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

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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 real income inequality. Rising rents and inequality both help explain why housing has become less affordable.

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

JEL Numbers: D12, E31, R21

1 Introduction

Food, clothing, and shelter are all considered to be basic needs for life, yet their consumption patterns have differed widely over the past several decades. In the United States since 1959, the fraction of Personal Consumption Expenditures (PCE) devoted to food and clothing fell from 27.4 percent to 10.6 percent, while expenditures on housing and utilities actually rose from 16.1 to 18.1 percent.[1] In the American Housing Survey and the Consumer Expenditure Survey, the rise has been even more dramatic, about 7 percentage points since 1970 (see Figure 1B). The increase has been even sharper for renters, even while the homeownership rate has not risen appreciably (Figure 1C). The percentage of renting households facing "moderate" or "extreme" affordability burdens more than 30 or 50 percent of their income spent on housing has risen by 20 and 15 percentage points. These trends 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).[2]

The increasing share of expenditures on housing appears to contradict the view that housing is a necessity, as incomes have risen over time (see Figure 1D). One possible resolution to this apparent paradox may be that the price of housing (or shelter) services has risen 35 over percent relative to other goods since 1970 according to the Consumer Price Index (CPI). If demand is price inelastic, this rising price could have caused housing's share to rise, even as incomes grew.

Figure 2 graphs these ideas using a production possibility frontier (PPF) and indifference curves, for housing and non-housing goods. It seems that the PPF has expanded further in the direction of non-housing goods, as many of these may be traded internationally and subject to greater technological improvements. With this expansion, 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) lead households to increase their consumption of non-housing goods

[1] Food here is defined as "Food and beverages purchased for off-premises consumption," while clothing corresponds to "Clothing and footwear."

[2] 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.

more than of housing. 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 if substitution response is limited (compare C and E).

Demand may have changed for other reasons. In particular, demographic changes have led to smaller families and households, also seen in Figure 1D. Housing consumption has a somewhat public, or non-congestible, component. Thus, having fewer members per household should raise demand as a fraction of consumption (Barten, 1964; Deaton and Paxson, 1998). Alternatively, tastes for housing may have simply grown, perhaps as a demand for privacy.

Below, we investigate housing demand using a novel, but intuitive framework. In section 3 demonstrate that cross-sectional data lends itself to estimating compensated (Hicksian) housing demand functions, as mobility equalizes the utility households receive from living in different locations. On the other hand, time-series data lends itself only to estimating uncompensated (Marshallian) demand. 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 in section 5.1 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 that is not reliably explained by demographic changes. 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.

In a final section on applications, we provide a numerical non-homothetic, constant elasticity-of-substitution utility and expenditure functions that researchers may incorporate into their quantitative models. With this function, we illustrate how higher housing costs have a greater impact on the poor in more expensive cities. We also document how rising housing costs appear to have exacerbated increases in real income inequality since 1970. Furthermore, we decompose the increase in standard measures of housing affordability burdens into the increases predicted by rising rents and income inequality and the decreases predicted by changing household compositions and rising average incomes.[3]

2 Motivation and Related Literature

Economists' interest in housing demand and expenditures has a 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) estimate of -0.7 and Hanushek and Quigley's (1980) estimates of -0.64 in Pittsburgh and -0.45 in Phoenix.[4] 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.[5]

As for the income (or more precisely, expenditure) elasticity of housing demand, classical studies, such as Engel (1857) and Schwabe (1868), found values of less than one, which became known as "Schwabe's Law of Rent".[6] As summarized by DeLeeuw (1971), Mayo (1981) and

[3]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.

[4]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. 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.

[5]Few articles estimate elastic price demand, with elasticities greater than one. 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.

[6]Some confusion regarding Engel's findings stems from Wright's (1875) confused statement of the results in En-

later Harmon (1988), a few studies have been inconsistent with Schwabe's Law. For instance, Muth (1960) estimated an income elasticity well over one. One source of contention is how to measure income: most researchers suggest using a measure of "permanent income" to correct for attenuation bias caused by transitory income.[7]

Housing demand is a key factor affecting house prices, tax incidence, and population density. With such disparate findings, theoretical models have taken great latitude in modeling housing demand. Many models 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 recently used in Desmet and Rossi-Hansberg (2013). Other models, such as the search and matching one of Piazzesi and Schneider (2010), assume quasilinear preferences, with which demand is not responsive income. Cobb-Douglas, implying price and income elasticities of one, are a common modeling choice; 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, these disparate assumptions make it hard to integrate different findings and may lead to incorrect analyses.

Indeed, housing affordability is much more of a concern when housing is a necessity and demand is price inelastic. This is especially true for low income households, who have experienced little income gains relative to the wealthiest, particularly 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).[8]

glish; see Stigler (1954) for a discussion.

[7]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.

[8]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.

The secular rise in housing expenditures appears to be understudied. Piketty (2014) finds that the value of residential capital relative to economic output has increased substantially over the last hundred years.[9] 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).[10] 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).[11]

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.[12] Households earn total income

[9]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.

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

[11]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.

[12]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 (CEX) 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.

$m_j = I + (1-\tau)w_j$, determined by a unearned income, I, which does not vary by city, 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

$$\hat{s}_y^j = \hat{p}^j + \hat{y}^j - \hat{m}^j.\text{[13]} \tag{1}$$

We take local price and income levels as parametric to the households, so that the only behavioral variable in the share is housing consumption, y, which 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.[14] If housing is a normal good, then $\epsilon_{y,m} > 0$, and housing obeys the law of demand that $\epsilon_{y,p} < 0$. It is *a priori* unclear whether housing is a gross substitute for non-housing goods, i.e., whether $\epsilon_{y,c} > 0$,

[13] A hat over a variable represents its log deviation from the (geometric) national average, i.e., $\hat{z}^j = d \ln z^j = dz^j/\bar{z}$.

[14] Equation 2 is an identity for infinitesimal changes, and an approximation for larger changes.

because the cross-price elasticity will exhibit positive substitution effects and negative income effects of unknown magnitudes. Housing may be a gross complement or substitute for amenities, i.e. $\epsilon_{y,Q} \gtreqless 0$, if they alter the marginal rate of substitution between housing and non-housing goods.[15]

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 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 subtract the means of the right-hand side variables, the regression coefficients are related to the demand parameters as: $\alpha_0 = \ln \bar{s_y}$, $\alpha_1 = 1 + \epsilon_{y,p}$, $\alpha_2 = \epsilon_{y,c}$, 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, so $\epsilon_{y,Q}$ cannot be identified in a fully cardinal sense without additional assumptions. The same holds

[15] 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 (2015) 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.

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 is converted into a compensated (Hicksian) demand function by substituting in the expenditure function, i.e. $y^H(p, c, m; Q) = y(p, c, e(p, c, u; Q); Q)$. Log-linearizing the expenditure function directly yields

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

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 and simplifying by the Slutsky equations gives the following relationships among the uncompensated (Marshallian) and compensated (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 non-housing prices, respectively.[16] Rationality requires that compensated demand functions are homogeneous of degree zero in prices, so that the own and cross-price elasticities of compensated demand 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:

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

[16]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.

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.

We assume that similarly-skilled households are equally well-off across cities. When households are mobile, households should be indifferent across locations they inhabit, and utility by type of household will not vary across cities. Rather, utility differences will 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 of wage-earning skills, and w^j is the city-wide wage level that compensates household for living in that city.[17]

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 $\epsilon^H_{y,u} = \epsilon_{y,m}$.[18] These simplifications yield

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

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

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

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

where $\beta_0 = \ln \bar{s_y}$, $\beta_1 = \epsilon^H_{y,p} + 1 - s_y = -\beta_2$ and $\beta_3 = \epsilon_{y,m} - 1$. 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 is that $\beta_1 + \beta_2 = 0$, which may be seen as a joint test of both

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

[18] Note that we implicitly impose the restriction that the skill index affects housing consumption through income, and not through differences in tastes.If households with more skills like housing less (more) than those with fewer skills, the income elasticity estimate will be biased downwards (upwards). Our index also does not handle how earnings over the life-cycle may differ from permanent income.

demand theory and mobility.[19] When this restriction holds we use the elasticity of substitution between housing and non-housing goods, $\sigma_D \equiv -(\hat{y}^j - \hat{x}^j)/(\hat{p}^j - \hat{c}^j) = -\epsilon^H_{y,p}/(1 - \bar{s_y})$, 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 reference to income, which our skill-index may not fully capture.

Quality of life amenities may affect the income share of housing if $\epsilon^H_{y,Q} \neq \epsilon_{m,Q}$, which means amenities and housing are either are net complements or substitutes. If $0 > \epsilon^H_{y,Q} > \epsilon_{m,Q}$, compensated improvements in quality of life reduce housing consumption less than other consumption.[20]

3.4 Non-Homothetic Utility and Expenditure Functions for Housing

Because housing expenditures are a large portion of the consumption bundle, it may often be worth using a utility function that allows for income effects. 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

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

[20] For example, 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 extreme weather could cause them to consume more housing.

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 $\sigma = 1 - \beta_1/(1-e^{\beta_0}), \delta = 1 - e^{\beta_0/\sigma}, \gamma = -\epsilon_{m,u}\beta_3/\beta_1$. [21]

The expenditure function may be used to construct an ideal cost-of-living index (COLI) that incorporates realistic substitution and income effects. 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 to a base level of housing consumption $\bar{s_y}$ by solving 13, $u^{\gamma(1-\sigma)} = \left[(1-\bar{s_y})(1-\delta)^{\sigma}\bar{p}^{1-\sigma}\right] / \left(\bar{s_y}\delta^{\sigma}\bar{c}^{1-\sigma}\right)$. 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.

[21] Because 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.

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

Whether housing affordability measures that depend on housing shares, s_y, tell us much about household well-being hinges on the demand function, as equations (8) and (13) clarify. Only if housing is a normal good, i.e., $\epsilon_{y,m} < 1$, do high housing shares indicate lower levels of well-being.[22] Housing shares are positively related to housing-price levels only if demand is price inelastic, $\epsilon_{y,p} < 1$, although this variation may not be pertinent to well-being. If households are mobile, then from high rents reflect high local wage levels or quality of life. A household living in an unsafe area with bad schools may spend little on housing, but still be worse off than a household in a more expensive area.

If household mobility is imperfect, then the uncompensated framework is more appropriate, and high prices may indeed indicate lower welfare, although amenities still complicate welfare analysis. Other factors may shift demand. These include demographics like children or a cohabiting partner. Cultural norms and tastes for privacy may also differ.[23] 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.[24] These data generate metro-level indices of income, m^j, predicted income, ζ^j, the rental-price index p^j, and the housing share, s_y^j, as explained below. For the price of non-housing goods, we use a series from

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

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

[24]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.

Carrillo et al. (2013), or "CEO," who construct the series from data by the American Chambers of Commerce Research Association (ACCRA).[25]

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.[26] With the CEX, we take housing expenditures as a fraction of all reported expenditures, consistent with the belief that expenditures are a better predictor of permanent income than transitory income. (Poterba, 1989)

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.[27] 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 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.

To estimate a predicted wage, we run a wage regression 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 char-

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

[26] 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. 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.

