1. Introduction

In 1999, the median value of an owner-occupied housing unit in the San Francisco-Oakland-San Jose, CA metropolitan area was $353,000. The median owner-occupied home in the McAllen-Edinburg-Mission, TX metropolitan area cost $52,400. Such extraordinary variation in housing prices, and the question of housing market "bubbles" in high-cost metropolitan areas, continuously fuel speculation on trends in housing prices and availability across the United States. This paper seeks to understand why some cities are consistently more expensive than others, and how much of the geographical variation in housing prices, rents, and wages can be explained by the amenities of each metropolitan area.

Housing supply and demand vary across cities, as do fixed locational differences such as amenities, geography, and other city-wide characteristics. Since the measurement of housing supply and demand is difficult, quality of life research has sought other ways to explain why some locations command a premium in the housing (and labor) markets. Several previous studies have analyzed spatial and temporal differences in housing costs and wages, used such differences to estimate implicit local (i.e. metropolitan-level) amenity prices, and accordingly constructed urban quality of life indexes. I propose a variant on this strategy. Rather than estimating implicit prices for specific amenities, I construct metropolitan area-level averages of the residuals from individual-level wage, rent, and house value regressions. These averaged residuals represent the cross-locational differences in wages and housing prices that are unexplained by a rich set of demographic, human capital, and housing structure data. This strategy also allows me to account for the endogeneity between wages and housing prices within each location.

Several questions underlie the elements of this analysis. Do differences in unobservable factors driving spatial differences in wages and housing costs persist over time? Do spatial differences in wages and housing costs reflect amenity differences – an "equilibrium" interpretation – or compensating differentials signaling utility differences and housing affordability "disequilibrium" across MAs? And if a given household – living in a particular dwelling in a particular metropolitan area – moves to a different location, how would its wages and housing costs change?

This study is the first to include recently available 2000 census PUMS microdata to measure metropolitan area quality of life (QOL); I link the 2000 data to 1980 and 1990 census microdata, allowing me to analyze QOL in three cross sections as well as two decadal changes. The PUMS is the largest and most geographically detailed dataset available for the calculation of individual households' wages and rents. Its use frees a QOL analysis from reliance upon aggregated data, multiple data sources, or limitation to a single cross section – three restrictions which previous studies have been forced to adopt.

This study applies an instrument that is previously unused in the QOL literature. Earlier research estimated implicit amenity prices via separate hedonic housing and wage equations, and used the implicit prices to construct quality of life indexes. Such work notes but does not empirically account for the endogeneity of wages and rents[1]: in MAs where average rents and housing prices are more expensive, firms must offer employees higher wages in order to prevent them from moving to cheaper locations. Prospective

[1] Stover and Leven (1992) do model interrelated labor and housing markets, but argue that either a wage differential adjusted for land values or a rent differential adjusted for wages alone is sufficient to obtain an unbiased amenity value estimator. Since wage hedonics had previously been associated with poor results, they choose to estimate a housing hedonic, in which wage hedonic variables only enter indirectly.

inmigrants may choose not to move to a high-cost location unless high prevailing wages convince them that their expected earnings will cover the higher cost of housing. I estimate the quality of life in each metropolitan area in three ways: I estimate wages via two-stage least squares, using an index of the restrictiveness of housing regulation as an instrument for MA-average housing prices. I estimate rents and house values via ordinary least squares.

The sample size and level of detail in the PUMS allow me to define and analyze the quality of life in 250 geographically consistent metropolitan areas (MAs) across the U.S. in 1980, 1990, and 2000.[2] Table 1 details the number of household-level observations and weighted household counts, separately for renters and homeowners, in each of the 250 MAs used in the analysis. I utilize a total of XX million household-level observations in 1980, 2.2 million in 1990, and 2.6 million in 2000. Not only is the PUMS the largest publicly-available sample with which one can measure wages and housing prices for the same households, but the number of MAs I define in the 1990 and 2000 PUMS greatly exceeds that of earlier studies.[3] As noted in Gyourko et al. (1997), small sample sizes and poor data quality produced imprecise QOL estimations in early research. The larger samples used in this paper allow for more precise estimations.

The three specifications (wages, rents, and house values), which I estimate in the three most recent census cross sections, yield nine sets of QOL estimates. I define the "quality of life estimate" of each specification simply as the metropolitan area-average of

[2] Geographically consistent MAs are more appropriate than census MA definitions for a study of housing costs, wages, and affordability over time, as census MA definitions change to reflect metropolitan area expansion.

[3] Blomquist et al. (1988), Stover and Leven (1992), and Gyourko and Tracy (1991) use the 1980 one in 1000 public-use (A) sample of the 1980 Census to analyze urban QOL. The first two papers consider a total of 34,414 households and 46,004 wage earners residing in 253 urban counties (185 MAs). The third paper utilizes 5,263 housing units and 38,870 worker observations, all of which are associated with the central city of 130 MAs.

the residuals from that regression. Thus my QOL measures reflect the collective unobserved characteristics associated with each metropolitan area. Each set of QOL estimates implies a ranking of the 250 MAs; I compare the correlations of rankings across specifications to gauge of their reliability. I compare the MA residuals to selected amenities, geography, and demographic characteristics of cities; the goal is to determine whether there are any particularly promising explanations for the differences in measured quality of life across cities.

On a basic level, one purpose of this study is to explain the substantial spatial and temporal variation exhibited by wages and housing prices across the U.S. during the past 15 years. Figures 1, 2, and 3 (not yet attached) show the 1980-1990-2000 distributions of MA-median wages, rents, and house values, respectively. In each Figure, Panel A plots the distributions of MA medians in each of the three cross sections; Panel B plots the distributions of the change in MA medians for each of the two decades, 1980-1990 and 1990-2000.

Much of the cross-sectional variation shown in Figures 1A and 1B is due to the varying amenity levels – e.g. climate, environmental factors, or "produced" amenities such as lack of crime – associated with each metropolitan area. Such characteristics comprise the set of "equilibrium" motivations for household migration. However, to the extent that interregional differences in housing affordability reflect utility rather than amenity differences across locations, households also have "disequilibrium" incentives to migrate amongst cities. These two competing explanations for spatial differences in housing affordability, while not necessarily mutually exclusive, form the crux of the above-mentioned debate in the migration literature.

My main results indicate that no matter the specification – wages, rents, or house values – MA quality of life differences persist over time. Places that were attractive in 1980 remained attractive in 1990 and 2000; people consistently paid a premium to live in these locations. Comparing results across specifications yields mixed results. Within a given cross section, the same places tend to be designated as "amenable" by both the rent and house value specifications. Places designated as "amenable" by the wage specifications do not necessarily match up to the rent and house value results.

The paper is structured as follows. I briefly review relevant literature in Section 2, and describe my empirical strategy and the data in Sections 3 and 4, respectively. In Section 5 I present my main findings. Section 6 explores two extensions: whether my measures of MA attractiveness more accurately reflect amenities or regional "disequilibrium"; and whether MA attractiveness is viewed consistently across permanent income groups. Section 7 concludes.

2. Literature review

i. Regional equilibration and metropolitan quality of life

Urban areas in the United States can be characterized as a system of interrelated cities. Shocks to the labor or housing markets of one urban area affect outcomes in that area as well as outcomes in the labor and housing markets of other cities within the system. Households and firms respond to shocks by migrating amongst areas in a manner consistent with the concepts of utility- and profit-maximization.

Several strands of the regional economics literature investigate outcomes pertinent to a study of the quality of life across metropolitan areas. The following review highlights and integrates some of the more relevant analyses and findings.

Blanchard and Katz's (1992) comprehensive study provides a general analysis of U.S. regional markets and how they have equilibrated since the 1940s. They focus on labor market adjustments as explanations for regional changes in relative employment, unemployment, wages, and prices. Labor mobility, the process that smoothes shocks to states' growth, is driven by changes in unemployment. The authors note that housing prices – and not consumption wages – respond strongly to employment shocks, but do not otherwise focus on the housing market.[4]

Roback (1982) first formalized the theory of household and firm locational choice in a general equilibrium utility-maximization model incorporating housing costs; her work spawned a large literature which focuses on quality of life differences across urban areas. Such research generally estimates wage and housing or land price equations in separate reduced-form equations. The primary goals of these studies are to estimate implicit prices for local amenities, and use them to rank urban areas by a quality of life index.[5] Hoehn et al. (1987) and Blomquist et al. (1988) consider interactions between interregional labor and housing markets as well as intraurban market variation; Gyourko and Tracy (1991) extend the Roback model to include government services and allow for possible group effects.[6] All three studies find that local amenities are capitalized into

[4] Other authors following Blanchard and Katz (1992) have analyzed regional equilibration via the labor market in the Netherlands (Broersma and Van Dijk 2001), in Italy (Dunford 2001), and in the U.S. for various population subgroups (Bound and Holzer 2000).
[5] See Gyourko et al. (1997) for an overview.
[6] City-specific group effects may represent unmeasured housing structure or human capital, which should not be included in quality of life rankings, or they may reflect omitted amenity or fiscal variables that

both wages and land prices. Stover and Leven (1992), concerned with the reliability of hedonic wage equation estimates, derive a single-equation housing expenditure hedonic. Unlike earlier work, their specification is not in reduced form, since they model housing prices as a function of local wage rates. Greenwood et al. (1991) relax the standard equilibrium assumption in the QOL literature by not requiring that households be indifferent to location at current implicit amenity prices. However, they do not find much support for disequilibrium pricing. I contrast equilibrium and disequilibrium perspectives further below.

A second, somewhat disparate strand of literature also stemming from Roback (1982) tests theories of inter-urban area equilibration via the labor or housing markets. Some extensions include Gyourko and Tracy (1989), who include local fiscal conditions and estimate the extent to which local attributes are capitalized into wage – although not housing price – differentials. Greenwood et al. (1991) similarly focus on the labor market. They measure population growth due to migration as a function of amenities and "relative income," defined as the difference between states' actual relative real after-tax earnings and the authors' corresponding point estimate equilibrium values.

Several other studies consider locational differences in rents and/or amenities but largely disregard wages in the adjustment process. Gyourko and Voith (1992) focus on inter-metropolitan area differences in housing price appreciation rates; they find lower appreciation rates in areas with higher real home prices.[7] Saiz (2003) restricts his analysis to immigrants, a nonrandom subpopulation of migrants to U.S. cities. After

should be included in hedonic estimations. The authors remain agnostic regarding the inclusion of group effects in their model.

