Only	Rentals & Owned		Renters Only	Renters & Owners
Ocala, FL	259,712	0.91	0.22	0.16	-0.15	-0.33	-0.06	-0.04	-0.08
Little Rock-North Little Rock, AR	584,977	0.91	0.23	0.16	-0.15	-0.20	-0.06	0.00	0.01
Evansville, IN-KY	252,410	0.91	0.20	0.15	-0.21	-0.21	-0.11	0.02	0.02
Lakeland-Winter Haven, FL	482,562	0.91	0.21	0.15	-0.15	-0.27	-0.06	-0.05	-0.08
Bakersfield, CA	650,891	0.91	0.23	0.17	-0.11	-0.14	-0.01	-0.08	-0.09
Dover, DE	125,613	0.91	0.22	0.17	-0.09	-0.14	0.01	0.01	-0.02
Grand Junction, CO	111,922	0.91	0.25	0.20	-0.13	-0.08	-0.03	-0.02	0.03
Cleveland, OH	2,255,480	0.91	0.21	0.17	-0.06	-0.03	0.04	0.00	0.02
Grand Rapids, MI	984,107	0.91	0.21	0.16	-0.07	-0.11	0.03	-0.05	0.03
Lubbock, TX	243,899	0.91	0.25	0.17	-0.15	-0.30	-0.05	-0.02	-0.03
Vineland-Millville-Bridgeton, NJ	146,275	0.91	0.25	0.16	-0.05	-0.12	0.05	-0.19	-0.12
Janesville-Beloit, WI	151,640	0.90	0.20	0.15	-0.12	-0.16	-0.02	-0.03	0.00
Oklahoma City, OK	892,347	0.90	0.22	0.16	-0.15	-0.24	-0.05	0.01	0.01
Jacksonville, NC	149,091	0.90	0.22	0.17	-0.16	-0.25	-0.05	0.06	-0.02
Kalamazoo-Portage, MI	451,406	0.90	0.21	0.16	-0.13	-0.19	-0.03	-0.02	0.02
Dayton, OH	954,465	0.90	0.21	0.16	-0.14	-0.13	-0.03	0.00	0.02
Yuba City, CA	137,870	0.90	0.22	0.19	-0.15	-0.09	-0.04	-0.03	-0.06
Asheville, NC	225,195	0.90	0.23	0.18	-0.11	-0.06	0.00	0.02	-0.01
Clarksville-Hopkinsville, TN-KY	134,209	0.90	0.21	0.17	-0.18	-0.30	-0.08	0.05	-0.01
Waterbury, CT	108,117	0.90	0.22	0.17	-0.04	-0.02	0.07	-0.08	-0.12
Providence-Warwick-Pawtucket, RI-MA	1,025,944	0.90	0.21	0.18	-0.09	0.04	0.02	-0.03	-0.01
Topeka, KS	168,994	0.90	0.21	0.15	-0.17	-0.28	-0.06	0.02	0.03
Merced, CA	209,707	0.90	0.24	0.20	-0.13	-0.06	-0.02	-0.15	-0.16
Birmingham, AL	803,700	0.89	0.21	0.16	-0.16	-0.16	-0.05	0.02	0.03
Columbia, MO	136,063	0.89	0.24	0.18	-0.14	-0.21	-0.02	0.10	0.07
Roanoke, VA	236,363	0.89	0.21	0.16	-0.21	-0.22	-0.09	0.00	0.00
Pensacola, FL	411,270	0.89	0.24	0.17	-0.15	-0.24	-0.03	0.03	0.00
Sheboygan, WI	111,021	0.89	0.17	0.15	-0.18	-0.14	-0.06	0.03	0.02
Fresno, CA	924,612	0.89	0.24	0.19	-0.06	-0.04	0.06	-0.13	-0.10
Greenville-Spartanburg, SC	796,528	0.88	0.20	0.16	-0.21	-0.21	-0.08	-0.02	-0.01
Binghamton, NY-PA	254,116	0.88	0.23	0.14	-0.16	-0.28	-0.04	0.01	0.04
Kankakee, IL	104,042	0.88	0.21	0.16	-0.13	-0.12	0.00	-0.08	-0.03
Spokane, WA	418,375	0.88	0.25	0.18	-0.10	-0.13	0.02	0.04	0.04
Bloomington-Normal, IL	152,616	0.88	0.22	0.15	-0.08	-0.14	0.05	0.05	0.09
Davenport-Rock Island-Moline, IA-IL	268,781	0.88	0.20	0.15	-0.17	-0.20	-0.05	0.01	0.01