[27] 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.

acteristics, 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 $\hat{\beta}_W X_W^{ij}$ as our predicted wage indices.[28]

For robustness, we consider four additional housing-price indices. The first is derived from Malpezzi, Chun, and Green (1998), who estimate the housing coefficients separately for each metro area, and use these to value the entire national locally. The second is the CEO rental index, derived from the 2000 Section 8 Consumer Satisfaction Survey (CSS) for 173,000 units. Third, is an index constructed from American Housing Survey, just like we use for the Census, except with much more detailed housing characteristics, but a much smaller sample. 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 of occupied houses. The BEA measure of housing expenditures is from the PCE, and imputes rental-equivalent measures for owner-occupied units. From the CEX we take measures of average rental expenditures relative to all expenditures.[29] Both datasets include owner-occupiers.

4.4 Potential Biases in Elasticity Estimates

We attempt to correct for potential biases that may arise from omitting non-housing prices, potential earnings, and home-ownership. As they vary positively with housing prices, omitting non-housing prices biases the own-price elasticity. Suppose $\hat{c}^j = \rho \hat{p}^j + v^j$, where $\rho > 0$ and v^j is white noise. Substituting this projection into equation 8, together with the elasticity of substitution, gives

[28]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.

[29]We again focus on all expenditures as the denominator rather than income as it is closer to the ideal presented in the static model.

that the estimated elasticity of substitution is $\hat{\sigma}_D = 1 - \beta_1/[(1 - e^{\beta_0})(1 - \rho)]$. The higher is ρ, the more ignoring non-housing prices will bias $\hat{\sigma}_D$ upwards.

If housing is a necessity, omitting income or skill levels biases the price elasticity away from zero, as higher skilled individuals, with lower demand for housing, tend to locate in areas with higher rents (Moretti 2013).

Another bias may stem from using renters. Suppose that the propensity to rent rises with rent levels (possibly from financing constraints), so that more-skilled households rent in expensive cities. If housing is a necessity, and our controls for utility are incomplete, this could negatively bias the estimated price elasticity. This potential bias motivates controlling for the home-ownership rate.

Finally, there is the issue of unobserved taste-based sorting. Households that care more for housing will sort to where rents are low, negatively biasing the expenditure-rent gradient. Such sorting behavior would likely cause the rationality restrictions to fail. To check for this sorting, we compare estimates using rent variation across metros with those using variation within metros, where sorting is likely to be a more important issue.

For income, the main concern is attenuation bias from using current-period income.[30] Averaging at the metro level should reduce this bias, although cities themselves may be subject to transitory income shocks. The predicted wage measure is purged of any location effects and should suffer far less from measurement error issues. It is still limited in that it only captures a snapshot of earnings over the life cycle.

[30]Classical measurement error in income implies that we observe $\hat{m}_*^j = \hat{m}^j + \eta^j$, where η^j is white noise. Defining $\lambda = 1 - var(\eta^j)/var(\hat{m}_*^j|\hat{p}^j, \hat{c}^j)$ as the reliability ratio, conditional on the other variables, the OLS estimate of α_3 will give $\lambda(\alpha_3 + 1) - 1$, and the inferred value of $\varepsilon_{y,m}$ is attenuated classically to zero by the factor λ. Haider and Solon (2006) estimate that as a measure of lifetime earnings, λ peaks in the middle of the life cycle at a value of about two-thirds.

5 Empirical Results

5.1 Cross-sectional Estimates across Metro Areas

Table 1 presents metro-level estimates using the compensated model from equation (10), starting with the median rental share in columns 1-4. Column 1 displays the results of a simple regression, yielding a geometric mean of the median expenditure share, s_y, of 22.3 percent, and an implied price elasticity, $\varepsilon_{y,p}$ of -0.82.

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.[31] The regression line has slope $\beta_1 = -\beta_2$ in equation (10), with $\beta_3 = \beta_4 = 0$ imposed. Both relationships are positive and statistically significant, indicating demand is price-inelastic, although 4B features a steeper slope and a tighter fit.

Following section 4.4, the coefficient on rents, β_1, increases when the non-housing price index and the predicted wage index are included in column 2. The implied price and income elasticities are -0.69 and 0.64. The two price coefficients have opposite and nearly equal magnitudes, not rejecting the rationality restriction of demand theory, with a p-value of 0.84. This motivates the restricted estimates in column 3, our preferred specification, which implies an elasticity of substitution, σ_D of 0.70.[32] The results are unaffected by controlling for local home-ownership rates in column 4.

Column 5 uses out-of-pocket expenditures of home-owners, while column 6 includes owners and renters. In these specifications, the rationality restriction fails. The average expenditure share is lower on average, and the estimates imply lower income and price elasticities, as suggested in figure 4B. These results must be viewed with reservation, as out-of-pocket expenditures include net investments and exclude implicit rents.

[31] Accordingly, the former uses a price-index for rental units; the latter, for all housing units.

[32] 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 exaggerates 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 does not account for income or non-housing prices.

Column 7 uses the aggregate expenditure share, which weights households in proportion to their expenditures. producing estimates just slightly more elastic than column 3 that that continue to satisfy rationality. [33]

To examine household sorting, column 8 presents results using within-metro variation 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. The estimates fail the rationality test, suggesting that taste-based sorting taints these estimates.

Table 2 considers how estimates vary using different years or data sets, maintaining our preferred specification from column 3 of table 1. The first three columns use similar Census datasets from 1980, 1990, and 2010 (technically 2007-11). 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 0.85 in 1980 and 2010. In those cases, the fit of the model is notably poorer.

Column 4 introduces a rental price index for the year 2000 in the style of Malpezzi et al. (1998). The results are almost indistinguishable from our baseline results. Column 5 uses the 2000 CEO rental index. The results imply slightly more price-elastic demand, although attenuation bias may play a role here.[34] Column 6 uses price indices from the AHS and suggests a somewhat higher expenditure share, a greater price elasticity, and a lower income elasticity. Finally, column 7 uses the CEX data, which suggests a substantially higher expenditure share and expenditure elasticity close to one.

Table 3 presents uncompensated specifications corresponding to equation 4, which feature a 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 -0.096, passing the homogeneity restriction with a p-value of 0.19. The restricted regression in column 2 estimate much smaller price and income elasticities of -0.42 and 0.31. These estimates do appear to suffer from possible measurement error

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

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

problems.

Column 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 may suggest housing on hillier terrain has better views and is more easily seen.[35]

5.2 Household Level Demand Equations

In Table 4 we consider household level regressions. Since the income of a household depends on its composition, we consider 6 types of households, depending on whether there are one, two, or three or more adults, and whether children are present.[36] Comparing columns, it is apparent that households with more adults spend a smaller share on housing. This accords with the results in Deaton and Paxson (1998), that housing expenditures fall with household size, holding per-capita income constant.[37] Households with children consume more housing, and this increases with the number of children in the household.

Heterogeneity in the price and income elasticities are relatively minor. Households with children have slightly greater price and income elasticities. The income elasticities show a slight trend upwards in the compensated regressions and a downward trend in the uncompensated ones.

5.3 Household Demand for Housing over Time

Table 5 presents uncompensated demand estimates using the time series data presented in figure 1. Both columns use nominal prices and incomes. To conserve space, we focus on restricted models satisfying homogeneity of degree zero in prices and income, which are not rejected by formal tests

[35] This finding is complementary but distinct from the one in Albouy and Ehrlich (2012) that housing is more expensive to construct in hilly terrain.

[36] We do not distinguish households by gender composition or marital status to account for potential variation in how people label themselves across space and time. The compensated regressions contain fewer households as we are not able to impute wage income for some workers.

[37] This result follows Barten (1964), who models housing as a semi-public good.

in our preferred specifications.[38] The specifications include two additional terms. One is a linear time trend, t, that may capture secular changes in household preferences or increasing complementarity of housing with local amenities as households have shifted locations.[39] The second term is the logarithm of household size, $ln(n)$, in the spirit of Barten (1964). The multi-collinearity between prices, incomes, and household size pushes the limit of what the time-series can identify.

In the bottom panel, we decompose the growing share of income spent on housing discussed in the introduction. Rearranging (7) and replacing Q with n and t, we have

$$\hat{s}_y = (1 - \bar{s_y} + \epsilon^H_{y,p})(\hat{p} - \hat{c}) + (\epsilon_{y,m} - 1)[(\hat{m} - \hat{c}) - \bar{s_y}(\hat{p} - \hat{c})] + \alpha_n \hat{n} + \alpha_t t + e \tag{15}$$

The first component represents the change due to the pure compensated price effect. This effect is positive when the relative price of housing increases if $\sigma < 1$, as $1 - s_y + \epsilon^H_{y,p} = (1 - s_y)(1 - \sigma)$. The second component is the income effect, from a parallel rise in the budget set, making the proper adjustment for changes in relative prices. The third component, $\alpha_n \hat{n}$, accounts for changes in household size; the fourth, $\alpha_t t$, the time trend; the fifth, e, is a residual.

Estimates from the BEA numbers, shown in column 1, remarkably pass the rationality test. They imply an own-price elasticity of -0.60 and an income elasticity of 0.53, which are rather close to the compensated metro-level regression in column 3 of table 1. The estimated time trend is 0.01 per year, while the coefficient on household size is -0.35 and significant. If non-housing consumption is purely private, the Barten (1964) model implies that one plus the ratio of this coefficient to the price coefficient is equal to the degree of "congestibility" of housing consumption within the household. The estimated value is statistically indistinguishable from zero, suggesting that housing is largely a public good within the household.

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 the decomposition, this could be attributed

[38]Because the unrestricted regressions include separately the log CPI-U for shelter and the log CPI-U for all items less shelter, they remain agnostic about the proper deflator.

[39]The time trend may also reflect simple measurement error resulting from limitations in the data and its ability to identify low-frequency responses in housing consumption from shifting prices and income.

to the price effect, or the estimated effect of smaller households. The income effect, however, is large and highly negative, but was largely offset by the secular increase in housing demand reflected in the estimated time trend, which predicts a 41 point increase. These offsetting trends are somewhat puzzling, but may reflect growing inequality, as median incomes grew much less than mean incomes. Rising incomes at the top of the distribution may have lowered housing consumption less than rising incomes among lower earners would have done.

Column 2 uses the expenditure shares from the CEX for renters. These estimates are less precise and produce income and substitution elasticities much closer to one. As a result the decomposition produces hardly anything except for a large time trend effect, especially as the reported real increase in expenditures in the CEX is small.[40]

Overall, the BEA data seem to produce more precise and meaningful numbers than the CEX, and provide some support for the narrative of conflicting income and substitution effects given in the introduction. They also support the hypothesis that falling household sizes increased housing consumption. Nevertheless, the estimated time trend suggests that secular increases in the demand for housing not explained by our model played an important role in the rising housing share.

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 functions in section 3.4. For illustration, we slightly round the parameters based off of estimates from column 3 of table 1, setting $\sigma = 2/3, \delta = 5/6, \gamma = 4/9$. Using these values in equations (11) and (12) yields the following utility and expenditure functions:

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

[40] The latter likely stems from the relative scarcity of very high income households in the CEX.