[7] This must hold in long-run equilibrium unless households in higher-priced areas have proportionately higher income growth, tied to higher productivity.

noting that other authors find little to no wage response amongst populations in high-immigration areas, he finds a positive relation between immigration and housing prices or rents. He thus suggests the price of housing as a mechanism through which metropolitan areas respond to labor supply shocks.

In this study, I use an index of housing regulation restrictiveness as an instrument for metropolitan area-average rents and house values. The correlations between local housing regulation and housing prices (positive) and regulation and housing supply (negative) have been well-documented. Malpezzi (1996), Malpezzi et al. (1998), Glaeser et al. (2003), and Quigley and Raphael (2004) directly assess regulations' impact on the level of rents or housing prices, and universally agree that regulation is associated with higher housing costs. Katz and Rosen (1987) and Pollakowski and Wachter (1990) reach similar conclusions regarding interjurisdictional zoning and land use constraints in a local context. Malpezzi (1996) finds that greater regulation is associated with lower homeownership rates within a metropolitan area. Glaeser and Gyourko (2003) claim that where housing affordability problems exist in the U.S., land-use controls and not high land prices are primarily responsible. Saks (2003) estimates that regulation explains approximately 80 percent of the widening median housing value distribution across U.S. metropolitan areas. Mayer and Somerville (2000) analyze the metropolitan area-level effects of land use regulations on new housing supply, finding lower levels and lower price elasticities of construction in more regulated areas.

Several of the authors cited above have noted that estimating the impacts of amenities and migration in either the housing or labor market while ignoring the complementary market renders their analyses incomplete. Many of the above studies were conducted before the availability of detailed microdata incorporating both rents and wages for large numbers of individual households. The census five percent PUMS sample allows one to analyze rents and wages for the same households. The 1980, 1990, and recently released 2000 PUMS sample provide three cross sections in which I estimate the housing and labor market impacts of amenities.

ii. Equilibrium versus disequilibrium modeling

The above-mentioned analyses, with the exceptions of Blanchard and Katz (1992) and Greenwood et al. (1992), assume that the system of metropolitan areas is inherently in equilibrium. The underlying assumption is one of efficient labor markets, housing markets, and migration: changes in the supply or demand of locational amenities, and not spatial variations in utility, are the primary motivations for interregional household migration. Since households and firms are indifferent as to location in equilibrium, spatial differences in "economic opportunity" – wages and employment – reflect compensating differentials associated with corresponding spatial differences in amenities.[8] This assumption again derives from Roback (1982), plus Rosen (1979): in their compensating differential model, workers and firms compete for scarce sites, with wages and land rents equilibrating so that the marginal worker and firm are indifferent among locations. One may still observe persistent intercity household migration so long as households are not assumed homogenous in preferences or labor market exposure.[9,10]

[8] Whether or not housing prices are higher and wages lower in high-amenity locations is indeterminate and depends on whether the amenity is productive or unproductive. Higher levels of a productive amenity (e.g. sunny days) reduce firms' costs of operation; in more amenable locations, equilibrium housing prices are higher but the effect on wages is ambiguous. If the amenity is unproductive (e.g. less pollution), firms have higher costs of operation in high-amenity locations. Equilibrium wages are lower and the effect on housing prices is ambiguous.

[9] Labor market exposure refers to the number of household members in the labor force.

There is a lengthy debate in the intercity migration literature as to whether equilibrium or disequilibrium perspectives more accurately describe empirical findings of persistent population movements. Disequilibrium theories assume that labor and housing markets do *not* immediately adjust following a disturbance. Thus observed spatial differences in wages and housing prices reflect utility differences, the "noncompensating" portion of wage and housing price differentials; intercity migration persists because households adjust to these differences very slowly. Evans (1990) argues that the equilibrium assumption cannot adequately explain continuing net migration across regions; Graves and Mueser (1993) rebut Evans' arguments, concluding that the majority of intertemporal systemic migration is due to equilibrium forces. They propose a model that allows migration to derive from both equilibrium and disequilibrium motivations. Hunt (1993) surveys the equilibrium-disequilibrium debate in migration modeling and concludes that the equilibrium perspective can not fully explain observed migration patterns. Measures of "economic opportunity", encompassing one equilibrium component that compensates for amenities and one disequilibrium component that provides a job search incentive for migration, are needed to explain spatial differences in wages and housing prices.

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[10] Gyourko et al. (1997) suggest one spatial and three life cycle motivations for migration that are consistent with the equilibrium perspective. First, household preferences for amenities and government services vary over the life cycle, so if attribute prices are relatively constant over time, households will migrate in order to achieve a more preferred bundle of local attributes. Second, households' exposure to the labor market may vary during the life cycle; households experiencing decreased exposure will relocate to cities where local attributes are more capitalized into the labor (and less into the housing) market. A third life cycle explanation is capital market imperfections: since many households can not smooth consumption perfectly as their real income changes, income increases cause them to relocate to areas offering a more desired amenity/fiscal services bundle. Finally, the acts of entering the labor market and forming households may create a spatial mismatch for individuals, who then have the motivation to migrate in order to maximize utility.

3. Empirical strategy

i. Wage and housing price estimations

Previous analyses estimate metropolitan quality of life by including multiple amenity measures in wage or housing price regressions, estimating implicit amenity prices, and using them to construct a QOL index. The quality of life associated with each MA is then ranked according to these index values. I similarly estimate wage and housing price regressions; but rather than estimating implicit prices, I average each set of residuals at the MA level. The averaged residuals proxy for a metropolitan area's vector of amenities; they are the means by which I measure and rank MA quality of life. I estimate wage equations via two-stage least squares, and rent and house value equations via ordinary least squares, in each of the three census years, 1980 through 2000. This yields three measures of metropolitan area QOL in three cross sections. By comparing the QOL measures across time and specifications, I determine whether the same places are considered the most amenable by both renters and homeowners, whether a location's attractiveness is capitalized more into wages or housing prices, and whether a high QOL persists in certain locations over time.

I consider two structural equations for the wage received and the rent or house value paid by a given household:

(1) $$\log(r_{ij}) = regulation_j \pi_{1r} + H_{ij}\pi_{2r} + Z_j \pi_{3r} + u_{ij}^{\ r}$$

(2) $$\log(w_{ij}) = \log\left(\frac{\sum_{i=1}^{N} r_{ij}}{N}\right)\pi_{1w} + X_{ij}\pi_{2w} + Z_j \pi_{3w} + u_{ij}^{\ w},$$

where $\log(w_{ij})$ = gross-of-tax average hourly wages for individual i in city j, and $\log(r_{ij})$ = annual rent for renter-occupied dwellings, or the house value of owner-occupied dwellings.[11] *regulation*$_j$ represents the restrictiveness of local housing regulation; I explain this instrument in greater detail below. X_{ij} is a vector of personal characteristics including demographic variables, human capital proxies such as education, and household structure.[12] Z_j is a proxy for local (i.e. MA-level) amenities; $\overline{r_j} = \frac{\sum_{i=1}^{N} r_{ij}}{N}$ is the average rent or house value for dwellings of the respective tenure in MA j. H_{ij} is a vector of housing structure characteristics.[13, 14]

Within an MA, each individual's wages w_{ij} depend on the average rent $\overline{r_j}$ prevailing in the MA. Employers in cities with higher average housing prices offer

[11] I only estimate w_{ij} for household heads. There are three reasons for the exclusions of other household members and non-wage income: feasibility, since including earnings of multiple household members would require including and weighting demographic and human capital data on all earners in wage regressions; abstraction from the substantially different housing price and affordability issues faced by non-wage earners; and comparability with previous studies. Thus, in many cases I underestimate the total wages earned within the household. I can not address behavioral questions of when a second household member decides to work, e.g. a spouse works only because the household could not otherwise afford the dwelling in which it resides.

[12] More specifically, X_{ij} includes dummies for the sex, age, race, ethnicity, education level, school attendance, and marital status of the household head, as well as household size and the number of the household head's own children in the household.

[13] H_{ij} contains dummies for number of rooms, number of bedrooms, age of structure, structure type/number of housing units in structure, presence of kitchen facilities, and presence of complete plumbing facilities.

[14] The error structure of equations (1) and (2) depends on the estimation technique used. Gyourko and Tracy (1989, 1991) find city-specific (group) error components in their data, and use random effects as well as ordinary least squares to estimate their wage and rent equations. They note that one should only include group effects in QOL calculations if they represent omitted city attributes; group effects should *not* be included in QOL calculations if they predominantly signify unobserved worker or housing quality differences across locations. Saiz (2003), Saks (2003), and Malpezzi et al. (1998) follow an instrumental variables strategy to estimate variants of (1) and (2), while earlier studies (e.g. Roback (1982)) use OLS. Several quality-of-life papers (Blomquist et al. (1988), Stover and Leven (1992)) estimate hedonic wage and housing price equations utilizing many of the same dependent and independent variables as in (1) and (2), but specifying functional forms:

$$\frac{Y^{\lambda}-1}{\lambda} = b_0 + \sum_{i=1}^{n} b_i * \frac{S_i^{\gamma}-1}{\gamma} + \varepsilon$$

Y represents wages or rents and the S_i are the independent variables (X_{ij}, H_{ij}, Z_j) discussed above.

higher wages to entice prospective employees to migrate to such high-cost locations; potential inmigrants will only move to such an area if their expected wages are large enough to counteract the high cost of housing. Thus, the system represented by equations (1) and (2) is endogenous: a household's rent is one determinant of its wages. One must instrument for $\overline{r_j}$ when estimating $\overline{w_j}$.

In the estimations that follow, I utilize an metropolitan-level index of regulatory restrictiveness developed by Malpezzi (1996) to instrument for $\overline{r_j}$. Regulation is plausibly exogenous: one would not expect it to affect wages independently of its effects on rents or housing values. The first-stage estimates presented in Table 3 indicate that the index of regulatory restrictiveness is positively correlated with both rents and housing values. This corresponds to other authors' findings. If local governments restrict land from additional or denser development or otherwise hinder construction, housing supply declines relative to demand, and housing prices increase.

