Quality Adjustment for Spatially-Delineated Public Goods: Theory and Application to Cost-of-Living Indices in Los Angeles

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Abstract

This paper illustrates how public goods may be incorporated into a cost-of-living index. When public goods are weak complements to a market good, quality-adjusted prices for the market good capture all the welfare information required. They are also consistent with a Laspeyres index that maintains the bound on a true cost-of-living index. The paper recovers this information from a discrete-choice model, using a simulation routine to solve for the appropriate price adjustments.

These concepts are applied to the case of housing, education, crime, and air quality in Los Angeles for 1989 to 1994. Over a period of time when they are improving, incorporating pubic goods into the index lowers the estimated change in the cost of living by 0.5 to 2.6 percentage points. In other years, when public goods diverge, the estimated annual adjustment differs by model, with a range of -0.2 to +1.3 percentage points.

Key Words: air quality, discrete choice models, green accounting, nonmarket valuation, price index.

JEL Classification Numbers: C51, D12, D60, E31, H40, R10.

Contents

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H. Spencer Banzhaf*

> If a poll were taken of professional economists and statisticians, in all probability they would designate (and by a wide margin) the failure of the price indices to take full account of quality changes as the most important defect of these indices. And by almost as large a majority, they would believe that this failure introduces a systematic upward bias in the price indices—that quality changes have on average been quality improvements.
>
> —The 1961 Price Statistics Review Committee (Stigler et al. p. 35)

I. Introduction

Apparently, not much has changed since the Stigler Commission wrote these words over 40 years ago. The Boskin commission, the latest review of the U.S. Consumer Price Index (CPI), has continued to highlight the problems of quality change and new goods, attributing to them more than half their estimated bias of 1.1% in the CPI (Boskin et al. 1996). These findings have motivated much important new research,[1] but one potentially significant source of such bias has not been quantified: the changing quality of public goods over time. For example, the U.S. crime rate more than tripled from 1960 to 1990 before falling 27% in the last decade (U.S. Dept. of Justice 2001). On the other hand, air quality has improved dramatically in this time period. From 1979 to 1998, average national ozone concentrations fell by 17% and sulfur dioxide levels fell 53% (U.S. EPA 2000, p. A-9). To the extent that consumers value these improvements, they should properly be included in an index of the cost of living.

This paper develops a framework for incorporating public goods into the CPI, estimating quality-adjusted price indices for a bundle of housing and spatially differentiated public goods in

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[1] See for example Bresnahan and Gordon (1997), Cutler et al. (1998), Hausman (1999), Nevo (2001) and Triplett (1999).

the Los Angeles area for the years 1989 to 1994. It focuses on three spatially delineated public goods— education, crime, and air qualitywhich are linked as weak complements to houses in particular neighborhoods. It recovers the required welfare information from a discrete choice model of neighborhood/housing choice with nonlinear income effects. Rather than consumer surplus, the welfare measure is computed as the price adjustments that are equivalent to the quality changes. This measure is theoretically and operationally consistent with a Laspeyres index such as the CPI, and maintains the index's upper bound on a true cost-of-living index.

My strategy is to estimate such quality-adjusted indices with and without public goods, and to compare them to gauge the effect public goods can have on the indices. The results show that including public goods in a cost-of-living index is feasible, and that when they are changing over time they can make a noticeable difference. In the first year of the period covered, public goods improved together. Accordingly, including them in the index lowers the estimated cost of living by 0.5 to 2.6 percentage points, depending on the model. In the later years, air quality and education moved in opposite directions, with air quality improving and teacher-student ratios worsening. Consequently, the impact of including public goods on the cost of living differs according to the estimated weights attributed to these goods, and ranges from a decrease of 0.2 percentage points to an increase of 1.3 percentage points annually.

This work is conceptually related to the literature on quality-adjusted price indices for private goods. Cutler et al. (1998) provide the closest application, adjusting an index for medical services by the improvement in final health outcomes they have produced over time. Nevo (2001), Timmins (2001), and Trajtenberg (1990) are closer methodologically, also employing discrete choice models. Accordingly, some of the methods used here could be used for these applications as well.