The units of x and y are as median income shares for renters, with baseline values of $x = 0.78$ and $y = 0.22$. 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 (COLIs) derived above. Figures 4A and 4B plot these four COLIs against the relative price of housing (p^j/c^j) for realistic variations over time and space. Figure 4B adjusts for a base level of income that is one half the median represented in 4A.

Figure 4A shows 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. 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.

Figure 4B shows that the non-homothetic CES COLI is steeper than those that fail to account for income effects. For poorer households, the other COLIs understate the burden of living in expensive areas, and overstate it in poorer areas. 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 distribution parameter δ. The advantage 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 to deflate changes in income over time has different effects along the income distribution. Because housing is a necessity, the welfare of poorer households is reduced more by increases in the price of housing. Substitution effects mitigate the welfare reduction for all groups. Table 6 compares the nominal changes at the 10th, 50th, and 90th percentiles of the household income distribution, and deflates 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 19 to 29 percent, while the share with moderate burdens rose from 39 to 53 percent.

To explain this decline in affordability, we consider five separate trends in the economy over the past 30 years. First is the change in household composition and age structure. To handle this, we divide households into 36 categories, crossing the six household types from section 5.2 with six age categories, defined by the mean age of adults.[41] The 2010 sample is re-weighted so that these groups have the same proportion as in 1980.

Second is the increase in income inequality. Lagging incomes among renters will reduce affordability if housing is a necessity. 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.[42] We denote household i's counterfactual income

[41]We define the age categories as 18-24, 25-34, 35-44, 45-54, 55-64, and 65+.

[42]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 $\tilde{m}_i =$

$\tilde{m}_i$. 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, $\hat{s}_i^1 = (\epsilon_{y,m} - 1)\ln(\tilde{m}_i/m_i)$.

Third, 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 account for the behavioral response through the formula: $\hat{s}_i^2 = (\epsilon_{y,p} + 1)\ln(\bar{p}_{1980}/\bar{p}_{2010})$. Lower rents increase affordability provided that $\epsilon_{y,p} > -1$.

Fourth, we consider increasing rental dispersion, which will reduce affordability if rent increases in particular areas created 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 $\hat{s}_i^3 = (\epsilon_{y,p}^H + 1 - \bar{s}_y)[\ln(p_{1980}^j/p_{2010}^j) - \ln(\bar{p}_{1980}/\bar{p}_{2010})]$.[43]

Fifth, 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, $\epsilon_{y,m} - 1$.[44]

Table 7 accounts for these factors' contributions to the 14.6 and 9.5 percentage point increase in households facing moderate and extreme affordability burdens. The change in household composition *improved* affordability in the sample we observe by 1.9 and 1.5 percentage points for the moderate and extreme burdens, respectively. Widening income inequality accounts for 3.2 and 1.7 point increases in the affordability burden, respectively, as renters' gains in nominal income were slower than homeowners'. Increases in overall rental prices account for further 2.9 and 1.7 percentage point increases. Changes in relative rent levels had very little effect on affordability, while changes in average real incomes produced moderate increases in housing affordability.

The results suggest that the largest observable drivers of increasing housing burdens from 1980 to 2010 are increasing income inequality and rising average rent levels. Yet, the leave a substantial fraction of the fall in affordability unexplained. Perhaps under-reporting of household incomes in

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$m_i[(\bar{m}_{2010}/\bar{m}_{1980})/(m_{2010}^k/m_{1980}^k)]$.

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

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

the Census numbers has increased over time. Alternatively, there may have been a secular increase in the taste for housing, as implied by the time series evidence. An increase in households' taste for housing relative to other goods would not have clear implications for welfare analysis.

7 Conclusion

The temporal and spatial relationships between housing prices and expenditure shares suggest that uncompensated housing demand is both price and income inelastic. Our most reliable estimates imply uncompensated own-price and income elasticities close to two-thirds in absolute value. This means that unit elasticities are better approximations than zero elasticities, although neither extreme can explain the observed variation in housing consumption across metro areas and over time. Taste-based sorting across space would bias our estimates towards finding greater price elasticity, but a large role for sorting seems incompatible with our use of inter-metropolitan price variation, which passes a demand restriction which would fail in the presence of sorting (as it does within metros). The estimated non-homothetic CES utility function we provide should be useful for realistic and tractable economic modeling across fields.[45] The temporal analysis suggests that rising rents have increased housing consumption, while rising incomes have lowered it. However, it also uncovers a secular rise in housing consumption that is difficult to explain.

Our estimates and framework 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. Moreover, nationally rising rents over time have increased real-income inequality considerably, even while spatial trends have not (Moretti, 2013). The growing affordability crisis among renters appears to have little to do with recent demographic changes, but is related to rising rents, stagnant (or declining) real incomes among renters, and a secular rise in housing demand that deserves further investigation.

[45] 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 FUNCTION ESTIMATES AT THE METROPOLITAN LEVEL USING 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 Spend. Share	Log Median Hous. Share	Log Aggreg. Rental Share	Log Median Rental Share
Regression Results:								
Rental/Housing Price Index	0.175	0.234	0.231	0.223	0.489	0.455	0.199	0.192
	(0.020)	(0.023)	(0.020)	(0.027)	(0.023)	(0.012)	(0.024)	(0.015)
Non-Housing Price Index		-0.250	-0.231	-0.223	-0.489	-0.455	-0.199	0.161
		(0.099)	(0.020)	(0.027)	(0.023)	(0.012)	(0.024)	(0.123)
Predicted Wage Index		-0.359	-0.361	-0.351	-0.420	-0.503	-0.176	-0.490
		(0.102)	(0.100)	(0.107)	(0.103)	(0.062)	(0.095)	(0.029)
Homeownership Rate				-0.034				
				(0.122)				
Constant	-1.502	-1.502	-1.502	-1.502	-1.828	-1.729	-1.643	-1.503
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.006)	(0.002)
Sample Size	380	380	380	380	380	380	380	2071
Adjusted R-squared	0.339	0.387	0.388	0.388	0.836	0.816	0.336	-0.033
Constrained Regression	No	No	Yes	Yes	Yes	Yes	Yes	No
Unconstrained Sum of Housing and Non-Housing Price Index Coefficients		-0.017	-0.017	-0.019	0.376	0.272	-0.020	0.353
		(0.086)	(0.086)	(0.086)	(0.097)	(0.096)	(0.094)	(0.122)
P-value of Test of Homog. of Demand		0.844	0.844	0.824	0.000	0.005	0.833	0.004
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	0.223	0.223	0.223	0.223	0.161	0.178	0.193	0.223
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Uncompensated Own Price Elasticity of Housing Demand	-0.825	-0.687	-0.689	-0.699	-0.444	-0.456	-0.766	-0.699
	(0.020)	(0.035)	(0.034)	(0.043)	(0.035)	(0.014)	(0.030)	(0.020)
Income Elasticity of Housing Demand	1.000	0.641	0.639	0.649	0.580	0.497	0.824	0.510
	Restricted	(0.102)	(0.100)	(0.107)	(0.103)	(0.062)	(0.095)	(0.029)
Elasticity of Substitution Between Housing and Consumption Goods			0.703	0.713	0.418	0.447	0.753	0.753
			(0.026)	(0.034)	(0.027)	(0.014)	(0.030)	(0.019)
Distribution Parameter			0.882	0.878	0.987	0.979	0.887	0.864
			(0.009)	(0.012)	(0.004)	(0.003)	(0.009)	(0.007)
Non-homotheticity Parameter			1.566	1.577	0.860	1.107	0.884	2.557
			(0.419)	(0.427)	(0.190)	(0.145)	(0.493)	(0.145)

Robust standard errors reported in parentheses. The predicted wage index is based on the wage level predicted by education, experience, race, immigrant status, occupation, and industry, partialing out the effect of lcation. Homogeneity of demand test is for whether the coefficients on the rental/housing price index and the non-housing price index sum to

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	0.154	0.220	0.181	0.220	0.178	0.182	0.394
	(0.038)	(0.024)	(0.020)	(0.020)	(0.034)	(0.038)	(0.056)
Predicted Wage Index	-0.222	-0.258	-0.423	-0.359	-0.331	-0.812	0.131
	(0.132)	(0.132)	(0.064)	(0.104)	(0.138)	(0.269)	(0.145)
Constant	-1.517	-1.479	-1.181	-1.502	-1.502	-1.309	-1.021
	(0.008)	(0.007)	(0.005)	(0.005)	(0.006)	(0.008)	(0.009)
Sample Size	379	379	380	380	380	135	165
Adjusted R-squared	0.134	0.453	0.374	0.364	0.212	0.169	0.336
Constrained Regression	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unconstrained Sum of Housing and Non-Housing Price Index Coefficients	-0.137	-0.230	0.159	-0.001	0.158	0.671	0.289
	(0.275)	(0.158)	(0.064)	(0.088)	(0.129)	(0.193)	(0.189)
P-value of Test of Homogeneity of Demand	0.620	0.145	0.013	0.995	0.221	0.001	0.128
Implied Demand Parameters:							
Geometric Mean Expenditure Share	0.219	0.228	0.307	0.223	0.223	0.270	0.360
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Uncompensated Own Price Elasticity of Housing Demand	-0.797	-0.721	-0.689	-0.700	-0.749	-0.599	-0.653
	(0.060)	(0.049)	(0.032)	(0.035)	(0.055)	(0.089)	(0.082)
Income Elasticity of Housing Demand	0.778	0.742	0.577	0.641	0.669	0.188	1.131
	(0.132)	(0.132)	(0.064)	(0.104)	(0.138)	(0.269)	(0.145)
Elasticity of Substitution Between Housing and Consumption Goods	0.802	0.715	0.739	0.717	0.772	0.751	0.384
	(0.049)	(0.032)	(0.029)	(0.026)	(0.044)	(0.053)	(0.088)
Distribution Parameter	0.849	0.873	0.798	0.877	0.857	0.825	0.930
	(0.016)	(0.011)	(0.012)	(0.009)	(0.016)	(0.022)	(0.042)
Non-homotheticity Parameter	1.440	1.175	2.332	1.632	1.867	4.460	-0.331
	(0.706)	(0.535)	(0.373)	(0.447)	(0.693)	(1.598)	(0.378)

All specifications are similar to column 3 in table 1. Columns 4 through 6 use housing income shares from the 2000 Census. Column 7 uses the expenditure share from the 2000 CEX. Since only constrained results are shown, the coefficient for non-houing prices is redundant.