Earlier studies, depending on the data available and the model tested, have included a wide variety of metropolitan-level characteristics affecting both wages and rents in Z_j,. Metropolitan-level data for such amenities such as climate, pollution, geography, crime, and unemployment draws from numerous sources and different years; such data rarely covers the entire 1980-2000 time period considered in this analysis. As a simpler – if somewhat cruder – proxy for MA amenities, I substitute MA-average residuals for Z_j in estimations of equations (1) and (2). While I am unable to partial out the extent to which a favorable climate versus a healthier environment correlates with increased housing costs and decreased wages in a location, the use of MA-average residuals allows me to draw conclusions regarding the effects of unobserved "amenities" or MA attractiveness on housing costs and wages across metropolitan areas.[15] I later compare how the MA-level residuals correlate to the MA characteristics and amenity data which is readily available.

ii. Ranking metropolitan areas by quality of life

Estimating the MA-average residuals from wage, rent, and house value regressions in each of three census years yields nine measures of the quality of life for each metropolitan area. I rank the MAs from 1 (most amenable) to 286 (least amenable) according to each of these QOL estimates. MAs with the largest positive rent or house value residuals, and MAs with the largest negative wage residuals, receive numerically small rankings; households indicate a preference for such locations by accepting higher rents, paying more for their houses, or receiving lower wages in order to reside in these places.

In order to determine the consistency of the various methods of estimating metropolitan area QOL, I compute the Spearman rank-order correlation across pairs of sets of QOL rankings.[16] I thus assess whether the three specifications (wages, rents, and housing values) generate similar MA rankings within each cross section; I also examine

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[15] A simpler strategy is to include MA fixed effects in equations (1) and (2). However, since the MA-average $\overline{r_j}$ and the regulation index used as an instrument for $\overline{r_j}$ are defined at the metropolitan level, MA fixed effects are perfectly collinear if entered directly into equation (2). Thus the estimates $\hat{\pi}_{3r}$ and $\hat{\pi}_{3w}$ are constructed through a two-step process. Wages and rents are first regressed on the exogenous variables specified in equations (1) and (2), and the residuals are retained; second, I take MA-level averages of the residuals.

[16] The Spearman correlation is a basic correlation coefficient calculation, using rankings rather than the residual values:

$$\rho_{xy} = \frac{\operatorname{cov}(X,Y)}{\sigma_x \sigma_y} \text{ , where } \operatorname{cov}(X,Y) = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu_x)(y_i - \mu_y).$$

cross-year, within-specification correlations to determine whether the same locations are viewed favorably in 1980, 1990, and 2000.

Finally, I compare the metropolitan QOL rankings to readily available data on metropolitan-level amenities, characteristics, and geography. The goal is to determine whether there is some simple, obvious explanation (e.g. average temperature, racial composition, or proximity to the coast) for the differences in measured QOL across MAs.

iii. Robustness checks

In order to assess whether households of different income levels view MA attractiveness consistently, I split each PUMS cross section into four "permanent income" subsamples[17]. Since I cannot observe the permanent (lifetime) income of a household in my data, I use the highest educational attainment of the household head as a proxy.[18] I estimate equations (1) and (2) separately in the three cross sections for each of these four groups, which might have differential responses to the higher housing costs and/or lower wages in more amenable MAs. On average, college-educated individuals are expected to earn more and be more mobile over the course of their lifetimes. Individuals with less education, e.g. recent immigrants, tend to move less and reside in more crowded households. I estimate wage, rent, and house value residuals separately by education group in each cross section, yielding nine QOL measures for each of the four groups.

[17] I do not split households by their reported income in the PUMS, since a household headed by a 25-year old with low current may have a wide range of future expected earnings. A 25-year old with low current earnings but a high level of education and high future expected earnings may be highly mobile; his or her migration decisions and opportunities may more closely resemble those of an older, wealthier household.
[18] The four educational attainment groups are less than high school, high school degree, some college, and college degree or more.

A second check assesses whether MA-level residuals truly capture locational amenity differences and thus signal migrational "equilibrium" across metropolitan areas. I calculate the correlations between each cross-sectional residual and the ensuing decade's percent change in population, median wage, median rent, and median house value in that MA. If the regional system is in equilibrium, then the unexplained differences in wages, rents, and house values represent amenity packages that vary across metropolitan areas. Thus, shifts in population, wages, or housing costs should not be correlated to levels of the estimated MA-average residuals. However, if the relationship between residuals and the ensuing decade's percent change in population, wages, or housing costs is not flat, then "disequilibrium" may exist. If this is the case, utility differences may drive the variation in measured "attractiveness" across MAs.

4. Data

i. Description and relevance

The primary data source for the present research is the Census Public Use Microdata System (PUMS; http://www.ipums.org/usa/). Extracts from the 1980, 1990, and 2000 five percent samples allow me to estimate wages, rents, and house values in the cross section. The MA-average residuals from these wage, rent, and house value regressions are what I use to generate QOL measures by metropolitan area.

The PUMS is the best available data set for estimating wages and housing costs at the individual or household level. The unparalleled sample size of the permits an MA-level analysis of population subgroups, e.g. renters versus homeowners, which is impossible with smaller datasets. I utilize XX million household-level observations in

1980, 2.2 million in 1990, and 2.6 million in 2000. To my knowledge, no existing work uses all three years of the PUMS for a detailed MA-level analysis of metropolitan QOL.

An advantage of the PUMS' large sample size is detailed geography. One can define areas as small as the Public Use Microdata Area (PUMA) for any household in the sample.[19] The census also defines MAs, P(rimary)MAs, and/or C(onsolidated)MAs for virtually all households; however, since the census updates MA definitions to reflect urban growth over time, few census-defined MAs maintain consistent geography between 1980 and 2000. An additional drawback to census-defined MAs is partial identification: weighted population counts in partially-identified MAs are as much as sixty percent below the true population. I utilize an alternate strategy, based on PUMAs and described further below, to construct MAs that are nearly geographically identical between 1980 and 2000.

I employ two relevant measures of housing costs from the PUMS data: renter households' annual gross rent (including utility and fuel costs) and owner-occupying households' self-reported house value. I calculate the average hourly wage of each household head as his or her previous year's wage income divided by the product of weeks worked last year and usual hours worked per week.[20]

The PUMS contains numerous demographic, human capital, and housing characteristics, which I use as independent variables in the regression analysis. Wage

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[19] Public Use Microdata Areas (PUMAs) are census-defined geographical units containing between 100,000 and 200,000 individuals. In more rural areas, PUMA boundaries tend to follow county lines, typically encompassing multiple counties; in more urban areas, PUMAs may be part of a county, an entire county, multiple counties, or parts of multiple counties.

[20] The PUMS topcodes income and restricts the number of weeks and hours individuals can report having worked during the previous year. However, since I combine these three variables in my calculation of average hourly wages, misreporting of income, hours, or weeks can generate anomalous hourly wage values. I restrict the samples to individuals with average hourly wages below \$1000/hour. Assuming 2000 hours worked per year, this implies an annual wage income of \$2 million, well above the census' topcode values for annual wages.

regressions control for the sex, age, race, ethnicity, education level, school attendance, and marital status of the household head, as well as household size and the number of the head's own children present in the household. Rent and house value regressions control for the number of rooms, number of bedrooms, age of structure, structure type or number of housing units in structure, presence of kitchen facilities, and presence of complete plumbing facilities. MA-average house values – the endogenous variable in equation (2) – are also calculated from PUMS data. Table 2 contains summary statistics of the PUMS variables as well as of the regulation instrument used in the regressions.

The regulatory indexes used as instruments for MA-average house values in the regressions exist for 250 MAs.[21] The indexes encompass seven measures of an MA's regulatory stringency, and proxy for the bureaucracy surrounding zoning changes and permit issuance, how land zoned for various housing types compares to demand, and how the adequacy of infrastructure compares to demand.[22]

ii. Construction of the MA variable

If one wishes to estimate the quality of life in metropolitan areas over time, census MA definitions are not adequate. The geographic areas of most census-defined MAs increase over time, as the MAs are continually redefined to reflect urban expansion. The census also merges, splits, and names new MAs according to well-defined standards.[23] In order to examine wages and housing costs for consistent geographical

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[21] Regulation indexes are downloaded from the University of Wisconsin Real Estate and Urban Land Economics website (http://www.bus.wisc.edu/realestate/resources/resdown.htm).

[22] These are the indexes created by and utilized in Malpezzi (1996) and Malpezzi et al. (1998). Estimations of equations (1) and (2) only include observations with nonzero regulatory indexes; I would otherwise be able to estimate wages, rents, and house values in 286 and not 250 MAs.

[23] The census defines 316 MAs in 1980, 333 in 1990, and 335 in 2000.

units, I ignore census MA labels and instead define metropolitan areas based on the PUMAs they span.[24] Since the census defines MAs by county, and PUMAs are not necessarily isomorphic to counties, my MA definitions often differ slightly from those of the census. Of the MAs I identify, New York has the largest total weighted number of households (3,462,138) in 2000; the MA with the smallest total weighted number of households in 2000 is Stafford County, NH (41,876).[25]

Metropolitan areas are the most relevant unit of observation for a spatial analysis of quality of life and (indirectly) migration. Several studies use states as a unit of observation, primarily due to data limitations. With the PUMS data, I can precisely estimate wages and housing costs at the more detailed metropolitan level. Additionally, the PUMS data cannot be disaggregated beyond the MA level and still generate precise estimates of the quality of life.

Using PUMAs to define MAs precludes the identification of several smaller MAs that the census methodology distinguishes.[26] However, XX percent of U.S. nonfarm households in the 1980 five percent PUMS sample live in one of the 250 MAs I identify, as do 81.0 percent in 1990 and 83.1 percent in 2000. Thus, I capture most of the population relevant to this analysis.

5. Results

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[24] MA geography follows Deaton and Lubotsky's (2002) definitions for (1980 and) 1990 census five percent data; I extend the definitions to the 2000 data by assigning to an MA any PUMA overlapping completely or partially with the 1990 PUMAs in that MA. Deaton and Lubotsky (2002) define 287 MAs; I have 286, 250 of which are used in the regression analysis.

[25] If one calculates weighted population counts in the PUMS, the largest MA in 2000 is Los Angeles-Long Beach, with a weighted population of 9,125,437; the smallest MA in 2000 is Anniston, AL, which has a weighted population of 105,945.

[26] The 250 MAs I identify in all three census years range between 85 and 86 percent of the number of MAs that the census identifies in those years; generally, I cannot identify the smaller MAs.