Fayetteville, NC	299,932	0.88	0.23	0.18	-0.12	-0.21	0.01	0.05	-0.03
Wichita Falls, TX	131,595	0.88	0.22	0.15	-0.19	-0.36	-0.06	0.03	0.00
Non-metropolitan OR	1,194,699	0.88	0.24	0.19	-0.11	-0.03	0.03	0.01	0.00
Rockford, IL	319,846	0.88	0.20	0.15	-0.14	-0.20	-0.01	-0.02	0.00
Pueblo, CO	135,990	0.87	0.25	0.18	-0.22	-0.23	-0.09	-0.06	-0.05
Montgomery, AL	333,479	0.87	0.23	0.17	-0.18	-0.22	-0.04	0.02	0.00
La Crosse, WI	105,700	0.87	0.21	0.16	-0.18	-0.19	-0.04	0.04	0.05

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Fort Wayne, IN	460,349	0.87	0.20	0.15	-0.18	-0.27	-0.04	0.00	0.01
Wausau, WI	127,099	0.87	0.19	0.15	-0.16	-0.25	-0.02	0.03	0.02
Yakima, WA	223,726	0.87	0.25	0.19	-0.14	-0.07	0.00	-0.12	-0.10
Biloxi-Gulfport, MS	318,936	0.87	0.22	0.16	-0.17	-0.24	-0.03	-0.02	-0.02
Louisville, KY-IN	921,599	0.86	0.21	0.16	-0.18	-0.15	-0.03	-0.02	0.00
Pittsburgh, PA	2,285,064	0.86	0.21	0.15	-0.16	-0.19	0.00	0.05	0.05
Non-metropolitan UT	531,967	0.86	0.22	0.19	-0.17	-0.17	-0.02	0.04	0.05
Sioux City, IA-NE	103,140	0.85	0.21	0.15	-0.20	-0.27	-0.04	-0.04	-0.03
Eau Claire, WI	147,758	0.85	0.21	0.16	-0.20	-0.24	-0.05	0.04	0.02
El Paso, TX	676,220	0.85	0.24	0.16	-0.25	-0.38	-0.09	-0.04	-0.10
Waterloo-Cedar Falls, IA	124,908	0.85	0.24	0.15	-0.20	-0.27	-0.04	-0.01	0.02
Waco, TX	212,313	0.85	0.23	0.16	-0.22	-0.33	-0.06	-0.03	-0.04
Columbus, GA-AL	186,426	0.85	0.22	0.17	-0.23	-0.25	-0.07	-0.03	-0.03
Non-metropolitan NY	1,744,930	0.85	0.23	0.15	-0.13	-0.26	0.03	0.02	0.01
Knoxville, TN	576,512	0.85	0.23	0.17	-0.25	-0.24	-0.08	0.02	0.03
Non-metropolitan WA	1,063,531	0.84	0.23	0.19	-0.13	-0.03	0.04	-0.01	0.00
Non-metropolitan MD	666,998	0.84	0.22	0.17	-0.18	-0.11	-0.01	-0.03	0.00
Odessa, TX	238,692	0.84	0.21	0.14	-0.22	-0.39	-0.05	0.01	-0.03
Benton Harbor, MI	163,682	0.84	0.20	0.16	-0.20	-0.20	-0.03	-0.01	0.01
Muncie, IN	119,028	0.84	0.24	0.16	-0.24	-0.31	-0.07	-0.03	0.00
Toledo, OH-MI	617,883	0.84	0.21	0.16	-0.20	-0.17	-0.02	-0.01	0.01
Utica-Rome, NY	300,337	0.84	0.22	0.15	-0.20	-0.30	-0.03	0.00	0.01
Greenville, NC	134,932	0.84	0.26	0.17	-0.22	-0.19	-0.05	-0.03	-0.01
Baton Rouge, LA	604,708	0.84	0.24	0.16	-0.17	-0.18	0.01	-0.03	0.00
Kokomo, IN	100,506	0.84	0.20	0.13	-0.20	-0.23	-0.02	0.00	0.00
Abilene, TX	126,952	0.83	0.22	0.16	-0.21	-0.36	-0.03	0.01	0.00
Tuscaloosa, AL	164,875	0.83	0.27	0.18	-0.20	-0.20	-0.02	-0.01	-0.01
Youngstown-Warren, OH	593,100	0.82	0.20	0.15	-0.29	-0.28	-0.10	0.00	0.00
Fargo-Moorhead, ND-MN	121,173	0.82	0.22	0.16	-0.21	-0.25	-0.01	0.04	0.03