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

	Marshallian Demand (1)	Marshallian Demand (2)	Marshallian Demand (3)	Hicksian Demand (4)
Dependent Variable:	Log Median Rental Share			
Regression Results:				
Housing Price Index	0.597	0.580	0.574	0.242
	(0.034)	(0.035)	(0.038)	(0.019)
Non-Housing Price Index	-0.006	0.106	-0.574	-0.242
	(0.088)	(0.021)	(0.038)	(0.019)
Household Income Index	-0.687	-0.686	-0.664	-0.410
	(0.047)	(0.048)	(0.049)	(0.099)
Inverse Distance to Coast (miles)			-0.052	-0.092
			(0.058)	(0.070)
Average Slope of Land (percent)			0.004	0.012
			(0.001)	(0.002)
Constant	-1.502	-1.502	-1.502	-1.503
	(0.003)	(0.003)	(0.003)	(0.004)
Sample Size	380	380	376	376
Adjusted R-squared	0.803	0.801	0.808	0.455
Constrained Regression	No	Yes	Yes	Yes
Unconstrained Sum of Housing Price, Non-Housing Price, and Household Income Coefficients	-0.096	-0.096	-0.136	-0.095
	(0.073)	(0.073)	(0.091)	(0.095)
P-value of Test of Homogeneity of Demand	0.190	0.190	0.136	0.318
Implied Demand Parameters:				
Geometric Mean Expenditure Share	0.223	0.223	0.223	0.223
	(0.001)	(0.001)	(0.001)	(0.001)
Uncompensated Own Price Elasticity of Housing Demand	-0.403	-0.420	-0.426	-0.667
	(0.034)	(0.035)	(0.038)	(0.031)
Income Elasticity of Housing Demand	0.313	0.314	0.336	0.590
	(0.047)	(0.048)	(0.049)	(0.099)
Elasticity of Substitution Between Housing and Consumption Goods		0.451	0.451	0.689
		(0.033)	(0.036)	(0.025)

All specifications include renters only. Robust standard errors in parentheses. Test of homogeneity of demand for the uncompensated regressions is that the coefficients on both price indices and income sum to zero. Columns 1 through 3 use reported log household income. Columnn 4 is a compensated regression and uses a predicted wage index.

TABLE 4: DEMAND FUNCTIONS BY HOUSEHOLD TYPE - INDIVIDUAL 2000 CENSUS DATA

Household Type	One adult, no children	One adult, with children	Two adults, no children	Two adults, with children	Three or more adults, no children	Three or more adults, with children
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Log Rental Share					
Panel A: Compensated Regressions						
Log Housing Price	0.368	0.287	0.352	0.414	0.333	0.490
	(0.021)	(0.027)	(0.029)	(0.023)	(0.044)	(0.031)
Log Mean Predicted Income of Adults	-0.638	-0.391	-0.472	-0.436	-0.414	-0.369
	(0.008)	(0.010)	(0.004)	(0.006)	(0.009)	(0.006)
No. of children minus 1		0.031		0.034		0.020
		(0.002)		(0.002)		(0.002)
No. of adults minus 3					-0.139	-0.155
					(0.005)	(0.003)
Constant	-1.439	-1.217	-1.669	-1.569	-1.690	-1.625
	(0.004)	(0.006)	(0.007)	(0.006)	(0.013)	(0.010)
Sample size (number of households)	306,488	113,162	271,878	281,541	81,701	84,856
Adjusted R-squared	0.121	0.053	0.125	0.133	0.116	0.141
P-value of Test of Homogeneity of Demand	0.842	0.126	0.353	0.066	0.837	0.029
Implied Demand Parameters						
Geometric Mean Expenditure Share	0.237	0.296	0.188	0.208	0.184	0.197
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Uncompensated Own Price Elasticity	-0.481	-0.597	-0.559	-0.495	-0.591	-0.437
of Housing Demand	(0.022)	(0.027)	(0.030)	(0.023)	(0.046)	(0.031)
Income Elasticity of Housing Demand	0.362	0.609	0.528	0.564	0.586	0.631
	(0.008)	(0.010)	(0.004)	(0.006)	(0.009)	(0.006)
Elasticity of Substitution Between Housing	0.517	0.593	0.566	0.477	0.592	0.390
and Consumption Goods	(0.028)	(0.039)	(0.037)	(0.029)	(0.055)	(0.039)
Panel B: Uncompensated Regressions						
Log Housing Price	0.547	0.473	0.622	0.576	0.588	0.551
	(0.024)	(0.035)	(0.025)	(0.029)	(0.041)	(0.034)
Log Household Income Per Adult	-0.574	-0.494	-0.700	-0.697	-0.763	-0.754
	(0.008)	(0.009)	(0.011)	(0.005)	(0.011)	(0.006)
No. of children minus 1		0.007		0.017		0.005
		(0.003)		(0.002)		(0.001)
No. of adults minus 3					-0.196	-0.185
					(0.004)	(0.004)
Constant	-1.313	-1.149	-1.602	-1.520	-1.623	-1.557
	(0.004)	(0.006)	(0.005)	(0.006)	(0.012)	(0.012)
Sample size (number of households)	522,930	148,323	334,487	316,181	90,995	93,943
Adjusted R-squared	0.480	0.326	0.598	0.576	0.577	0.579
P-value of Test of Homogeneity of Demand	0.000	0.852	0.001	0.203	0.472	0.712
Implied Demand Parameters:						
Geometric Mean Expenditure Share	0.269	0.317	0.202	0.219	0.197	0.211
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Uncompensated Own Price Elasticity	-0.453	-0.527	-0.378	-0.424	-0.412	-0.449
of Housing Demand	(0.024)	(0.035)	(0.025)	(0.029)	(0.041)	(0.034)
Income Elasticity of Housing Demand	0.426	0.506	0.300	0.303	0.237	0.203
	(0.008)	(0.009)	(0.011)	(0.005)	(0.011)	(0.034)
Elasticity of Substitution Between Housing	0.463	0.536	0.398	0.458	0.455	0.503
and Consumption Goods	(0.031)	(0.050)	(0.029)	(0.036)	(0.049)	(0.043)

Estimated at the household level. All regressions are constrained to exhibit homogeneity of demand. Standard errors are clustered at the metro level to reflect variation in the rental index. The predicted income measure in Panel A is the mean predicted income of all adults in the household. Thse include only households for which a predicted income could be imputed.

TABLE 5: NATIONAL HOUSING DEMAND OVER TIME

	(1)	(2)
Dependent Variable:	Log Housing Share	Log Rental Share
Data Source:	BEA	CEX
Restricted Regression Results:		
Log CPI-U: Shelter minus Log CPI-U: All Items Less Shelter	0.405	0.054
	(0.047)	(0.190)
Log Average Income/Expenditures Per Capita minus Log CPI-U: All Items Less Shelter	-0.466	-0.197
	(0.066)	(0.203)
Linear Time Trend (years)	0.010	0.009
	(0.002)	(0.001)
Log Household Size	-0.352	0.260
	(0.088)	(0.838)
Constant	-1.718	-1.232
	(0.003)	(0.004)
Sample size (years)	42	28
P-value of Test of Homogeneity of Demand	0.746	0.691
Implied Demand Parameters from Restricted Regressions:		
Geometric Mean Expenditure Share	0.179	0.292
	(0.000)	(0.001)
Uncompensated Own-Price Elasticity of Housing Demand	-0.595	-0.946
	(0.047)	(0.190)
Income Elasticity of Housing Demand	0.534	0.803
	(0.066)	(0.203)
Decomposition of Long-run Change in Expenditure Share:		
Total Change in Log Share	0.080	0.241
Change Attributable to Household Size Effect	0.081	-0.017
	(0.020)	(0.054)
Change Attributable to Time Trend	0.407	0.246
	(0.085)	(0.039)
Change Attributable to Compensated Relative Price Effect	0.088	-0.001
	(0.013)	(0.031)
Change Attributable to Income Effect	-0.498	-0.017
	(0.070)	(0.018)
Residual	0.003	0.030
	(0.010)	(0.014)

Newey-West standard errors reported in parentheses. Income/expenditure measure in per capita terms. 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 shown impose this constraint making one estimate redundant. For non-BEA series, a moving average with weight of 0.5 for the year after and the year before is used.

TABLE 6: 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	5.476	1.115	1.121	-0.006
50th Percentile	6.002	5.407	1.110	1.102	0.008
90th Percentile	7.869	5.349	1.471	1.445	0.026

Income ratio in nominal terms. Ideal deflator uses estimated *COL4* index. Fixed-bundle deflator uses *COL1* index. Ideal correction takes difference.

TABLE 7: UNDERSTANDING INCREASES IN HOUSING AFFORDABILITY BURDENS FOR RENTERS, 1980-2010

	Median Expenditure Share (1)	Share with Moderate Burden (over 30%) (2)	Share with Extreme Burden (over 50%) (3)
Renter Households in 2010	0.310	0.535	0.288
Counterfactuals for 2010 (exercises applied cumulatively)			
1. Undoing Changes in Household Composition	0.320	0.554	0.303
2. Undoing Increases in Income Inequality	0.304	0.522	0.286
3. Undoing Increase in Average Rents	0.290	0.493	0.269
4. Undoing Changes in Relative Rents	0.290	0.494	0.268
5. Undoing Increase in Average Income	0.295	0.504	0.275
Renter Households in 1980	0.244	0.389	0.193

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 change in household composition 1980-2010. Counterfactual 2 assumes no increase in income inequality 1980-2010. Counterfactual 3 additionally assumes no increase in national rents 1980-2010. Counterfactual 4 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 1A: Personal Consumption Expenditures by Major Category, 1959-2014