Some economists may be uncomfortable with the extension of such methods to public goods, preferring to limit the CPI to a sub-index of market goods only. Yet, so long as the CPI is to be interpreted as a cost-of-living index, this limitation is only tenable if (1), utility is separable in public goods and market goods, and (2) prices of market goods are unaffected by the levels of public goods. In fact, empirical work has tended to reject such separability. Furthermore, regulations that provide public goods often increase prices. For example, Hazilla and Kopp (1990) find that the regulations associated with the Clean Air and Water acts had caused an increase of more than 6% in general prices by 1990. Thus, omitting public goods from the CPI is not truly neutral with respect to public goods as intended, but instead incorporates their cost without incorporating their benefits. Accordingly, incorporating public goods into the cost-of-living index may make the index more balanced as well as more complete.

Similar extensions also have been advocated for national income measures, and this work is congruent with the literature on such "green accounts." That literature has tended to focus on depreciating changes in natural resources in a Net Gross Domestic Product context, but a recent report by the national academy of sciences has endorsed extending the concept to flows of environmental services (Nordhaus and Kokkelenberg 1999). The cost-of-living index offered here is, broadly speaking, the dual to these suggestions.[2]

The paper is divided into six sections. Section II develops the basic cost-of-living concepts and links them to the information about public goods recovered from discrete-choice models. Section III summarizes the data that is used to estimate the price indices. Section IV presents the empirical estimation of the price indices and Section V compares these results to a more standard hedonic regression analysis. Section VI discusses the implications of the results and concludes the paper.

II. Quality-Adjusted Price Indices for Public Goods: Theory and Estimation Strategy

The cost-of-living index and quality change

A cost-of-living index is defined for a single household as a ratio of Hicksian expenditure functions. Let $m(\boldsymbol{p}, u)$ denote this function at prices $\boldsymbol{p}$ and utility level u and let superscripts a and b index the reference and comparison scenarios respectively. Then a cost-of-living index comparing b to a is

$$\mathrm{I}^{ab}\left(\boldsymbol{p}^{b}, \boldsymbol{p}^{a}, u^{a}\right) = \frac{m(\boldsymbol{p}^{b}, u^{a})}{m(\boldsymbol{p}^{a}, u^{a})} \tag{1}$$

It gauges the proportionate increase (or decrease) in expenditures required to maintain the utility level of the reference period at the new prices. A similar index can be defined at comparison-period utility.

[2] Nordhaus (1999) issues a call for just such an "augmented cost-of-living index," but in his illustration only nets out the costs of public goods without considering actual benefits.

The cost-of-living index may be generalized to include nonmarket public goods. One approach is to model them as weak complements to a nonessential market good.[3] Weak complements are goods that are enjoyed only when their associated complements are consumed in positive quantities. For example, public goods in community *j* are enjoyed only when living in a house in community *j*. In this way, spatial public goods may be modeled for all practical purposes as qualitative differences among houses.

Following this logic, suppose there are two types of goods, quality-differentiated housing *h* with *J* varieties and all other goods *x*. Housing is differentiated by *k* characteristics (including weakly complementary public goods), $\boldsymbol{z}$. Depending on the interpretation, the *j* varieties may index individual houses, in which case the household will consume only a discrete quantity (h_j={0,1}), or house-types in a particular community, in which case the consumer may choose a continuous "quantity" of housing. Regardless of the interpretation, the model is consistent with a cost-of-living index of the form

$$\mathrm{I}^{ab}\left(u^a\right)=\frac{\widetilde{m}\left(\boldsymbol{p}_h^b,\boldsymbol{Z}^b,\ p_x^b,\ u^a\right)}{\widetilde{m}\left(\boldsymbol{p}_h^a,\boldsymbol{Z}^a,\ p_x^a,\ u^a\right)}. \tag{2}$$

$\boldsymbol{p}_h$ is the Jx1 vector of housing rental rates and $\boldsymbol{Z}$ is the Jxk matrix of characteristics. The conditional expenditure function $\widetilde{m}$ ( ) now replaces the ordinary expenditure function *m*( ) to make explicit the fact that quality is held constant in the expenditure-minimization problem (Neary and Roberts 1980).