In this section I present ordinary least squares and two-stage least squares estimates of the quality of life in metropolitan areas. I compare within-year, across-specification results as well as within-specification, across-year results for the three census years and three outcomes (wages, rents, and house values) in the sample. I rank the 250 MAs according to the QOL values resulting from each wage, rent, and house value equation, and compare these nine sets of rankings. I assess whether MA "attractiveness" is capitalized into both wages and housing prices. Finally, I consider the geography, amenities, and other city-level characteristics associated with the 250 MAs to determine whether there exists some simple correlation that may explain residual wage, rent, and house value differences across MAs. I consider numerous climate and pollution measures, average demographics in each metropolitan area, per capita crime levels, density, unemployment, and whether the MA abuts a major body of water.[27] A more complete analysis of the specific amenities associated with MA attractiveness remains an area of future research.

i. Estimates of MA quality of life from wage and rent equations

Figures 4 and 5 present correlations of MA-average residuals generated from the reduced form wage, rent, and house value estimations (1) and (2). Figure 4 examines the correlation of MA-average residuals within specifications, across census years: Figures 4A, 4B, and 4C plot residuals from wage estimations; Figures 4D, 4E, and 4F plot residuals from rent estimations; and Figures 4G, 4H, and 4I show residuals from the house value regressions.

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[27] "Major bodies of water" include the Atlantic and Pacific Oceans, Great Lakes, and Gulf of Mexico.

Looking first at Figures 4A – 4C, a positive (MA-average) wage equation residual indicates that within the MA, there is a positive wage premium *not* explained by wage earners' demographic and human capital characteristics. Firms pay employees a premium to reside in that MA; the location therefore has fewer amenities or more disamenities relative to other MAs. Figures 4A (1980 and 1990), 4B (1990 and 2000), and 4C (1980 and 2000) demonstrate that wage equation residuals are positively correlated across all three census years. Places viewed as more desirable in 1980, as signaled by a negative wage premium, are the same places viewed as more desirable in 1990. The same logic applies between 1990 and 2000, and 1980 and 2000.

Figures 4D (1980 and 1990), 4E (1990 and 2000), and 4F (1980 and 2000) illustrate correlations between the MA-average residuals estimated via rent equations; Figures 4G, 4H, and 4I do the same for residuals from house value regressions. Unlike the wage estimations, a positive residual in the rent or house value equations implies a more amenable location: households with positive residuals pay more to reside in those locations than one would expect, given their dwellings' structural characteristics. Positive residuals represent a premium that households pay in order to live in those areas. The locations preferred by renters in 1980 – as evidenced by higher rent equation residuals – are the same locations preferred by renters in 1990 (Figure 4D). One draws the same conclusion when comparing rent equation residuals in 1990 versus 2000 (Figure 4E), and in 1980 versus 2000 (Figure 4F). The same pattern holds in comparisons of the three cross-sectional residuals for homeowners (Figures 4G, 4H, and 4I). In all three cross-decade comparisons, the correlations between rent residuals and those between house value residuals are stronger than the correlations between wage residuals.

Figures 5A through 5I compare MA-average residuals within census year and across specifications, examining the relationship between residuals from the wage versus rent estimations (Figures 5A, 5B, and 5C), wage versus house value estimations (Figures 5D, 5E, and 5F), and rent versus house value estimations (Figures 5G, 5H, and 5I). . Since metropolitan area amenities are capitalized positively into both rents and house values, residuals from these two equations should be positively correlated. The rent versus house value residuals shown in Figures 5G-5I show this expected correlation.[28] Since metropolitan area amenities are capitalized negatively into wages, residuals from the wage equations should negatively correlate to residuals from the rent or house value equations. However, the six comparisons in Figures 5A-5F do not show this pattern. The "most amenable" MA as described by the wage estimations – the MA which consistently has the most negative wage residual – is Jacksonville, NC. The most amenable MAs described by the wage and house value regressions – those consistently associated with the largest positive residuals – are San Francisco and San Jose.

ii. Comparisons of MA quality of life rankings

One can rank the MAs from 1 (most amenable) to 286 (least amenable) according to each of the nine sets of QOL estimates generated from the wage, rent, and house value equations. MAs with the largest positive rent or house value residuals, and MAs with the

[28] Regressions producing the MA-average residuals plotted in Figures 4 and 5 control for numerous demographic, human capital, and housing structure characteristic variables. Wage regressions are limited to household heads under age 65 with positive wage earnings; I include dummies for gender, 49 ages, four races, five (Hispanic) ethnicities, six marital status categories, school attendance, and eight educational attainment levels. The wage regressions also include six household size dummies and four indicators controlling for the number of the household head's own children residing in the household. Rent and housing value regressions include nine room dummies and six bedroom dummies, as well as indicators for eight structure ages, nine structure types/numbers of units in structure, the presence of incomplete kitchen facilities, and the presence of incomplete plumbing facilities.

largest negative wage residuals, receive numerically small rankings; households indicate a preference for such locations by accepting higher rents, paying higher house prices, or receiving lower wages in order to reside in these places.

Table 4 presents correlations between pairs of QOL rankings. Panel A compares within-specification rankings between 1980, 1990, and 2000; the correlation coefficients all exceed 0.70. The cross-decade rank correlations tend to be strongest in the rent specifications. Panel B compares rankings of MA attractiveness estimated from wage, rent, and house value specifications in the same census year. Correlations between rent and house value rankings are large and positive, as expected. Correlations between wage and rent rankings, and wage and house value rankings, do not show the expected pattern.

Tables 5, 6, and 7 contain complete rankings from the wage, rent, and house value regressions, respectively. I focus on the rent and house value rankings. Numerous coastal California and New York-area metropolitan areas (San Jose, San Francisco, Santa Rose-Petaluma, Santa Cruz, San Diego, Nassau-Suffolk, Newark, New York) consistently receive high rankings, as do Seattle, Portland, Boston, Chicago, Detroit, and Denver. Cities consistently ranking near the bottom – those where the prevailing rents and house values are the lowest relative to their predicted values – tend to be smaller metropolitan areas in Texas, the Midwest, and the south.

iii. Amenities, MA geography, and QOL rankings

Tables 8-10.

6. Robustness checks

i. Do MA attractiveness measures represent amenities or regional disequilibrium?

Tables 11-14.

ii. Are MA rankings consistent across permanent income groups?

Figures 6-9, Table 15, Appendix Tables A1-A4.

7. Conclusions

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Table 4

Correlations Among MA Quality of Life Rankings from OLS Wage, Rent, and House Value Specifications

QOL Rank Correlation Coefficients:	
Panel A: Within Specification, Across Census Year	
1980 wage & 1990 wage	0.73
1990 wage & 2000 wage	0.87
1980 wage & 2000 wage	0.74
1980 rent & 1990 rent	0.87
1990 rent & 2000 rent	0.93
1980 rent & 2000 rent	0.82
1980 house value & 1990 house value	0.79
1990 house value & 2000 house value	0.86
1980 house value & 2000 house value	0.85
Panel B: Within Census Year, Across Specification	
1980 wage & rent	-0.81
1990 wage & rent	-0.64
2000 wage & rent	-0.73
1980 wage & house value	-0.84
1990 wage & house value	-0.59
2000 wage & house value	-0.64
1980 rent & house value	0.83
1990 rent & house value	0.93
2000 rent & house value	0.88

Table 5
MA Rankings Based on 2SLS Wage Residuals

msa name	80 wage	90 wage	00 wage
San Francisco, CA	247	192	244
San Jose, CA	250	245	250
Santa Cruz, CA	235	165	196
Santa Rosa-Petaluma, CA	237	151	215
Seattle, WA	241	169	216
Santa Barbara-Santa Maria-Lompoc, CA	219	118	154
Portland, OR	200	103	156
Salinas-Seaside-Monterey, CA	220	96	201
Chicago, IL	244	239	237
San Diego, CA	209	127	161
Denver, CO	216	128	198
Detroit, MI	248	249	246
Los Angeles-Long Beach, CA	242	225	219
Nassau-Suffolk, NY	240	248	248
Boston-Lawrence-Salem-Lowell-Brockton, MA	167	221	227
Vallejo-Fairfield-Napa, CA	232	216	236
Sacramento, CA	215	164	208
Newark, NJ	243	246	247
Minneapolis-St. Paul, MN/WI	227	199	221
New York, NY	231	244	239
Eugene-Springfield, OR	153	27	32
Milwaukee, WI	233	196	211
Salt Lake City-Ogden, UT	156	83	127
Riverside-San Bernadino, CA	213	229	229
Bremerton, WA	212	122	146
Albuquerque, NM	101	56	84
Honolulu, HI	230	98	123
Boise City, ID	118	30	85
Tacoma, WA	192	140	190
Grand Rapids, MI	157	215	209
Cleveland, OH	229	217	202
Kenosha, WI	238	228	210
Olympia, WA	175	97	130
Medford, OR	116	10	15
Phoenix, AZ	172	132	204
Racine, WI	236	231	224
Cincinnati, OH/KY/IN	190	195	206
Flint, MI	246	250	232
Gary-Hammond, IN	249	247	242
Fort Collins-Loveland, CO	142	29	62
Green Bay, WI	158	150	177
Atlanta, GA	147	204	226
Stockton, CA	218	200	220
Nashville, TN	107	117	153
Hartford-New Britain-Middletown-Bristol, CT	222	238	243
Richland-Kennewick-Pasco, WA	194	158	142
St. Louis, MO/IL	199	202	184
Indianapolis, IN	183	194	203
Spokane, WA	141	64	50
Bellingham, WA	195	60	81
Dallas, TX	188	189	233
Modesto, CA	185	171	213
Reno, NV	198	149	176
Fort Lauderdale-Hollywood-Pompano Beach, FL	170	187	200
Ann Arbor, MI	239	220	217
Akron, OH	201	193	167
Redding, CA	173	75	60
Baton Rouge, LA	206	153	169