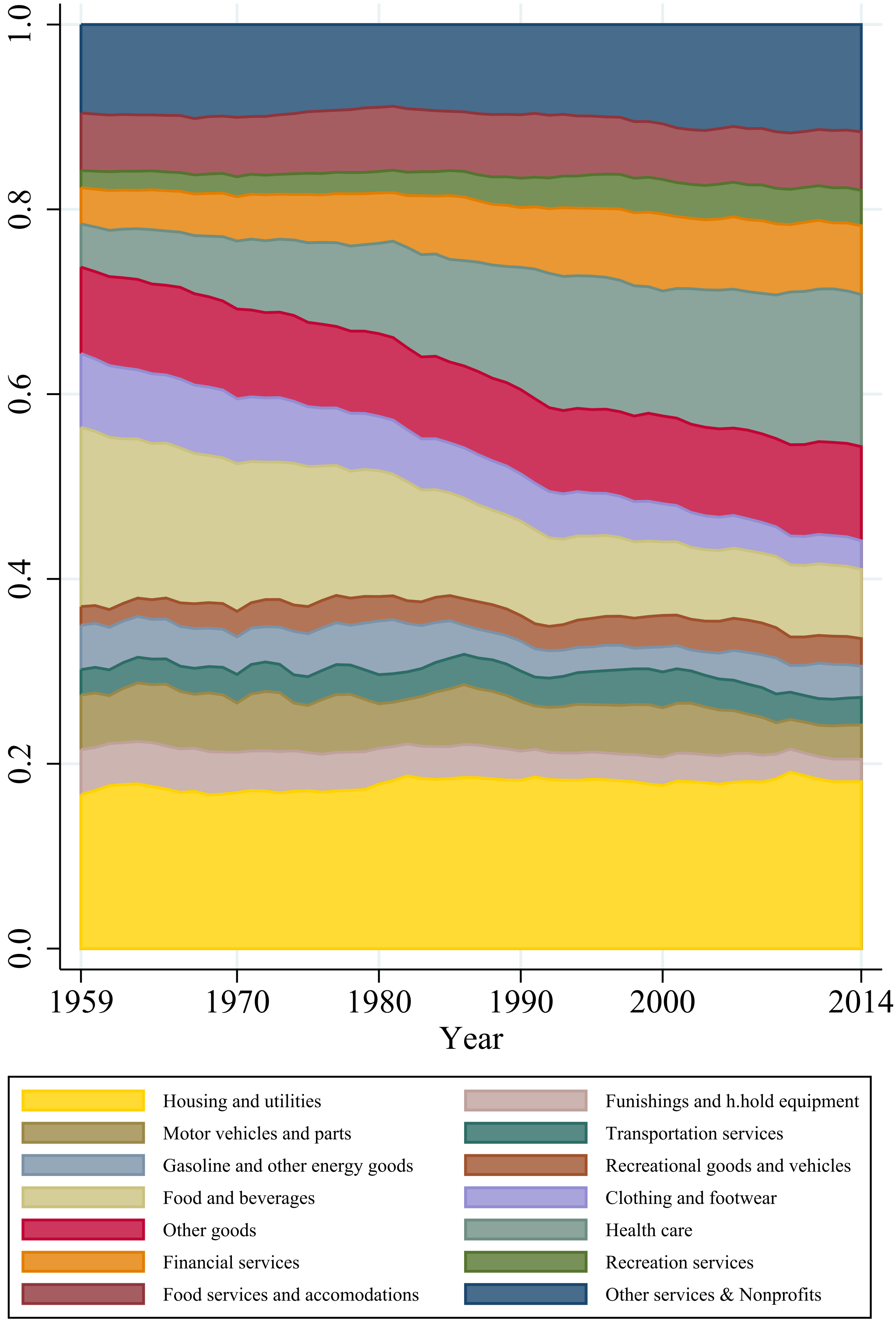
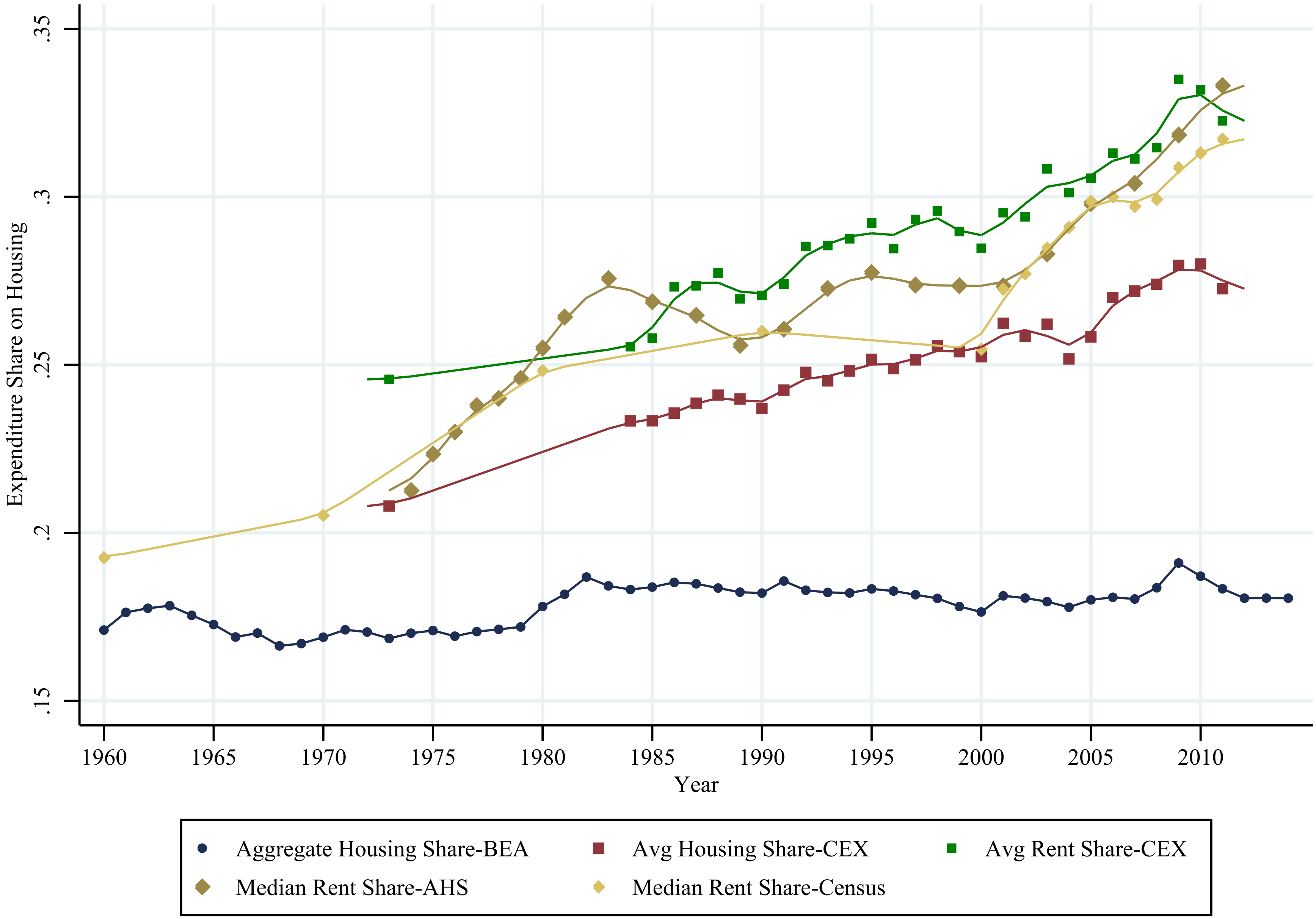
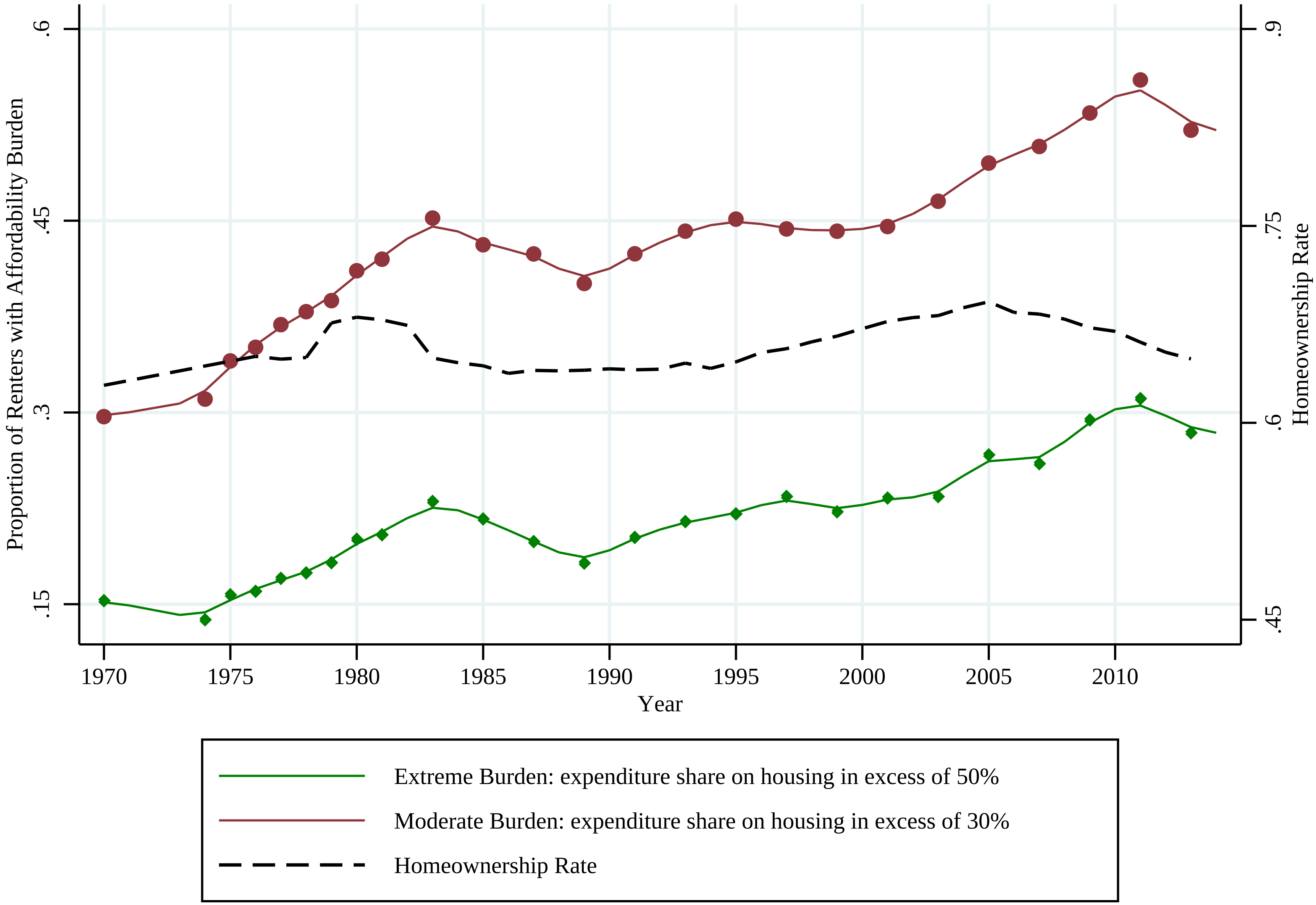


Figure 1B: Expenditure Share on Housing 1960-2014



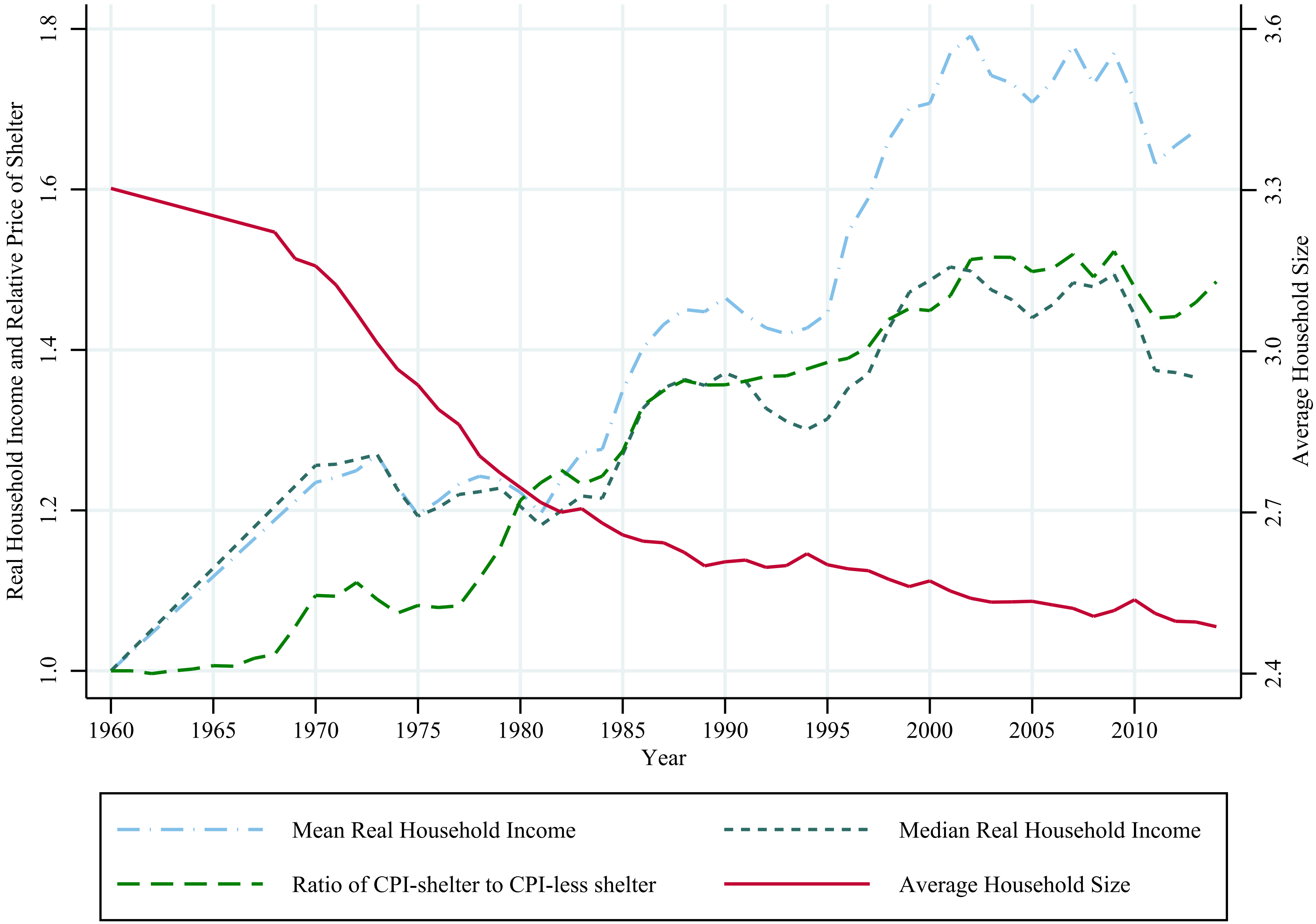
Note: For non-BEA series, a moving average with weight of 0.5 for the year after and the year before is shown in the curve.