Billings, MT	128,660	0.82	0.22	0.16	-0.22	-0.25	-0.03	0.06	0.03
Auburn-Opelika, AL	116,435	0.82	0.30	0.17	-0.27	-0.25	-0.07	0.04	0.00
Longview-Marshall, TX	170,557	0.82	0.21	0.15	-0.26	-0.36	-0.07	0.01	0.00
Shreveport, LA	393,700	0.82	0.22	0.16	-0.29	-0.33	-0.09	-0.06	-0.04
Flint, MI	240,153	0.82	0.23	0.14	-0.21	-0.32	-0.01	-0.09	-0.12
Mobile, AL	540,100	0.82	0.24	0.17	-0.28	-0.27	-0.08	-0.02	-0.01
Augusta, GA-SC	451,061	0.82	0.22	0.16	-0.25	-0.28	-0.05	-0.03	-0.02
Erie, PA	279,521	0.82	0.21	0.16	-0.25	-0.26	-0.04	0.02	0.01
Saginaw, MI	400,853	0.81	0.22	0.15	-0.21	-0.24	0.00	-0.05	0.01
Rocky Mount, NC	143,674	0.81	0.21	0.16	-0.27	-0.24	-0.06	-0.11	-0.08
Hickory, NC	342,072	0.81	0.19	0.15	-0.25	-0.23	-0.04	-0.04	-0.06
Jackson, MI	160,391	0.81	0.20	0.15	-0.22	-0.21	-0.01	-0.04	0.01
Macon, GA	321,450	0.81	0.22	0.15	-0.25	-0.31	-0.04	-0.03	-0.02

TABLE A1: INTER-METROPOLITAN INDICES, YEAR 2000

MSA Name	MSA Population	Relative Price of Housing Index	Median Expenditure Share on Housing		Housing Price Index		Non-Housing Price Index	Predicted Wage Index	
			Renters Only	Renters & Owners	Rentals Only	Rentals & Owned		Renters Only	Renters & Owners
Canton, OH	408,072	0.81	0.21	0.16	-0.25	-0.20	-0.04	-0.01	0.00
Chattanooga, TN-GA	434,752	0.81	0.21	0.16	-0.23	-0.25	-0.02	0.01	0.00
St. Joseph, MO	101,442	0.81	0.22	0.16	-0.29	-0.34	-0.08	0.01	-0.01
Visalia-Tulare-Porterville, CA	367,566	0.81	0.24	0.19	-0.16	-0.11	0.06	-0.20	-0.19
Albany, GA	120,551	0.80	0.22	0.15	-0.30	-0.33	-0.08	-0.02	-0.05
Laredo, TX	190,074	0.80	0.23	0.18	-0.29	-0.34	-0.07	-0.09	-0.13
Springfield, MO	327,829	0.80	0.23	0.17	-0.25	-0.28	-0.04	0.01	0.00
Hattiesburg, MS	111,694	0.80	0.26	0.17	-0.29	-0.37	-0.07	0.03	0.02
Las Cruces, NM	173,843	0.80	0.25	0.17	-0.31	-0.27	-0.09	-0.02	-0.08
Hagerstown, MD	128,316	0.80	0.19	0.17	-0.23	-0.14	-0.01	-0.02	-0.02
Non-metropolitan AZ	942,343	0.80	0.22	0.17	-0.24	-0.20	-0.02	0.00	-0.07
Beaumont-Port Arthur-Orange, TX	381,559	0.80	0.22	0.13	-0.28	-0.40	-0.06	-0.05	-0.02
Jamestown-Dunkirk, NY	140,116	0.80	0.22	0.15	-0.25	-0.39	-0.03	-0.01	0.00
Huntsville, AL	344,491	0.80	0.20	0.15	-0.24	-0.26	-0.01	0.01	0.06
New Bedford, MA	174,864	0.79	0.19	0.18	-0.20	0.04	0.03	-0.09	-0.07
Non-metropolitan ME	1,033,664	0.79	0.21	0.17	-0.24	-0.22	-0.01	0.04	0.02
Non-metropolitan ID	863,855	0.79	0.22	0.17	-0.26	-0.24	-0.03	0.01	0.01
Lynchburg, VA	213,723	0.79	0.20	0.16	-0.30	-0.30	-0.07	-0.04	-0.02
St. Cloud, MN	168,856	0.79	0.20	0.15	-0.24	-0.27	0.00	0.02	0.01