Table 5
MA Rankings Based on 2SLS Wage Residuals

msa name	80 wage	90 wage	00 wage
Las Vegas, NV	207	172	228
Tucson, AZ	126	33	58
Louisville, KY/IN	143	161	150
Philadelphia,PA/NJ	197	236	240
Saginaw-Bay City-Midland, MI	211	227	165
Kansas City, MO/KS	163	170	186
Appleton-Oshkosh-Neenah, WI	145	175	160
Yakima, WA	110	112	138
Charlotte-Gastonia-Rock Hill, NC/SC	86	162	191
Austin, TX	76	68	188
Madison, WI	132	85	114
Lafayette, LA	202	74	79
Houston, TX	234	214	231
Columbus, OH	155	163	183
Colorado Springs, CO	47	17	54
Des Moines, IA	125	126	128
Jackson, MI	191	223	187
Dayton-Springfield, OH	168	201	185
Wilmington, DE/NJ	182	241	241
Toledo, OH	208	222	173
Fresno, CA	177	141	148
Cedar Rapids, IA	174	142	104
New Haven-Waterbury-Meriden, CT	165	237	238
Canton, OH	196	183	151
Providence-Pawtuckett-Woonsocket, RI	90	146	171
Greeley, CO	138	38	111
Miami-Hialeah, FL	159	166	143
New Orleans, LA	181	93	99
Janesville-Beloit, WI	166	198	192
Baltimore, MD	210	233	225
New London-Norwich, CT	146	191	218
Billings, MT	115	6	3
Davenport-Rock Island-Moline, IA/IL	226	173	126
Hamilton-Middletown, OH	228	212	212
Greensboro-Winston-Salem-High Point, NC	63	131	139
Lancaster, PA	121	186	174
Tulsa, OK	144	114	97
Springfield, MA	74	144	162
Omaha, NE/IA	103	78	93
Lansing-East Lansing, MI	193	226	175
Fort Wayne, IN	151	190	194
Rockford, IL	217	209	223
West Palm Beach-Boca Raton-Delray Beach, FL	160	182	199
Birmingham, AL	139	133	157
Visalia-Tulare-Porterville, CA	120	65	137
Jacksonville, FL	56	135	135
Allentown-Bethlehem-Easton, PA	180	181	182
Raleigh-Durham, NC	85	130	158
Wilmington, NC	50	66	46
Bakersfield, CA	189	235	207
Sarasota, FL	75	23	48
Tampa-St. Petersburg-Clearwater, FL	43	55	113
Trenton, NJ	203	243	249
Mobile, AL	100	91	68
Greenville-Spartanburg, SC	44	143	134
Portland, ME	31	40	31
Elkhart-Goshen, IN	140	210	214
Oklahoma City, OK	104	87	67

Table 5
MA Rankings Based on 2SLS Wage Residuals

msa name	80 wage	90 wage	00 wage
Richmond-Petersburg, VA	150	207	189
Chico, CA	102	31	40
Amarillo, TX	92	71	51
Harrisburg-Lebanon-Carlisle, PA	137	188	181
Benton Harbor, MI	135	139	129
Springfield, IL	136	168	132
Peoria, IL	245	205	145
York, PA	119	177	149
Wausau, WI	124	147	109
Rochester, NY	184	230	180
Pittsburgh, PA	205	184	140
Kalamazoo, MI	161	203	152
Youngstown-Warren, OH	223	218	166
Evansville, IN	133	116	110
Waterloo-Cedar Falls, IA	214	167	90
Orlando, FL	62	90	124
Columbia, SC	55	110	119
Galveston-Texas City, TX	224	219	230
Little Rock-North Little Rock, AR	80	77	83
South Bend-Mishawaka, IN	149	185	159
Lima, OH	186	206	155
Chattanooga, TN/GA	72	92	82
Charleston, WV	169	104	105
Albany-Schenectady-Troy, NY	114	179	172
Provo-Orem, UT	130	18	63
Pueblo, CO	187	49	13
Knoxville, TN	48	72	37
St. Cloud, MN	97	113	71
Memphis, TN/AR/MS	83	134	178
Charleston, SC	68	62	73
Sioux Falls, SD	106	13	25
Pittsfield, MA	82	124	112
Lincoln, NE	78	15	34
Mansfield, OH	122	224	136
Wichita, KS	95	123	101
Kokomo, IN	134	211	222
Biloxi-Gulfport, MS	25	34	88
Hickory-Morgantown, NC	16	76	103
Montgomery, AL	66	105	91
Asheville, NC	21	32	24
Beaumont-Port Arthur, TX	225	213	197
Eau Claire, WI	59	84	49
Savannah, GA	52	111	100
Reading, PA	123	208	205
Erie, PA	117	125	122
Fort Myers-Cape Coral, FL	54	36	72
Buffalo, NY	162	178	170
Dubuque, IA	152	106	56
Lake Charles, LA	176	160	141
Augusta, GA/SC	20	176	168
Lakeland-Winter Haven, FL	35	80	107
Longview-Marshall, TX	112	67	118
Shreveport, LA	105	48	78
Steubenville-Weirton, OH/WV	204	148	66
Duluth, MN/WI	129	107	64
Melbourne-Titusville-Palm Bay, FL	93	102	95
San Antonio, TX	36	70	144
Tyler, TX	96	51	125

Table 5
MA Rankings Based on 2SLS Wage Residuals

msa name	80 wage	90 wage	00 wage
Roanoke, VA	73	100	47
Jackson, MS	65	52	108
Macon-Warner Robins, GA	70	180	163
Jersey City, NJ	154	234	234
Norfolk-Virginia Beach-Newport News, VA	91	88	80
Florence, SC	46	157	98
Pensacola, FL	22	37	36
Lexington-Fayette, KY	109	45	87
Owensboro, KY	131	99	117
Bloomington-Normal, IL	148	136	193
Atlantic City, NJ	179	242	235
Springfield, MO	19	5	2
Sharon, PA	178	156	59
La Crosse, WI	77	50	42
Fayetteville-Springdale, AR	17	3	12
Joplin, MO	7	9	6
Decatur, IL	221	240	195
Syracuse, NY	128	197	164
Terre Haute, IN	88	137	96
Sioux City, IA/NE	29	11	9
Hagerstown, MD	94	108	120
Sherman-Denison, TX	41	115	116
Las Cruces, NM	27	26	16
Huntsville, AL	60	120	133
Lynchburg, VA	33	101	89
Vineland-Millville-Bridgeton, NJ	113	232	245
Fort Walton Beach, FL	11	7	21
Tallahassee, FL	40	57	44
Corpus Christi, TX	87	79	147
Victoria, TX	89	89	179
Daytona Beach, FL	14	21	29
Parkersburg-Marietta, WV/OH	127	159	74
Alexandria, LA	39	25	41
Binghamton, NY	71	109	94
Odessa, TX	111	174	92
Ocala, FL	18	12	27
Williamsport, PA	57	119	39
Columbia, MO	53	19	8
Altoona, PA	69	95	55
Lafayette-West Lafayette, IN	98	69	131
Muncie, IN	108	145	121
Lubbock, TX	49	35	43
Gadsden, AL	81	152	75
St. Joseph, MO	51	94	19
Danville, VA	28	155	69
Tuscaloosa, AL	37	82	52
Huntington-Ashland, WV/KY/OH	164	154	57
Bangor, ME	9	41	4
Johnson City-Kingsport-Bristol, TN/VA	38	54	20
Fort Smith, AR	12	16	28
Johnstown, PA	171	73	23
Cumberland, MD/WV	67	121	61
Texarkana, TX/AR	24	63	76
Champaign-Urbana-Rantoul, IL	99	44	106
Charlottesville, VA	84	81	53
Lawrence, KS	64	59	38
Waco, TX	32	47	102
Fayetteville, NC	4	8	35

Table 5
MA Rankings Based on 2SLS Wage Residuals

msa name	80 wage	90 wage	00 wage
Wichita Falls, TX	26	43	26
Glens Falls, NY	34	129	86
Abilene, TX	13	28	7
Anniston, AL	23	42	45
Pine Bluff, AR	58	138	115
Columbus, GA/AL	15	61	65
Bloomington, IN	45	58	10
Utica-Rome, NY	30	86	77
Clarksville-Hopkinsville, TN/KY	8	4	5
El Paso, TX	42	46	70
Iowa City, IA	79	24	33
Killeen-Temple, TX	5	1	17
State College, PA	61	53	30
San Angelo, TX	10	14	22
Brownsville-Harlingen, TX	6	22	18
McAllen-Edinburg-Mission, TX	2	39	11
Jacksonville, NC	1	2	1
Laredo, TX	3	20	14

Table 6
MA Rankings Based on OLS Rent Residuals

msa name	80 rent	90 rent	00 rent
San Jose, CA	5	2	1
Nassau-Suffolk, NY	1	1	2
San Francisco, CA	2	3	3
Santa Rosa-Petaluma, CA	22	5	4
Seattle, WA	7	20	5
Denver, CO	20	41	6
Chicago, IL	9	6	7
Fort Lauderdale-Hollywood-Pompano Beach, FL	3	7	8
Vallejo-Fairfield-Napa, CA	75	17	9
Santa Cruz, CA	23	13	10
Dallas, TX	31	19	11
Minneapolis-St. Paul, MN/WI	13	10	12
Boston-Lawrence-Salem-Lowell-Brockton, MA	17	11	13
Atlanta, GA	89	26	14
Detroit, MI	6	8	15
Philadelphia,PA/NJ	21	9	16
San Diego, CA	33	15	17
Portland, OR	25	42	18
Austin, TX	74	113	19
Houston, TX	12	31	20
Phoenix, AZ	18	32	21
Sacramento, CA	58	16	22
Santa Barbara-Santa Maria-Lompoc, CA	32	24	23
Newark, NJ	26	18	24
Riverside-San Bernadino, CA	30	4	25
Las Vegas, NV	8	29	26
New York, NY	36	39	27
Boise City, ID	51	58	28
Salt Lake City-Ogden, UT	62	100	29
Los Angeles-Long Beach, CA	19	12	30
Orlando, FL	110	38	31
West Palm Beach-Boca Raton-Delray Beach, FL	46	30	32
Salinas-Seaside-Monterey, CA	54	35	33
Trenton, NJ	47	36	34
Rochester, NY	41	22	35
Kansas City, MO/KS	63	37	36
Milwaukee, WI	24	27	37
Miami-Hialeah, FL	29	43	38
Grand Rapids, MI	90	34	39
Indianapolis, IN	88	51	40
Wilmington, DE/NJ	57	33	41
Hartford-New Britain-Middletown-Bristol, CT	34	14	42
Kenosha, WI	67	62	43
Gary-Hammond, IN	44	49	44
St. Louis, MO/IL	52	25	45
Colorado Springs, CO	185	155	46
Tampa-St. Petersburg-Clearwater, FL	106	60	47
Cleveland, OH	40	44	48
Flint, MI	11	21	49
Galveston-Texas City, TX	65	63	50
Bremerton, WA	112	102	51
Ann Arbor, MI	16	47	52
Olympia, WA	136	89	53
Des Moines, IA	35	57	54
Nashville, TN	124	85	55
Jacksonville, FL	117	66	56
Tacoma, WA	105	104	57
Albuquerque, NM	111	76	58