Because of the difficulty in recovering all the necessary preference information, in practice, cost-of-living indices are approximated by standard price index formulas of price relatives (p^b/p^a), such as a Laspeyres (*L*) or Paasche (*P*) index. In the case of price changes the Laspeyres index is an upper bound on a cost-of-living index at base-period utilities, and the Paasche index is a lower bound on a cost-of-living index at comparison-period utilities:

$$L^{ab} \ \equiv\ \sum\nolimits_q \frac{p_q^b}{p_q^a} w_q^a \ \geq\ I^{ab}(\boldsymbol{p}^b, \boldsymbol{p}^a, u^a) \tag{3}$$

[3] See Banzhaf (2002) for discussion of alternate possibilities.

$$P^{ab} \equiv \sum_q \frac{p_q^b}{p_q^a} w_q^b \leq I^{ab}(\boldsymbol{p}^b, \boldsymbol{p}^a, u^b). \tag{4}$$

where w_q^t is the expenditure share for good q computed at period t quantities and baseline prices. The traditional Laspeyres and Paasche indices are defined over prices only, but Robert Willig (1978, lemma 1) has extended the basic concepts to include quality change. In particular, the adjusted price that compensates the household for foregoing the quality change when income is already adjusted to obtain reference utility can be substituted for p^b in the Laspeyres index. An analogous price adjustment can be defined for the Paasche index. More formally, denote y^t as actual income in period t. Then when λ^* and λ^{**} are defined implicitly by the equations

$$v(\lambda^* \boldsymbol{p}_h^a, \boldsymbol{Z}^a, p_x^b, m(\boldsymbol{p}_h^b, \boldsymbol{Z}^b, p_x^b; u^a)) = v(\boldsymbol{p}_h^a, \boldsymbol{Z}^a, p_x^a, y^a) \tag{5}$$

$$v(\lambda^{**} \boldsymbol{p}_h^b, \boldsymbol{Z}^b, p_x^a, m(p_h^a, \boldsymbol{Z}^a, p_x^a; u^b)) = v(\boldsymbol{p}_h^b, \boldsymbol{Z}^b, p_x^b, y^b), \tag{6}$$

it can be shown that the following bounds for the Laspeyres and Paasche indices still hold:

$$L^{*ab} \equiv \lambda^* w_h^a + \frac{p_x^b}{p_x^a} w_x^a \geq I^{ab}(p^b, p^a, \boldsymbol{z}^b, \boldsymbol{z}^a, u^a) \tag{7}$$

$$P^{**ab} \equiv \lambda^{**} w_h^b + \frac{p_x^b}{p_x^a} w_x^b \leq I^{ab}(p^b, p^a, \boldsymbol{z}^b, \boldsymbol{z}^a, u^b). \tag{8}$$

L^* is the Laspeyres index with λ^* replacing p^b/p^a, while P^{**} is analogously defined. They are the usual Laspeyres and Paasche concepts, with a sub-index defined in cost-of-living terms replacing the usual price relative for the good with quality change.[4]

[4] An alternative approach would be to define a partial or conditional sub cost-of-living index as in Pollak (1989, Ch. 2). Instead of finding p^* or p^{**}, this approach would find the least-cost house in period b contributing at least as much utility as the house chosen in period a. That is:

$$\min\{p_j^b\} \text{ s.t. } u(\boldsymbol{z}_j^{\boldsymbol{b}}, y_i\text{-}p_j^b) \geq \max_j \{u(\boldsymbol{z}_j^{\boldsymbol{a}}, y_i\text{-}p_j^a)\}.$$

However, in the random utility context in which utility has an additive error term ε, this approach has two difficulties. First, in practice, the house in period b satisfying the relationship will often (for some vector ε) be strictly preferred to the house purchased in period a. Second, at other times the index will be undefined because, for a sufficiently high ε_j for a house available in period a, no house in period b will be at least as good.

In this way, it is possible to link public goods to housing through weak complementarity and then, following Willig, estimate quality-adjusted price indices. Moreover, the first of these sub-indices is consistent with the overall CPI as shown in equation (7). Strictly speaking, these are group price indices for both housing and weakly complementary public goods. However, for convenience I shall refer to them more loosely as quality-adjusted housing indices.

Without reference to Willig's proof, this index has been discussed in to the context of quality-adjusted prices for market goods using discrete choice models (Trajtenberg 1990, Nevo 2001), but it has never been implemented due to its computational complexity.[5] This complexity only increases when the standard assumption of a constant marginal utility of income—inappropriate for a good such as housing that occupies a large budget share—is relaxed (McFadden 1999). The following sub-section describes the empirical strategy for estimating the appropriate indices in this context.