Fort Smith, AR-OK	169,401	0.79	0.19	0.15	-0.35	-0.36	-0.11	-0.03	-0.05
Non-metropolitan MI	2,178,963	0.79	0.21	0.15	-0.28	-0.26	-0.05	0.01	0.00
Lake Charles, LA	183,144	0.79	0.20	0.14	-0.33	-0.32	-0.09	-0.04	-0.03
Johnson City-Kingsport-Bristol, TN-VA	314,402	0.78	0.21	0.16	-0.38	-0.33	-0.13	0.03	0.01
Scranton-Wilkes-Barre, PA	624,276	0.78	0.20	0.17	-0.27	-0.21	-0.03	0.02	0.01
Williamsport, PA	121,501	0.78	0.20	0.16	-0.28	-0.26	-0.03	0.01	-0.01
Decatur, IL	114,926	0.78	0.22	0.14	-0.29	-0.35	-0.05	0.02	0.00
Peoria, IL	346,102	0.78	0.20	0.15	-0.25	-0.23	0.00	0.03	0.04
Non-metropolitan FL	1,222,532	0.78	0.22	0.16	-0.22	-0.26	0.03	-0.08	-0.08
Non-metropolitan WI	1,866,585	0.78	0.19	0.15	-0.27	-0.25	-0.02	0.01	0.00
Non-metropolitan IN	1,791,003	0.77	0.19	0.15	-0.31	-0.30	-0.06	-0.01	-0.02
Joplin, MO	155,401	0.77	0.21	0.15	-0.36	-0.42	-0.10	-0.02	-0.01
Lafayette, LA	247,230	0.77	0.22	0.15	-0.31	-0.27	-0.05	0.02	0.00
Mansfield, OH	130,084	0.77	0.19	0.15	-0.32	-0.28	-0.06	-0.01	-0.01
Non-metropolitan KS	1,366,517	0.76	0.21	0.15	-0.32	-0.43	-0.05	0.04	0.01
Sharon, PA	120,147	0.76	0.19	0.15	-0.32	-0.32	-0.05	0.05	0.01
Non-metropolitan WY	493,849	0.76	0.20	0.16	-0.30	-0.26	-0.03	0.04	0.02
Non-metropolitan TX	4,030,376	0.76	0.20	0.14	-0.39	-0.47	-0.11	-0.04	-0.06
Houma-Thibodaux, LA	103,563	0.75	0.20	0.15	-0.34	-0.33	-0.06	-0.07	-0.07
Non-metropolitan VA	1,640,567	0.75	0.20	0.16	-0.35	-0.34	-0.06	-0.02	-0.05
Duluth-Superior, MN-WI	199,548	0.75	0.21	0.14	-0.30	-0.31	-0.02	0.04	0.06
Lima, OH	156,274	0.75	0.18	0.14	-0.35	-0.33	-0.06	0.01	0.01
Non-metropolitan IA	1,863,270	0.75	0.19	0.14	-0.35	-0.37	-0.06	0.02	0.00

TABLE A1: INTER-METROPOLITAN INDICES, YEAR 2000

MSA Name	MSA Population	Relative Price of Housing Index	Median Expenditure Share on Housing		Housing Price Index		Non-Housing Price Index	Predicted Wage Index	
			Renters Only	Renters & Owners	Rentals Only	Rentals & Owned		Renters Only	Renters & Owners
Terre Haute, IN	149,397	0.75	0.22	0.15	-0.34	-0.37	-0.05	0.01	0.00
Non-metropolitan MN	1,565,030	0.74	0.20	0.15	-0.34	-0.35	-0.05	0.00	0.01
Monroe, LA	146,975	0.74	0.23	0.16	-0.35	-0.32	-0.05	-0.05	-0.04
Non-metropolitan PA	2,023,193	0.74	0.20	0.15	-0.34	-0.34	-0.04	0.01	-0.02
Goldsboro, NC	113,118	0.74	0.20	0.16	-0.38	-0.30	-0.08	0.01	-0.05
Non-metropolitan DE	158,149	0.73	0.20	0.17	-0.33	-0.09	-0.02	-0.06	-0.03
Non-metropolitan OH	2,548,986	0.73	0.19	0.15	-0.34	-0.31	-0.03	0.00	-0.02