Table 6
MA Rankings Based on OLS Rent Residuals

msa name	80 rent	90 rent	00 rent
Sarasota, FL	72	78	59
Baltimore, MD	91	52	60
Charlotte-Gastonia-Rock Hill, NC/SC	175	105	61
Modesto, CA	130	53	62
Fort Collins-Loveland, CO	99	167	63
New Haven-Waterbury-Meriden, CT	48	23	64
New London-Norwich, CT	77	28	65
Allentown-Bethlehem-Easton, PA	73	40	66
Reno, NV	4	86	67
Honolulu, HI	49	64	68
Racine, WI	42	65	69
Columbus, OH	127	91	70
Cincinnati, OH/KY/IN	92	69	71
Eugene-Springfield, OR	97	117	72
Hamilton-Middletown, OH	79	83	73
Albany-Schenectady-Troy, NY	126	55	74
Madison, WI	108	101	75
Janesville-Beloit, WI	82	106	76
Rockford, IL	37	88	77
Raleigh-Durham, NC	164	131	78
Omaha, NE/IA	113	70	79
Richmond-Petersburg, VA	66	67	80
Stockton, CA	176	56	81
Fort Myers-Cape Coral, FL	76	94	82
Melbourne-Titusville-Palm Bay, FL	78	75	83
San Antonio, TX	188	124	84
Akron, OH	68	90	85
Richland-Kennewick-Pasco, WA	56	142	86
Lancaster, PA	87	84	87
Tulsa, OK	71	92	88
Spokane, WA	114	136	89
Oklahoma City, OK	55	68	90
Saginaw-Bay City-Midland, MI	38	50	91
Portland, ME	70	45	92
New Orleans, LA	69	81	93
Dayton-Springfield, OH	118	72	94
Fort Wayne, IN	85	82	95
Lansing-East Lansing, MI	53	71	96
Cedar Rapids, IA	39	99	97
Elkhart-Goshen, IN	146	95	98
Tucson, AZ	83	119	99
Appleton-Oshkosh-Neenah, WI	120	115	100
Pittsburgh, PA	43	87	101
South Bend-Mishawaka, IN	100	80	102
Harrisburg-Lebanon-Carlisle, PA	86	108	103
Syracuse, NY	102	59	104
Bakersfield, CA	81	48	105
Fresno, CA	133	74	106
Wichita, KS	60	73	107
Davenport-Rock Island-Moline, IA/IL	14	98	108
Wilmington, NC	209	163	109
Green Bay, WI	131	165	110
Toledo, OH	59	61	111
Atlantic City, NJ	96	77	112
Louisville, KY/IN	157	135	113
Redding, CA	116	111	114
Buffalo, NY	142	116	115
Memphis, TN/AR/MS	196	133	116

Table 6
MA Rankings Based on OLS Rent Residuals

msa name	80 rent	90 rent	00 rent
Baton Rouge, LA	121	107	117
Amarillo, TX	137	112	118
Springfield, IL	50	93	119
Beaumont-Port Arthur, TX	64	79	120
Medford, OR	98	126	121
Birmingham, AL	173	144	122
Charleston, SC	168	149	123
Columbia, SC	148	114	124
Jersey City, NJ	189	164	125
Bellingham, WA	152	170	126
Vineland-Millville-Bridgeton, NJ	144	134	127
Reading, PA	125	97	128
Waterloo-Cedar Falls, IA	28	141	129
Little Rock-North Little Rock, AR	160	103	130
Providence-Pawtuckett-Woonsocket, RI	122	54	131
Tyler, TX	165	157	132
York, PA	135	130	133
Springfield, MA	109	46	134
Lafayette, LA	27	110	135
Savannah, GA	190	145	136
Corpus Christi, TX	151	158	137
Jackson, MI	61	125	138
Yakima, WA	174	194	139
Greensboro-Winston-Salem-High Point, NC	197	152	140
Lakeland-Winter Haven, FL	166	143	141
Norfolk-Virginia Beach-Newport News, VA	143	132	142
Greeley, CO	181	208	143
Wausau, WI	115	150	144
Canton, OH	107	129	145
Binghamton, NY	128	96	146
Sioux Falls, SD	145	137	147
Mobile, AL	204	173	148
Greenville-Spartanburg, SC	208	166	149
Benton Harbor, MI	80	123	150
Billings, MT	94	140	151
Peoria, IL	10	128	152
Kalamazoo, MI	93	109	153
Visalia-Tulare-Porterville, CA	161	121	154
Longview-Marshall, TX	138	154	155
Biloxi-Gulfport, MS	219	186	156
Daytona Beach, FL	154	146	157
Lincoln, NE	156	175	158
Montgomery, AL	212	162	159
Kokomo, IN	159	176	160
Decatur, IL	45	120	161
Youngstown-Warren, OH	101	122	162
Pensacola, FL	199	182	163
Provo-Orem, UT	230	220	164
Jackson, MS	158	138	165
Macon-Warner Robins, GA	224	161	166
Bloomington-Normal, IL	95	180	167
Odessa, TX	15	139	168
Lubbock, TX	129	160	169
Wichita Falls, TX	186	179	170
Evansville, IN	141	156	171
Chico, CA	194	172	172
Lake Charles, LA	163	169	173
Shreveport, LA	201	147	174

Table 6
MA Rankings Based on OLS Rent Residuals

msa name	80 rent	90 rent	00 rent
Champaign-Urbana-Rantoul, IL	147	181	175
Eau Claire, WI	150	188	176
Erie, PA	103	177	177
Chattanooga, TN/GA	178	171	178
Charleston, WV	119	153	179
Hickory-Morgantown, NC	233	216	180
Sherman-Denison, TX	205	178	181
Victoria, TX	184	184	182
Pittsfield, MA	153	118	183
Knoxville, TN	207	189	184
Sioux City, IA/NE	140	185	185
Fayetteville, NC	216	207	186
Abilene, TX	169	159	187
Asheville, NC	232	223	188
Fort Walton Beach, FL	228	213	189
Tallahassee, FL	198	183	190
Mansfield, OH	167	168	191
Pueblo, CO	191	202	192
Lima, OH	139	148	193
St. Cloud, MN	123	127	194
Waco, TX	218	197	195
Dubuque, IA	84	187	196
Lafayette-West Lafayette, IN	192	212	197
Ocala, FL	226	211	198
Lexington-Fayette, KY	177	193	199
Muncie, IN	203	195	200
Columbia, MO	162	218	201
Joplin, MO	238	219	202
Augusta, GA/SC	215	151	203
Utica-Rome, NY	213	192	204
Roanoke, VA	211	201	205
Steubenville-Weirton, OH/WV	170	215	206
Sharon, PA	132	198	207
Owensboro, KY	180	203	208
Terre Haute, IN	187	204	209
Texarkana, TX/AR	239	191	210
Glens Falls, NY	179	174	211
Fayetteville-Springdale, AR	225	225	212
Springfield, MO	222	221	213
Altoona, PA	172	209	214
La Crosse, WI	155	217	215
Killeen-Temple, TX	235	236	216
Duluth, MN/WI	104	199	217
Lawrence, KS	200	230	218
Bangor, ME	149	190	219
Florence, SC	220	196	220
Huntsville, AL	221	200	221
St. Joseph, MO	206	222	222
Clarksville-Hopkinsville, TN/KY	214	239	223
San Angelo, TX	210	210	224
Iowa City, IA	182	241	225
Charlottesville, VA	134	214	226
Bloomington, IN	234	234	227
Williamsport, PA	193	224	228
Huntington-Ashland, WV/KY/OH	195	229	229
El Paso, TX	246	232	230
Tuscaloosa, AL	244	243	231
Parkersburg-Marietta, WV/OH	202	228	232

Table 6
MA Rankings Based on OLS Rent Residuals

msa name	80 rent	90 rent	00 rent
Pine Bluff, AR	227	205	233
Cumberland, MD/WV	231	242	234
Las Cruces, NM	237	226	235
Alexandria, LA	223	206	236
Lynchburg, VA	229	231	237
Hagerstown, MD	217	238	238
Fort Smith, AR	241	233	239
State College, PA	183	237	240
Brownsville-Harlingen, TX	236	235	241
Johnstown, PA	171	227	242
Danville, VA	248	246	243
Johnson City-Kingsport-Bristol, TN/VA	240	244	244
Columbus, GA/AL	243	240	245
McAllen-Edinburg-Mission, TX	249	248	246
Anniston, AL	245	245	247
Gadsden, AL	242	247	248
Jacksonville, NC	247	249	249
Laredo, TX	250	250	250

Table 7
MA Rankings Based on OLS House Value Residuals

msa name	80 value	90 value	00 value
San Francisco, CA	1	2	1
San Jose, CA	3	3	2
Santa Cruz, CA	2	4	3
Santa Rosa-Petaluma, CA	4	1	4
Seattle, WA	15	11	5
Santa Barbara-Santa Maria-Lompoc, CA	9	19	6
Portland, OR	16	57	7
Salinas-Seaside-Monterey, CA	8	14	8
Chicago, IL	11	13	9
San Diego, CA	6	10	10
Denver, CO	17	43	11
Detroit, MI	45	21	12
Los Angeles-Long Beach, CA	5	6	13
Nassau-Suffolk, NY	112	9	14
Boston-Lawrence-Salem-Lowell-Brockton, MA	98	17	15
Vallejo-Fairfield-Napa, CA	20	12	16
Sacramento, CA	13	7	17
Newark, NJ	26	16	18
Minneapolis-St. Paul, MN/WI	10	18	19
New York, NY	73	24	20
Eugene-Springfield, OR	31	117	21
Milwaukee, WI	14	35	22
Salt Lake City-Ogden, UT	23	76	23
Riverside-San Bernadino, CA	12	5	24
Bremerton, WA	40	52	25
Albuquerque, NM	49	33	26
Honolulu, HI	7	29	27
Boise City, ID	39	56	28
Tacoma, WA	67	75	29
Grand Rapids, MI	113	36	30
Cleveland, OH	30	42	31
Kenosha, WI	32	68	32
Olympia, WA	76	94	33
Medford, OR	42	95	34
Phoenix, AZ	35	34	35
Racine, WI	22	64	36
Cincinnati, OH/KY/IN	50	45	37
Flint, MI	84	46	38
Gary-Hammond, IN	53	66	39
Fort Collins-Loveland, CO	79	183	40
Green Bay, WI	59	131	41
Atlanta, GA	135	54	42
Stockton, CA	51	28	43
Nashville, TN	107	63	44
Hartford-New Britain-Middletown-Bristol, CT	37	8	45
Richland-Kennewick-Pasco, WA	46	100	46
St. Louis, MO/IL	64	27	47
Indianapolis, IN	99	59	48
Spokane, WA	69	104	49
Bellingham, WA	68	119	50
Dallas, TX	52	22	51
Modesto, CA	36	15	52
Reno, NV	29	82	53
Fort Lauderdale-Hollywood-Pompano Beach, FL	27	38	54
Ann Arbor, MI	82	154	55
Akron, OH	66	89	56
Redding, CA	34	50	57
Baton Rouge, LA	55	60	58