Figure 1C: Relative Housing Prices and Affordability Among Renters 1970-2013



Note: For affordability series, a moving average with weight of 0.5 for the year after and the year before is shown in the curve. Moderate and extreme burdens are defined as expenditure share on housing in excess of 30 and 50 percent, respectively.

Figure 1D: Average Household Size, Household Income and Relative Price of Shelter 1960-2013



Note: Real household income and the relative price of shelter are normalized to one in 1960.

Figure 2: Housing Consumption with Production Possibility Expansions

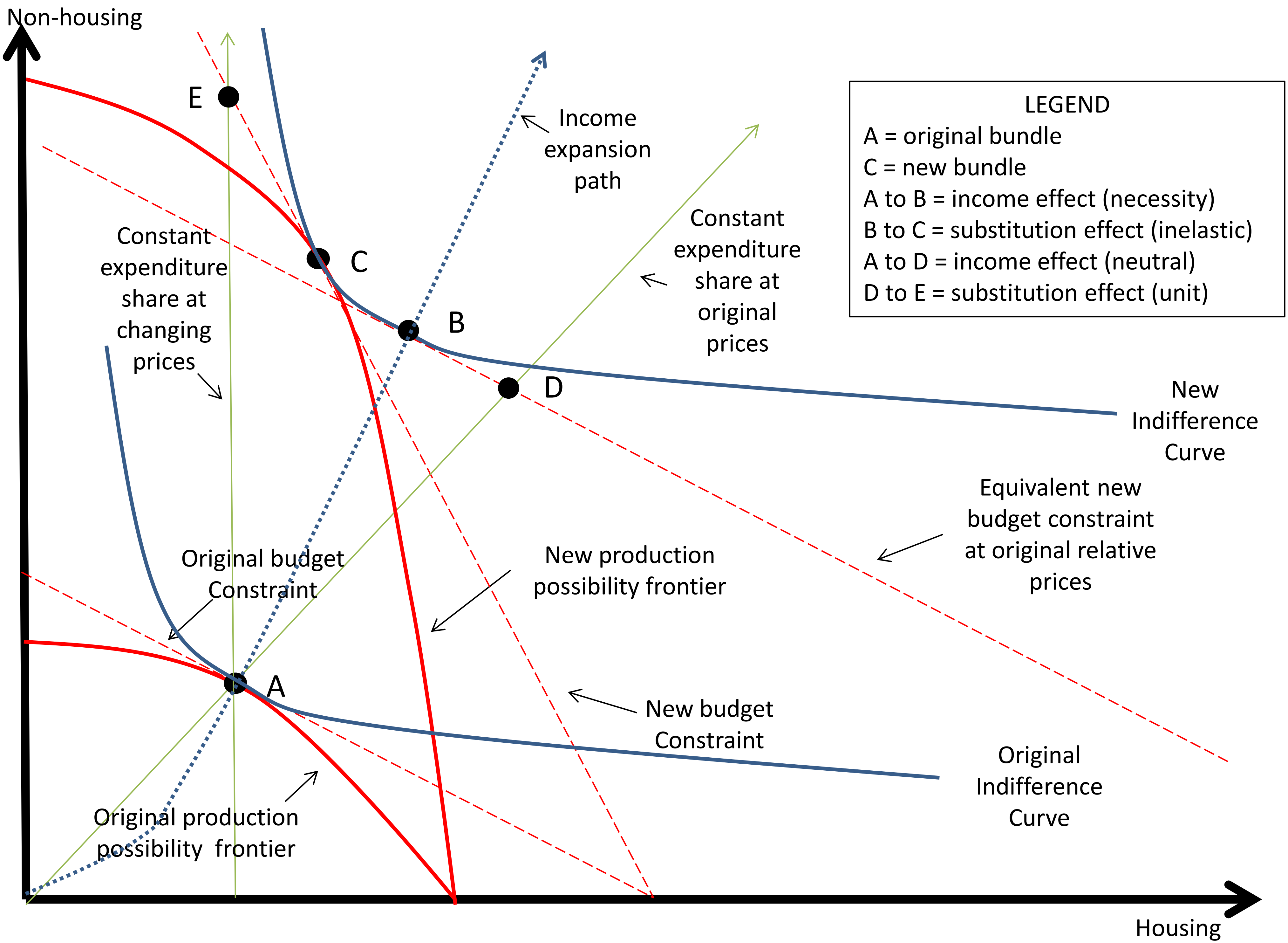


Figure 3A: Non-Housing Price Index vs. Housing Price Index, 2000

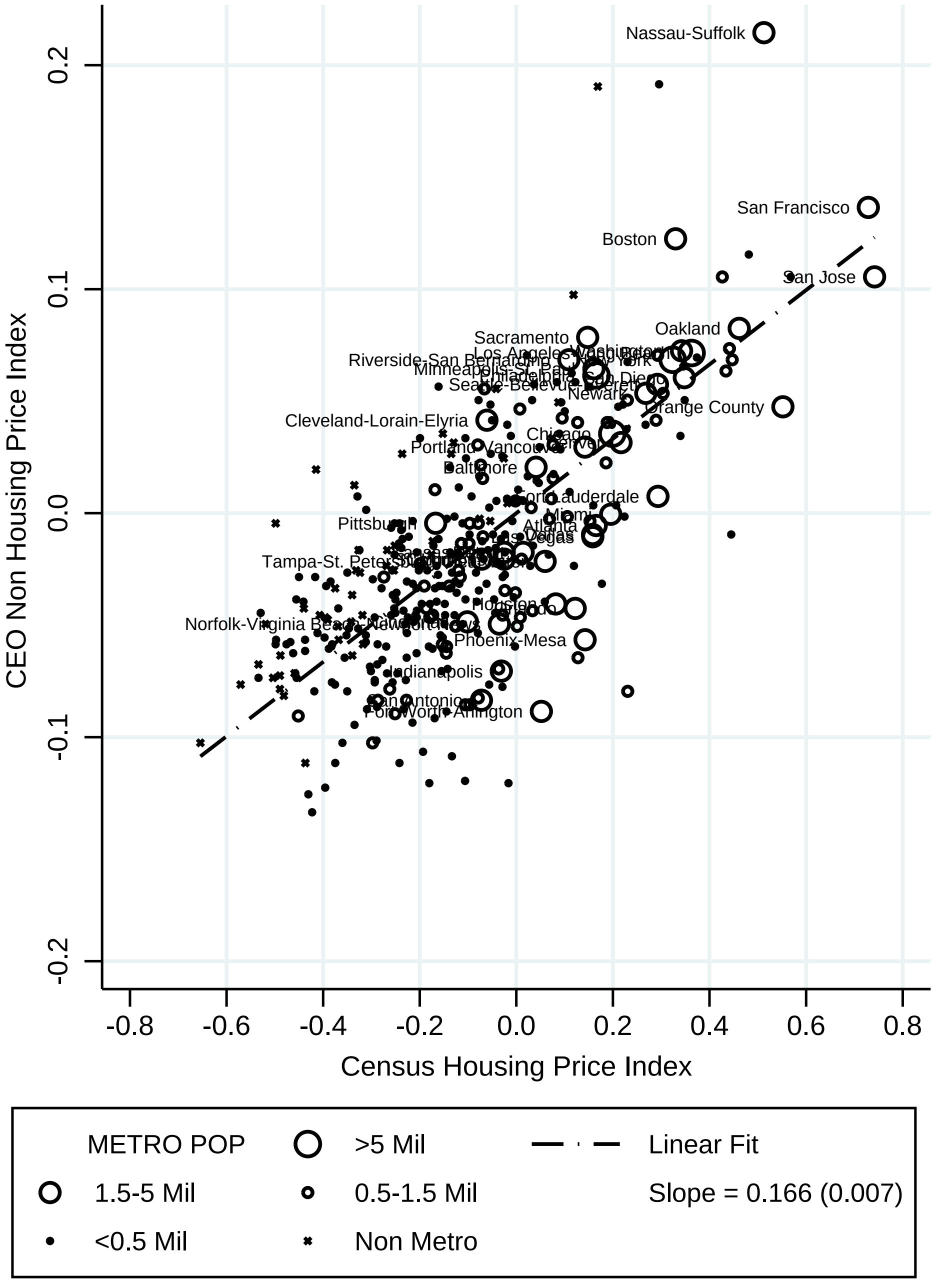
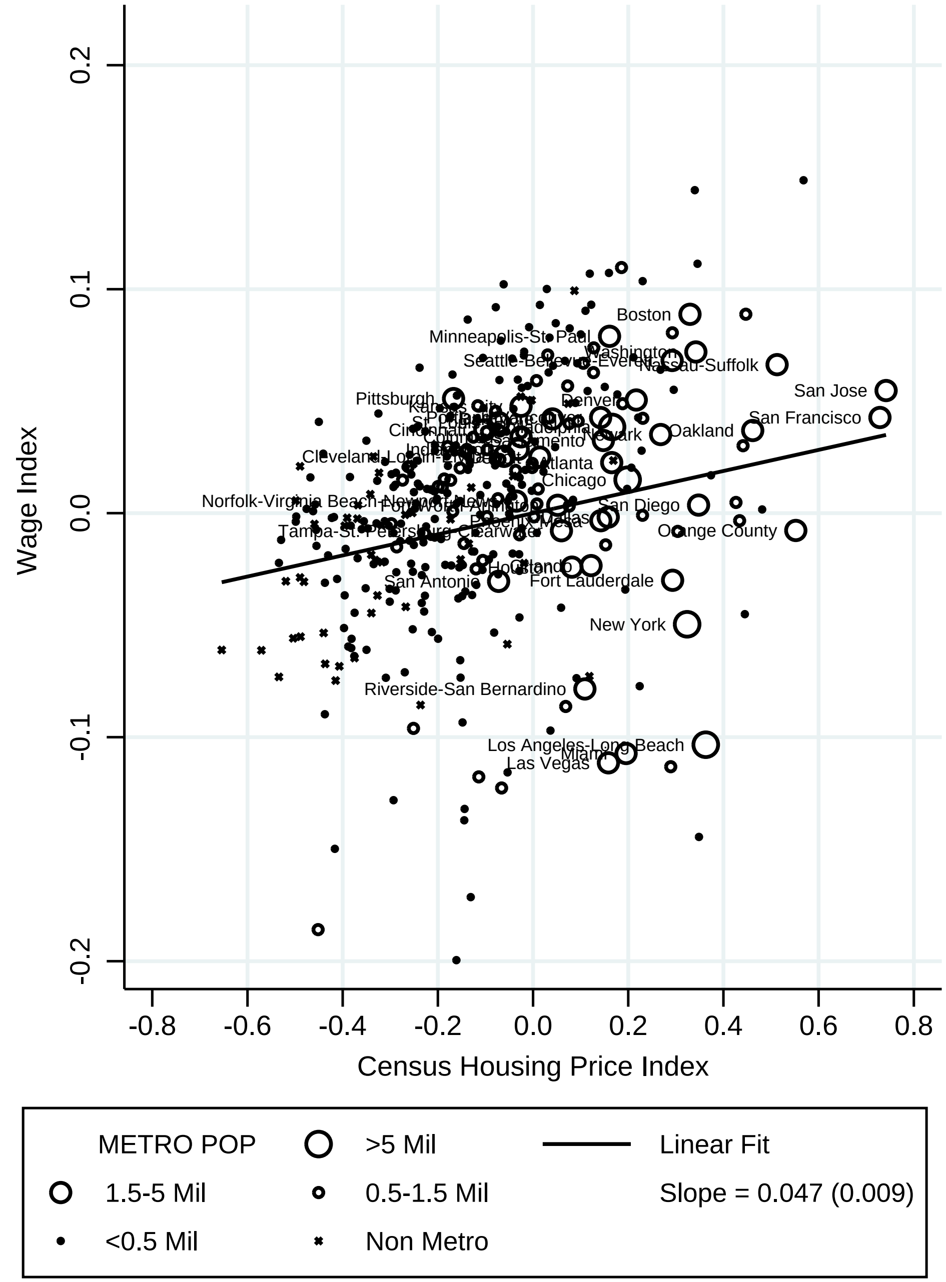