Non-metropolitan IL	2,202,549	0.73	0.20	0.14	-0.36	-0.37	-0.05	0.02	0.00
Sumter, SC	104,047	0.72	0.21	0.15	-0.35	-0.39	-0.03	0.03	-0.06
Altoona, PA	131,023	0.72	0.19	0.15	-0.37	-0.34	-0.04	-0.02	-0.02
Alexandria, LA	128,075	0.72	0.22	0.16	-0.39	-0.38	-0.06	-0.10	-0.06
Non-metropolitan MT	774,080	0.72	0.23	0.18	-0.31	-0.25	0.01	0.04	0.03
Jackson, TN	107,550	0.72	0.22	0.16	-0.33	-0.36	0.01	-0.10	-0.03
Non-metropolitan NE	878,760	0.71	0.19	0.14	-0.38	-0.45	-0.05	0.02	0.00
Decatur, AL	145,469	0.71	0.20	0.15	-0.42	-0.34	-0.08	-0.04	0.00
Non-metropolitan NC	2,632,956	0.71	0.21	0.16	-0.37	-0.28	-0.03	-0.07	-0.07
Non-metropolitan GA	2,744,802	0.70	0.20	0.15	-0.40	-0.35	-0.05	-0.07	-0.07
McAllen-Pharr-Edinburg, TX	565,800	0.70	0.22	0.16	-0.45	-0.58	-0.09	-0.11	-0.19
Non-metropolitan WV	1,809,034	0.70	0.21	0.15	-0.43	-0.44	-0.07	0.02	0.00
Non-metropolitan ND	521,239	0.70	0.20	0.14	-0.44	-0.51	-0.08	0.07	0.02
Dothan, AL	138,133	0.69	0.19	0.15	-0.44	-0.42	-0.06	-0.03	-0.04
Danville, VA	109,618	0.68	0.20	0.15	-0.44	-0.41	-0.06	-0.12	-0.10
Anniston, AL	110,594	0.68	0.21	0.15	-0.45	-0.44	-0.07	0.00	-0.03
Florence, AL	142,703	0.68	0.22	0.16	-0.46	-0.36	-0.07	-0.01	0.00
Brownsville-Harlingen-San Benito, TX	336,631	0.68	0.22	0.16	-0.41	-0.50	-0.03	-0.09	-0.16
Non-metropolitan OK	1,862,951	0.68	0.20	0.14	-0.46	-0.52	-0.07	0.00	-0.03
Non-metropolitan NM	783,050	0.67	0.21	0.16	-0.44	-0.36	-0.04	0.01	-0.06
Non-metropolitan MO	1,798,819	0.67	0.20	0.15	-0.48	-0.47	-0.08	0.01	-0.04
Non-metropolitan AR	1,607,993	0.66	0.21	0.15	-0.47	-0.47	-0.06	-0.05	-0.06
Non-metropolitan SC	1,616,255	0.66	0.20	0.15	-0.39	-0.32	0.02	-0.05	-0.08
Non-metropolitan KY	2,828,647	0.65	0.19	0.15	-0.47	-0.47	-0.05	0.01	-0.03
Non-metropolitan TN	2,123,330	0.65	0.19	0.15	-0.50	-0.43	-0.07	-0.03	-0.06
Non-metropolitan SD	629,811	0.64	0.21	0.15	-0.45	-0.46	0.00	0.05	0.01
Gadsden, AL	102,183	0.63	0.18	0.15	-0.53	-0.45	-0.07	-0.01	-0.01
Non-metropolitan MS	1,869,256	0.63	0.21	0.15	-0.53	-0.53	-0.07	-0.08	-0.08
Non-metropolitan LA	1,415,540	0.62	0.21	0.15	-0.56	-0.46	-0.08	-0.05	-0.05
Johnstown, PA	233,942	0.62	0.19	0.15	-0.53	-0.44	-0.04	0.02	-0.01
Non-metropolitan AL	1,504,381	0.58	0.19	0.15	-0.64	-0.51	-0.10	-0.03	-0.06

Rental price indices constructed from 2000 Census 5% microdata samples. Aggregate expenditure shares constructed by dividing some of all rental expenditure by sum of all income in MSA. Relative price of housing index is ratio of expontiated rental housing price index to exponentiated non-housing price index.