Table 7
MA Rankings Based on OLS House Value Residuals

msa name	80 value	90 value	00 value
Las Vegas, NV	21	47	59
Tucson, AZ	41	67	60
Louisville, KY/IN	147	107	61
Philadelphia,PA/NJ	104	26	62
Saginaw-Bay City-Midland, MI	109	80	63
Kansas City, MO/KS	90	49	64
Appleton-Oshkosh-Neenah, WI	74	86	65
Yakima, WA	122	176	66
Charlotte-Gastonia-Rock Hill, NC/SC	164	98	67
Austin, TX	120	115	68
Madison, WI	71	169	69
Lafayette, LA	19	41	70
Houston, TX	38	37	71
Columbus, OH	92	91	72
Colorado Springs, CO	127	163	73
Des Moines, IA	43	109	74
Jackson, MI	153	149	75
Dayton-Springfield, OH	87	70	76
Wilmington, DE/NJ	150	40	77
Toledo, OH	63	69	78
Fresno, CA	18	39	79
Cedar Rapids, IA	62	118	80
New Haven-Waterbury-Meriden, CT	61	20	81
Canton, OH	70	105	82
Providence-Pawtuckett-Woonsocket, RI	108	30	83
Greeley, CO	121	196	84
Miami-Hialeah, FL	57	121	85
New Orleans, LA	47	71	86
Janesville-Beloit, WI	88	148	87
Baltimore, MD	85	58	88
New London-Norwich, CT	91	25	89
Billings, MT	44	113	90
Davenport-Rock Island-Moline, IA/IL	25	74	91
Hamilton-Middletown, OH	58	90	92
Greensboro-Winston-Salem-High Point, NC	158	108	93
Lancaster, PA	97	62	94
Tulsa, OK	65	48	95
Springfield, MA	167	23	96
Omaha, NE/IA	125	120	97
Lansing-East Lansing, MI	118	130	98
Fort Wayne, IN	103	77	99
Rockford, IL	72	79	100
West Palm Beach-Boca Raton-Delray Beach, FL	75	85	101
Birmingham, AL	124	111	102
Visalia-Tulare-Porterville, CA	78	73	103
Jacksonville, FL	199	81	104
Allentown-Bethlehem-Easton, PA	94	32	105
Raleigh-Durham, NC	170	145	106
Wilmington, NC	212	175	107
Bakersfield, CA	33	31	108
Sarasota, FL	101	143	109
Tampa-St. Petersburg-Clearwater, FL	149	72	110
Trenton, NJ	138	65	111
Mobile, AL	160	125	112
Greenville-Spartanburg, SC	194	144	113
Portland, ME	145	51	114
Elkhart-Goshen, IN	140	114	115
Oklahoma City, OK	60	61	116

Table 7
MA Rankings Based on OLS House Value Residuals

msa name	80 value	90 value	00 value
Richmond-Petersburg, VA	142	92	117
Chico, CA	54	124	118
Amarillo, TX	161	83	119
Harrisburg-Lebanon-Carlisle, PA	131	110	120
Benton Harbor, MI	174	152	121
Springfield, IL	48	87	122
Peoria, IL	24	112	123
York, PA	116	84	124
Wausau, WI	93	167	125
Rochester, NY	133	44	126
Pittsburgh, PA	77	106	127
Kalamazoo, MI	143	164	128
Youngstown-Warren, OH	86	122	129
Evansville, IN	100	141	130
Waterloo-Cedar Falls, IA	28	142	131
Orlando, FL	154	97	132
Columbia, SC	168	134	133
Galveston-Texas City, TX	96	88	134
Little Rock-North Little Rock, AR	136	101	135
South Bend-Mishawaka, IN	155	135	136
Lima, OH	105	138	137
Chattanooga, TN/GA	203	157	138
Charleston, WV	56	133	139
Albany-Schenectady-Troy, NY	172	53	140
Provo-Orem, UT	95	233	141
Pueblo, CO	134	185	142
Knoxville, TN	190	171	143
St. Cloud, MN	114	151	144
Memphis, TN/AR/MS	175	129	145
Charleston, SC	191	170	146
Sioux Falls, SD	81	150	147
Pittsfield, MA	183	55	148
Lincoln, NE	115	181	149
Mansfield, OH	137	156	150
Wichita, KS	89	93	151
Kokomo, IN	139	165	152
Biloxi-Gulfport, MS	200	172	153
Hickory-Morgantown, NC	218	192	154
Montgomery, AL	169	147	155
Asheville, NC	214	213	156
Beaumont-Port Arthur, TX	151	103	157
Eau Claire, WI	152	203	158
Savannah, GA	204	166	159
Reading, PA	144	99	160
Erie, PA	123	158	161
Fort Myers-Cape Coral, FL	119	137	162
Buffalo, NY	148	96	163
Dubuque, IA	83	177	164
Lake Charles, LA	141	136	165
Augusta, GA/SC	221	146	166
Lakeland-Winter Haven, FL	202	132	167
Longview-Marshall, TX	129	127	168
Shreveport, LA	126	128	169
Steubenville-Weirton, OH/WV	110	173	170
Duluth, MN/WI	106	188	171
Melbourne-Titusville-Palm Bay, FL	117	116	172
San Antonio, TX	178	123	173
Tyler, TX	159	140	174

Table 7
MA Rankings Based on OLS House Value Residuals

msa name	80 value	90 value	00 value
Roanoke, VA	192	194	175
Jackson, MS	157	139	176
Macon-Warner Robins, GA	217	162	177
Jersey City, NJ	193	168	178
Norfolk-Virginia Beach-Newport News, VA	173	161	179
Florence, SC	210	179	180
Pensacola, FL	224	191	181
Lexington-Fayette, KY	156	184	182
Owensboro, KY	165	178	183
Bloomington-Normal, IL	102	215	184
Atlantic City, NJ	130	153	185
Springfield, MO	195	189	186
Sharon, PA	163	207	187
La Crosse, WI	111	214	188
Fayetteville-Springdale, AR	207	219	189
Joplin, MO	209	193	190
Decatur, IL	80	155	191
Syracuse, NY	185	102	192
Terre Haute, IN	188	220	193
Sioux City, IA/NE	132	202	194
Hagerstown, MD	189	211	195
Sherman-Denison, TX	226	174	196
Las Cruces, NM	219	197	197
Huntsville, AL	223	198	198
Lynchburg, VA	222	217	199
Vineland-Millville-Bridgeton, NJ	227	180	200
Fort Walton Beach, FL	232	227	201
Tallahassee, FL	206	222	202
Corpus Christi, TX	180	159	203
Victoria, TX	186	160	204
Daytona Beach, FL	196	186	205
Parkersburg-Marietta, WV/OH	166	210	206
Alexandria, LA	208	206	207
Binghamton, NY	162	126	208
Odessa, TX	128	78	209
Ocala, FL	233	199	210
Williamsport, PA	179	224	211
Columbia, MO	205	232	212
Altoona, PA	211	228	213
Lafayette-West Lafayette, IN	171	235	214
Muncie, IN	197	234	215
Lubbock, TX	181	182	216
Gadsden, AL	234	231	217
St. Joseph, MO	184	208	218
Danville, VA	237	226	219
Tuscaloosa, AL	239	240	220
Huntington-Ashland, WV/KY/OH	176	216	221
Bangor, ME	220	205	222
Johnson City-Kingsport-Bristol, TN/VA	225	229	223
Fort Smith, AR	228	221	224
Johnstown, PA	177	209	225
Cumberland, MD/WV	213	223	226
Texarkana, TX/AR	235	190	227
Champaign-Urbana-Rantoul, IL	146	225	228
Charlottesville, VA	201	238	229
Lawrence, KS	229	245	230
Waco, TX	215	201	231
Fayetteville, NC	245	237	232

Table 7
MA Rankings Based on OLS House Value Residuals

msa name	80 value	90 value	00 value
Wichita Falls, TX	187	195	233
Glens Falls, NY	241	187	234
Abilene, TX	182	204	235
Anniston, AL	244	239	236
Pine Bluff, AR	231	212	237
Columbus, GA/AL	242	236	238
Bloomington, IN	238	246	239
Utica-Rome, NY	236	200	240
Clarksville-Hopkinsville, TN/KY	246	242	241
El Paso, TX	216	230	242
Iowa City, IA	198	247	243
Killeen-Temple, TX	243	244	244
State College, PA	240	248	245
San Angelo, TX	230	218	246
Brownsville-Harlingen, TX	248	241	247
McAllen-Edinburg-Mission, TX	247	243	248
Jacksonville, NC	249	250	249
Laredo, TX	250	249	250

Figure 4
Correlations of MA-Average OLS Residuals Within Specifications and Across Census Years