Figure 3B: Wage Index vs. Housing Price Index, 2000



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

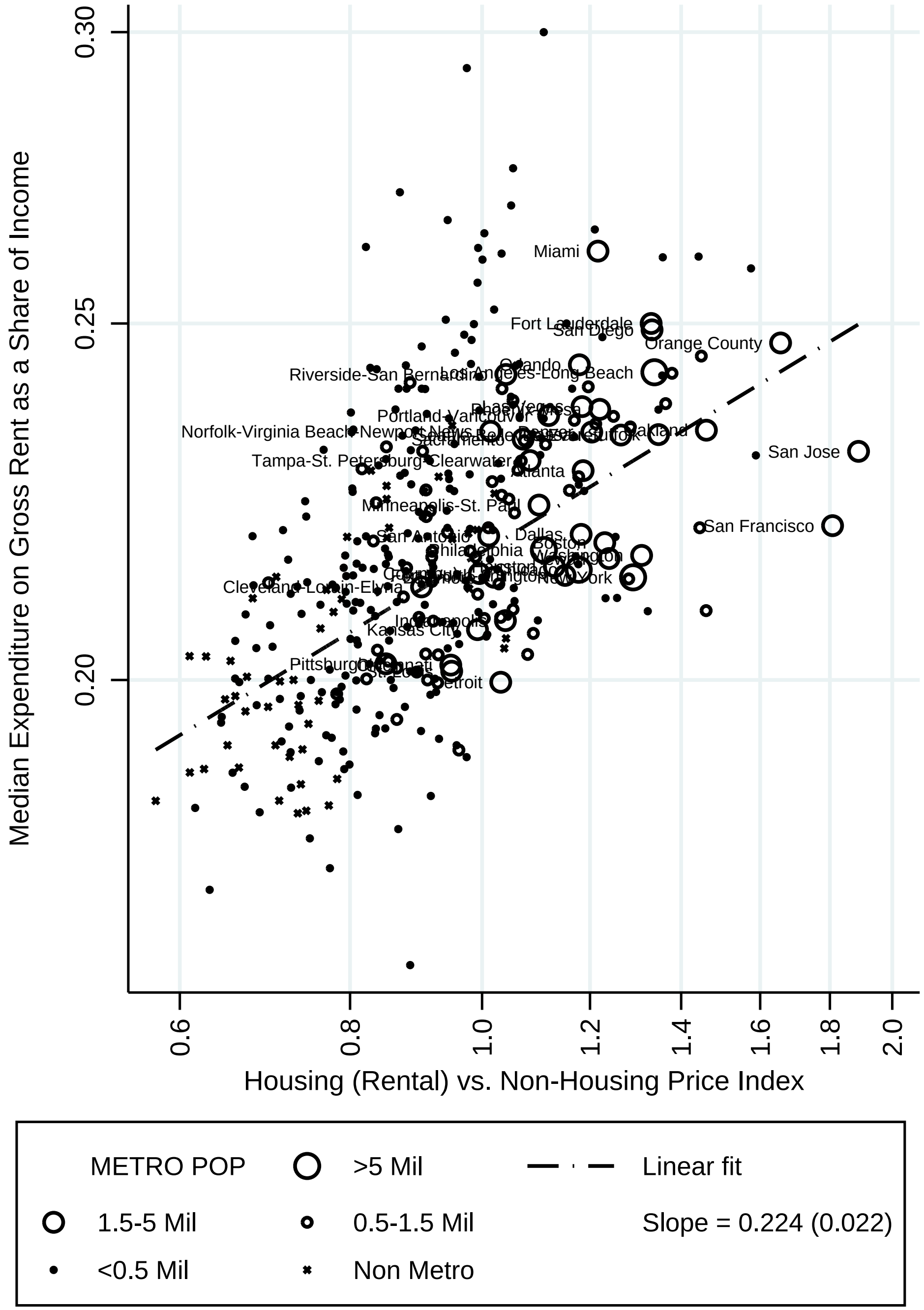


Figure 4B: Median Share of Income Spent on Housing
and the Relative Price of Housing, All Households 2000