Discrete Choice Measures

To implement this framework empirically, households are assumed to have random utility over housing choices, allowing the structural parameters to be recovered with discrete choice methods.[6] In this case, the indirect utility function for household i conditional on choosing house j is

$$v_{ij} = v_i(\mathbf{z}_j, (y_i - p_j)/p_z) + \varepsilon_{ij}. \tag{9}$$

The random term is usually interpreted as unobserved heterogeneity in the household's tastes and/or unobserved characteristics of the house and is assumed to be distributed according to the type I extreme value distribution. I use two functional forms for the conditional utility function, linear in logs and linear in square-roots of the k characteristics:

$$v_{ij} = \Sigma_k \beta_{ik} \ln(z_{jk}) + \beta_y \ln\{(y_i - p_j)/p_z\} + \varepsilon_{ij} \tag{9a}$$

$$v_{ij} = \Sigma_k \beta_{ik} (z_{jk})^{1/2} + \beta_y \{(y_i - p_j)/p_z\}^{1/2} + \varepsilon_{ij} \tag{9b}$$

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[5] Trajtenberg (1990) offers an approximation based on the assumption that only the mean prices change over time and not the variance. He also restricts the marginal utility of income to be constant.

[6] Discrete choice models have been applied to housing in a handful of applications (Blackley and Ondrich 1988, Nechyba and Strauss 1998, and Quigley 1985) including applications to air quality valuation (Chattopadhyay 2000, Palmquist and Israngkura 1999).

As indicated by the subscripts on the coefficients, there is heterogeneity in tastes for the housing characteristics. As discussed in more detail below, heterogeneity is captured in two ways in addition to the additive error term: through demographic interactions and through random coefficients (Revelt and Train 1998).

I first estimate the discrete choice models using micro-level data, recovering the parameters in Equations (9a) and (9b). I estimate separate models for each year, thereby facilitating a chained index that can account for taste change and changes in the price of the numeraire over time. I then use the estimated parameters from these structural models to construct sub-indices for housing by solving for the percentage price adjustments as shown in Equations (5) and (6). The indices (which have no closed-form solution) are estimated with a simulation routine described in Section IV. Note that the indices are estimated at the household level. Thus, some aggregation strategy is required. In Section IV, I report median indices as representative of the population.[7] These adjusted sub-indices can then be incorporated into the overall CPI as shown in Equation (7) for an "augmented" or "green" satellite index.

III. Data

This index is applied to the local cost of living for households in the Los Angeles area for the years 1989 to 1994. The housing market is defined as the urban area immediately around the city encompassed by a ring of mountains and national forests. Figure 1 displays a map of the entire area, plotting a sample of one in 20 houses from the data set and showing school district and county boundaries. The area includes the southern half of Ventura and Los Angeles Counties, the southwestern corner of San Bernardino County, western Riverside County, and all of Orange County.

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[7] An alternative aggregation strategy, much discussed in theory and compatible with the information available from this model, is an adapted "Social Laspeyres Index" (Pollak 1989, Ch. 6,7). The Social Laspeyres Index is defined as a weighted average of household Laspeyres indices with incomes as weights. Fisher and Griliches (1995) discuss this approach in the context of price indices for drugs, but they have access only to data from an aggregate-level model. The information provided by the model presented here is precisely what they require. Unfortunately, the average indices are sensitive to draws from the tails of the additive error terms, a common problem in welfare estimates of the value of new goods (see e.g. Petrin 2001). Recently, Berry and Pakes (1999) have proposed an alternative model overcoming this problem, but it has not yet been estimated.

To implement the estimator described above, data are required on housing prices and characteristics, characteristics of public goods, and household incomes and other demographics. Each of these types of data is discussed in turn below.

Housing Data

A large set of actual housing sales prices and characteristics obtained from Transamerica Intellitech provided the core database. After a 1% alpha-trim on the sales price and after removing a small number (about 1%) of observations with inconsistent values or values likely to be coding errors or non-arms-length transactions, this data set provides 319,641 observations from 1989 to 1994, each observation a unique house.Previous studies and local experts have reported that the California housing market peaked around 1990 after a long boom, and began to decline until recovering again in about 1996 (Case and Shiller 1994, Meyers 1997). The raw data support this description. Average sales prices were \$221,000 in 1989, rising to \$230,000 by 1991, but then declining again to 1989 values in 1992 and continuing to fall to \$205,000 by 1994. Thus, we expect housing price indices to be less than one for these years, at least before adjustment for public goods.The use of such transaction prices raises two issues. First, because these are assets prices, whereas the appropriate concept for a cost-of-living index is user cost, an explicit formula to annualize these costs based on interest rates and depreciation must be used. In the empirical illustration given below, I compute user cost at time t as

$$r^t = (i^t + \tau^t + \delta + \pi^t)\cdot P^t \qquad (10)$$

where r^t is the user cost, P^t is the asset price, i^t is the rate of return foregone by holding the house, τ^t is the property tax rate, δ is the depreciation rate, and π^t is expected asset appreciation at time t.