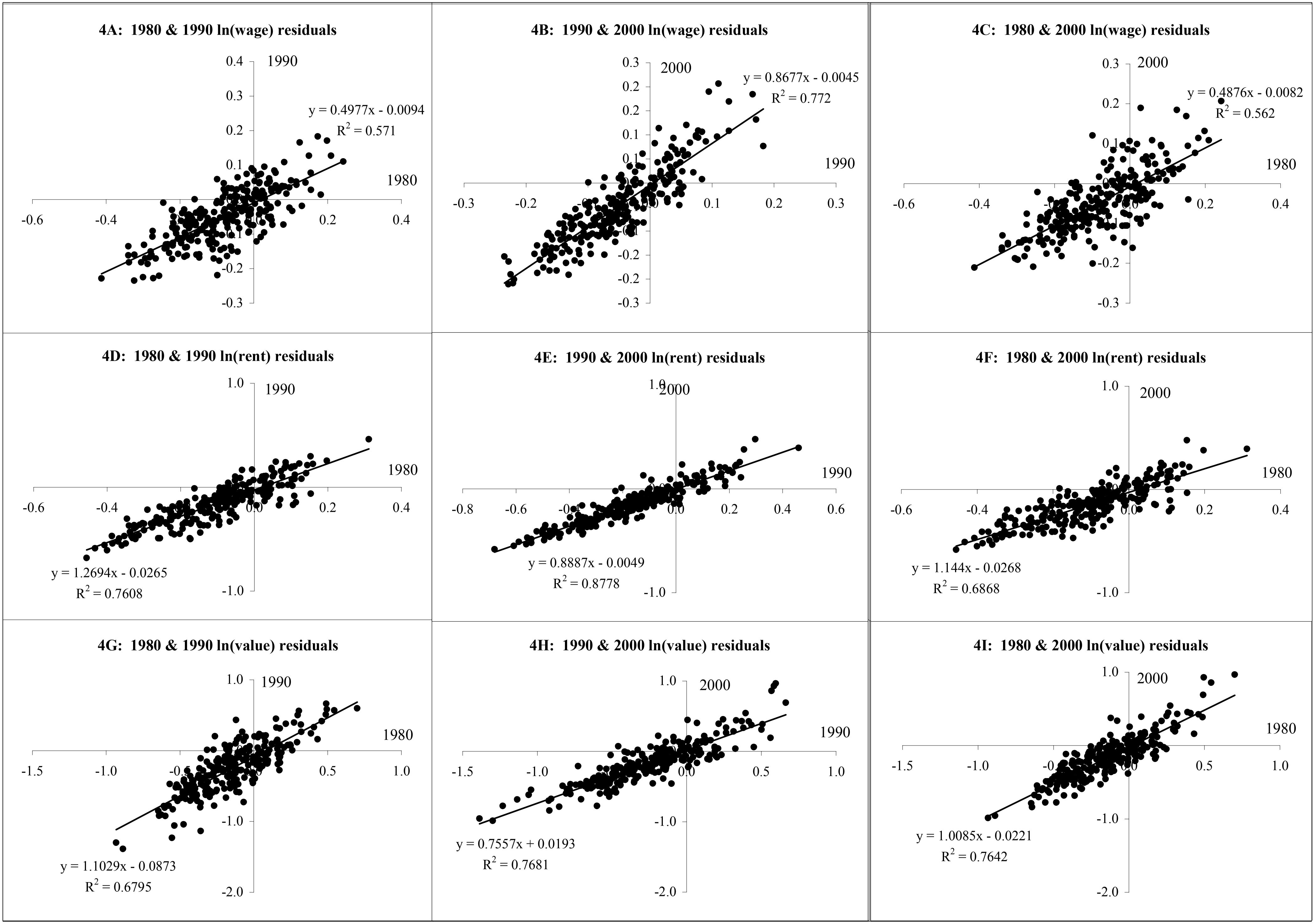

Figure 5
Correlations of MA-Average OLS Residuals Across Specifications and Within Census Years

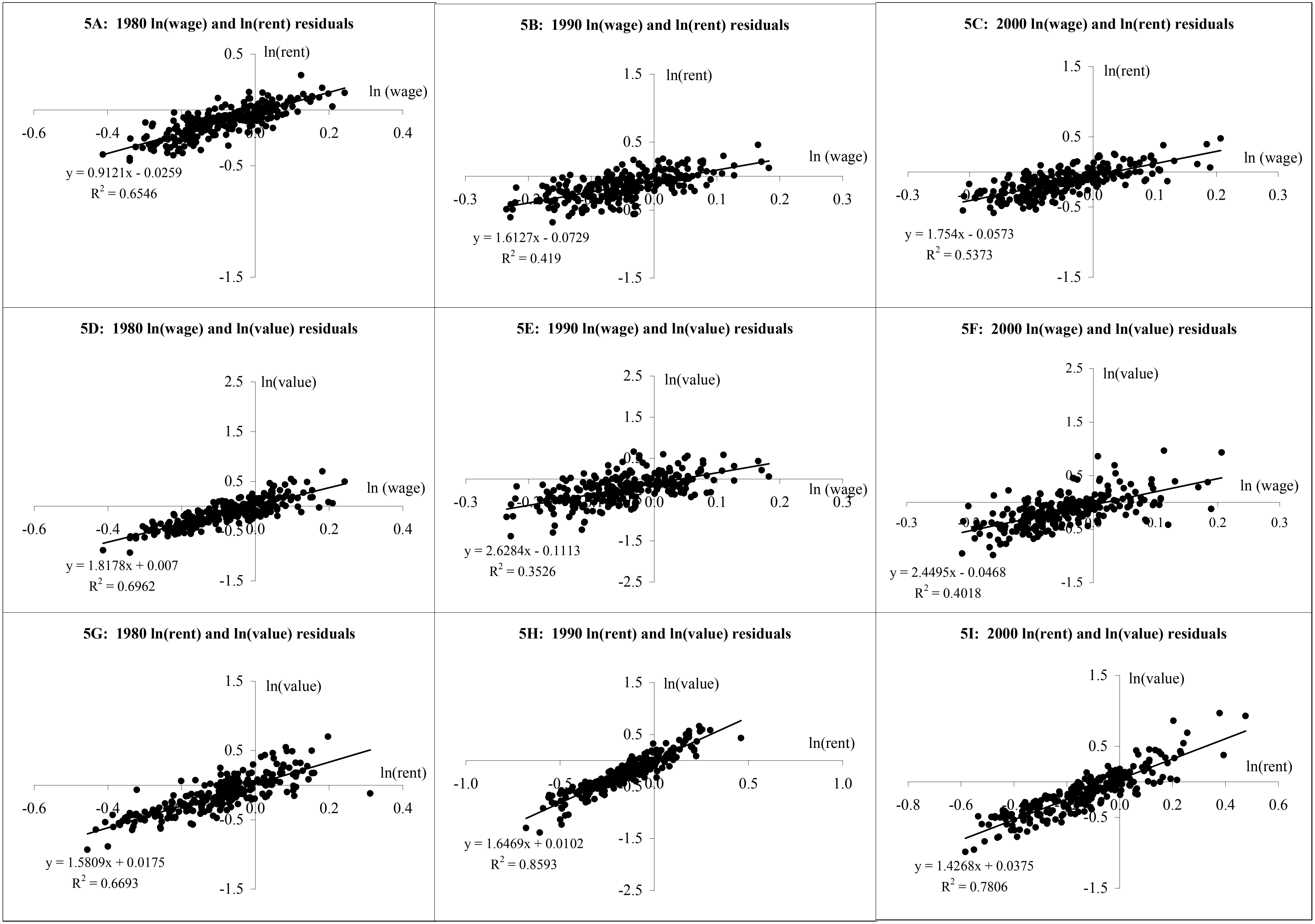

Table 11
MA-Level Residuals: Correlations Across Census Years

	wage residual 1990	wage residual 2000	wage residual 2000	rent residual 1990	rent residual 2000	rent residual 2000	house value residual 1990	house value residual 2000	house value residual 2000
wage residual 1980	0.498 (0.026)		0.488 (0.026)						
wage residual 1990		0.868 (0.033)							
wage residual 2000									
rent residual 1980				1.269 (0.044)		1.144 (0.050)			
rent residual 1990					0.889 (0.021)				
rent residual 2000									
house value residual 1980							1.103 (0.043)		1.009 (0.040)
house value residual 1990								0.756 (0.033)	
house value residual 2000									
Intercept	-0.009 (0.004)	-0.005 (0.003)	-0.008 (0.004)	-0.026 (0.008)	-0.005 (0.006)	-0.027 (0.009)	-0.087 (0.013)	0.019 (0.014)	-0.022 (0.012)
R-squared	0.571	0.772	0.562	0.761	0.878	0.687	0.679	0.768	0.764

Table 12
Changes in MA-Level Residuals: Correlations Across Census Years

	90-00 change in wage residual	90-00 change in rent residual	90-00 change in house value residual
80-90 change in wage residual	-0.108		
	(0.000)		
80-90 change in rent residual		-0.191	
		(0.000)	
80-90 change in house value residual			-0.587
			(0.000)
Intercept	0.005	0.002	0.019
	(0.000)	(0.000)	(0.000)
R-squared	0.049	0.081	0.484

Table 13
Correlations Between Decadal Changes in Wages, Rents, and House Values and Start-of-Period Residuals

	Percent change in:					
	wage 1980-1990	wage 1990-2000	rent 1980-1990	rent 1990-2000	house value 1980-1990	house value 1990-2000
wage residual 1980	-0.067					
	(0.043)					
wage residual 1990		-0.268				
		(0.038)				
rent residual 1980			0.143			
			(0.114)			
rent residual 1990				-0.080		
				(0.023)		
house value residual 1980					0.232	
					(0.123)	
house value residual 1990						-0.163
Intercept	-0.089	-0.062	0.793	-0.062	0.562	0.027
	(0.007)	(0.003)	(0.023)	(0.006)	(0.039)	(0.016)
R-squared	0.010	0.190	0.007	0.050	0.016	0.082

Table 14
Correlations Between Decadal Changes in Population and Start-of-Period Residuals

	Percent change in population:					
	1980-1990	1990-2000	1980-1990	1990-2000	1980-1990	1990-2000
wage residual 1980	-0.335					
	(0.085)					
wage residual 1990		-0.887				
		(0.150)				
rent residual 1980			-0.055			
			(0.076)			
rent residual 1990				-0.348		
				(0.080)		
house value residual 1980					-0.009	
					(0.042)	
house value residual 1990						-0.194
						(0.046)
Intercept	0.112	0.208	0.134	0.199	0.138	0.205
	(0.015)	(0.014)	(0.016)	(0.012)	(0.015)	(0.012)
R-squared	0.040	0.082	0.001	0.078	0.000	0.077