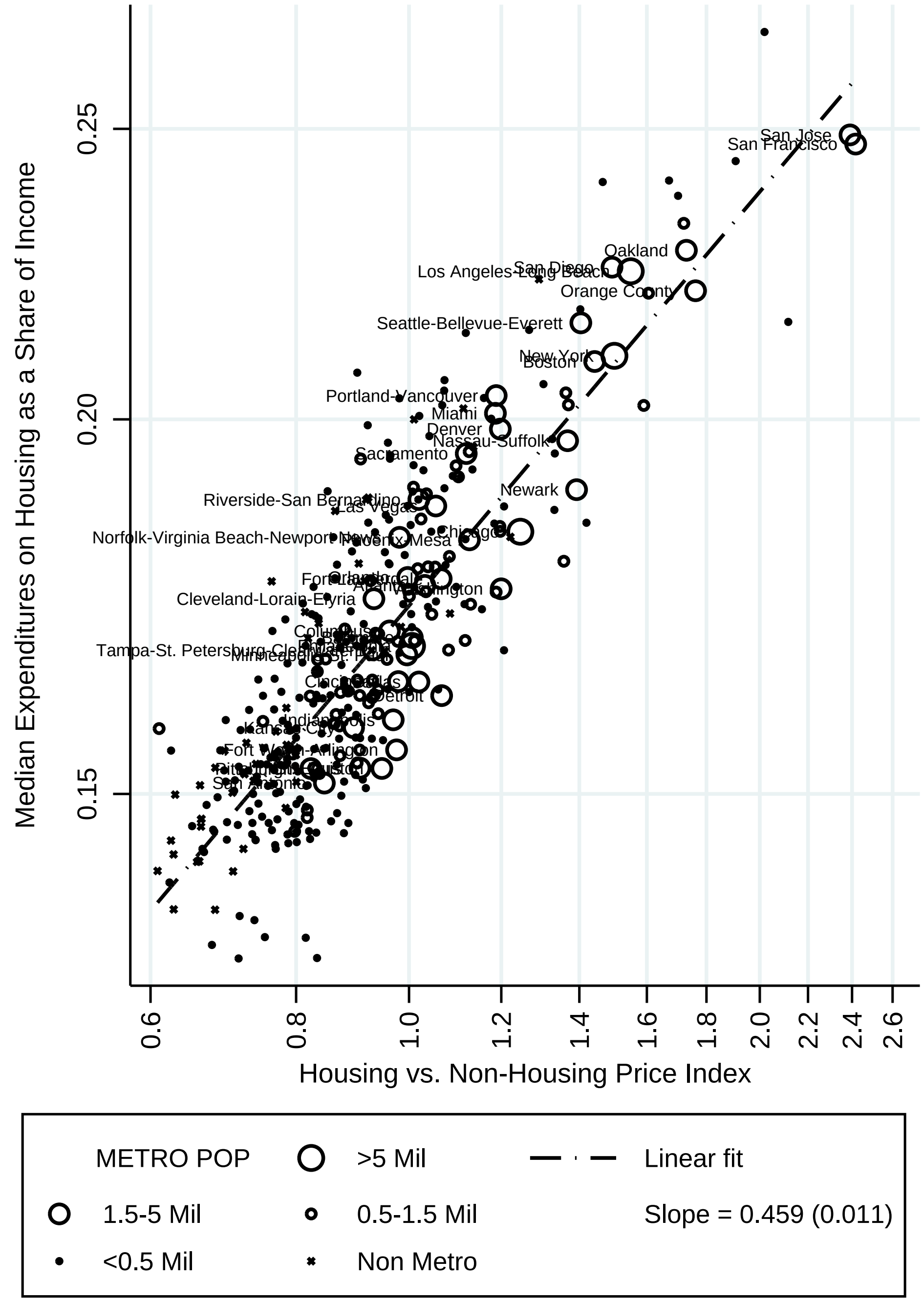


Figure 5A: Comparison of Cost-of-living Indices
at median household income

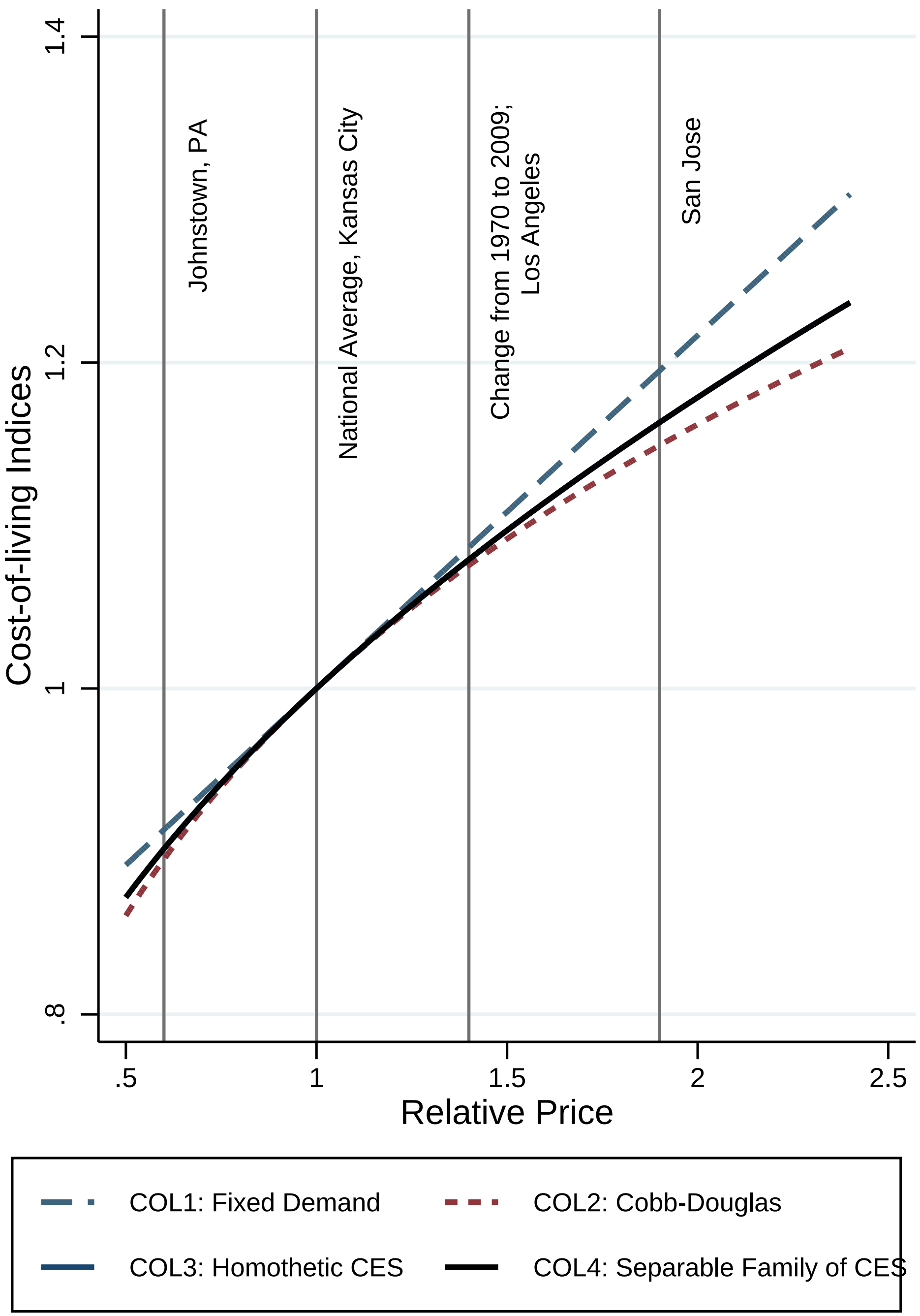
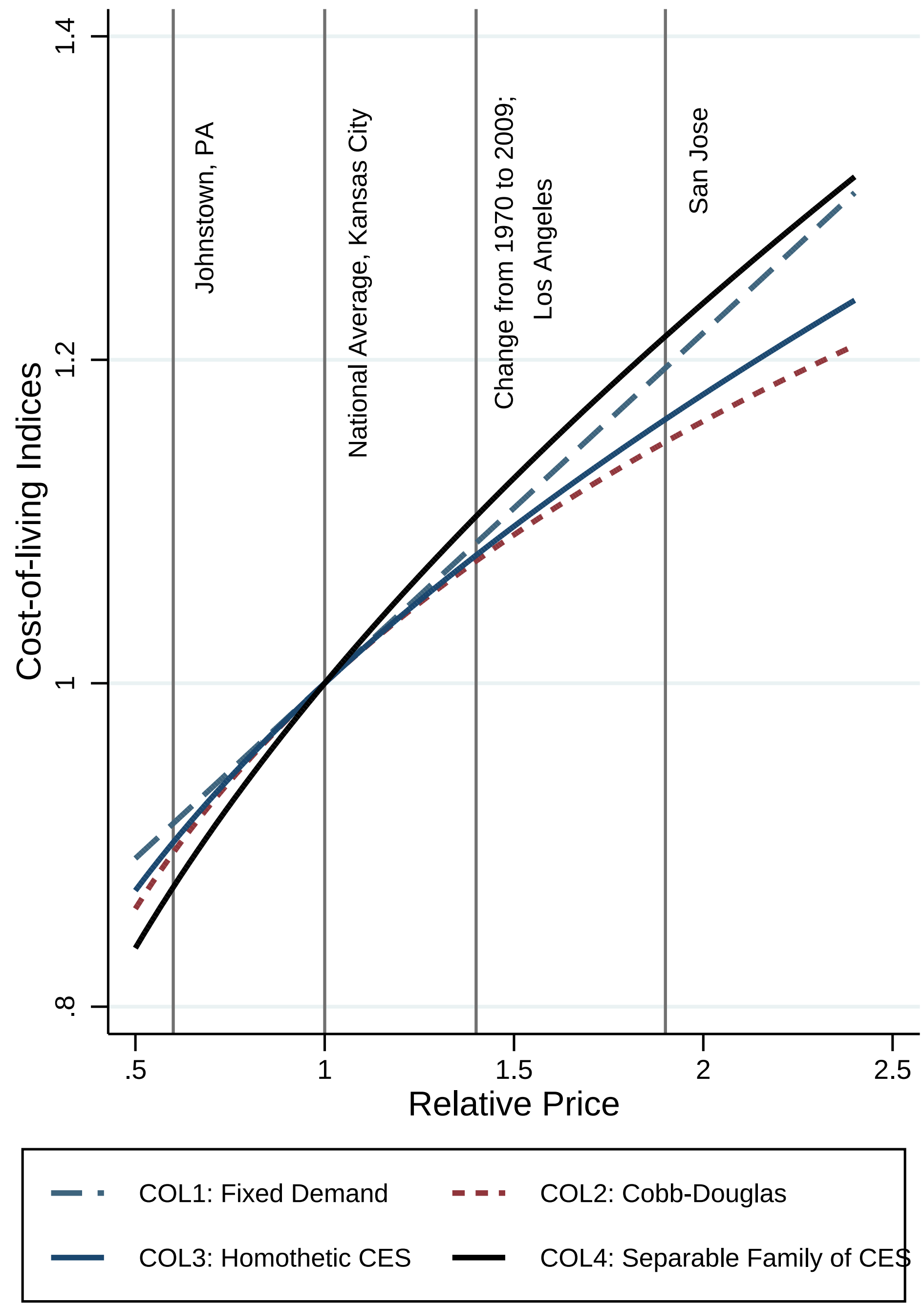


Figure 5B: Comparison of Cost-of-living Indices
at one half of median household income



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:

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

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 1997-2003 pooled 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:

- unit size and square of unit size;
- lot size and square of lot 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;
- 3 indicators for the number of half bathrooms;
- 2 indicators for the number of living rooms;
- 2 indicators for the number of kitchens;
- an indicator for porch in the unit;
- an indicator for room air conditioner;
- an indicator for central air conditioner;
- 12 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;
- rating of unit as a place to live;
- 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 1997-2003 pooled 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 .223 and the mean of the MSA-level meadian housing share for both renters and owners is 0.178.

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

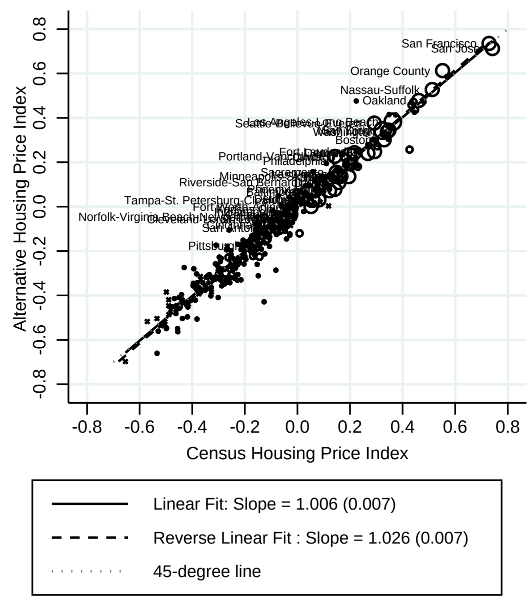


Figure B: CEO vs. Census Housing Price Index

Figure C: AHS vs. Census Housing Price Index

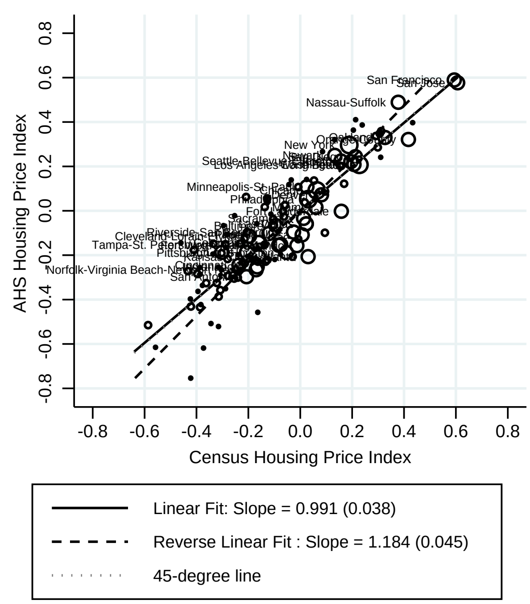
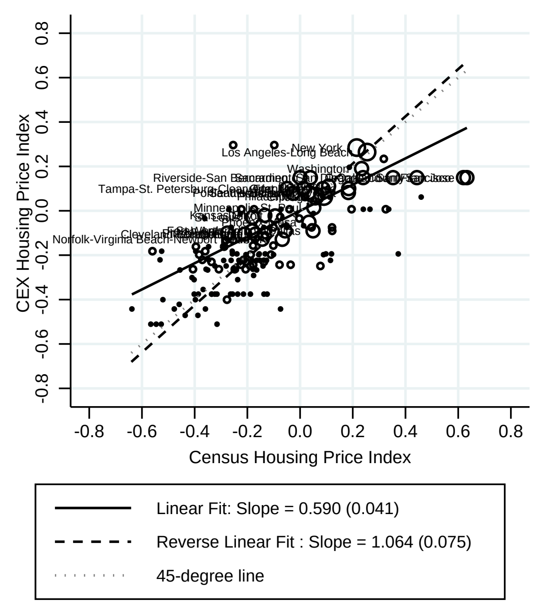


Figure D: CEX vs. Census Housing Price Index



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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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
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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MSA Name	MSA Population	Relative Price of Housing Index	Median Expenditure Share on Housing: Renters Only	Median Expenditure Share on Housing: Renters & Owners	Housing Price Index: Rentals Only	Housing Price Index: Rentals & Owned	Non-Housing Price Index	Predicted Wage Index: Renters Only	Predicted Wage Index: Renters & Owners
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.