Following Poterba (1992), I assume δ=0.04 and that the opportunity cost of holding the housing asset is the prevailing 30-year conventional fixed-rate mortgage for each year, obtained from the Federal Home Mortgage Corporation, plus a risk premium of 0.04. Based on work by O'Sullivan, Sexton, and Sheffrin (1995), I assume a constant effective property tax rate of τ=0.0055. Finally, I assume that the expected asset appreciation is a five-year moving average of realized appreciation, with the final year forward-looking:

$$\pi^t = \frac{1}{5}\sum_{s=t-4}^{t}\frac{P^{s+1}}{P^s} \qquad (11)$$

That is, at time t expected changes in asset price are an average of the actual change that occurs from time t to t+1 and the changes in the previous four years. Hedonic price regressions on the asset prices determine P^{t+1}/P^t.[8] The estimated annualization rate fell from 0.113 in 1989 to 0.100 in 1991, then rose again to 0.150 in 1994, with most of the increase in the final year. This pattern reflects the changes in interest rates in response to the 1991 recession.

Instead of using an explicit formula, the Bureau of Labor Statistics (BLS) currently uses only rental markets for its housing sub-index, re-weighted to reflect the stock of owner-occupied units. Each approach has its advantages. Focusing on rental units, the BLS approach, in theory, allows the market to implicitly make the conversion to user cost. Explicit adjustment in contrast is sensitive to the assumptions used (Gillingham 1983). On the other hand, inferring changes in owner-occupied housing prices from the rental market may be impossible if the largest houses are not rented. This may explain why the BLS's CPI index for Los Angeles continued to show owner-occupied housing inflation throughout the early 1990s, whereas Case and Shiller found deflation led by the top tier of the market. In any case, the empirical strategy illustrated here may be conducted with either type of data.

In addition to price, the records for each sale contain fairly detailed housing attributes. These variables include the size of the lot in acres, the area of the house in square feet, the number of bathrooms and bedrooms, the presence of a fireplace, the presence of a swimming pool, and the age of the house.[9] Table 1 summarizes the means of these variables by county.

Public Goods

Three types of public goods are included in the cost-of-living index: school quality, crime, and air quality. A fourth spatial amenity is proximity to the coast. These are the goods

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[8] For the purposes of computing user cost, π^t does not hold the quality of public goods constant. Rather, it is the forecasted joint effect on asset values of both prices and quality changes. That is, it is the estimate of $p^b(\boldsymbol{q}^b)/p^a(\boldsymbol{q}^a)$, not $p^b(\boldsymbol{q}^a)/p^a(\boldsymbol{q}^a)$. Thus, like a change in prices, an exogenous change in quality of the house is a wealth transfer that alters the opportunity cost of owning. Expected future increases in quality, inasmuch as they increase future asset values, decrease the opportunity cost of home ownership.

[9] Unfortunately, the data set does not have full coverage of other variables that have been included in hedonic housing models. Foremost among these is the presence of air conditioning and a garage. However, models restricted to just those counties that do have these variables suggest they are insignificant and add very little to the total fit.

most likely to affect households in Los Angels.[10] School quality and crime are important to any community. While air quality might not be a priority in other locations, Los Angeles is likely an exception. There, it has historically been a severe problem and has improved markedly over time, suggesting it may affect a of cost of living time series. Moreover, there is strong anecdotal evidence that it affects households' locational choices.[11] Consequently, air quality has the potential to affect the true cost of living. The means for variables for each of these categories are included in Table 1. In each case, a three-year moving average is used to smooth shocks and reflect long-term experience, which is more likely to drive observed behavior.

Proxy variables for school quality were obtained from the National Center for Education Statistics. The main variable used is the teacher-student ratio, which was obtained for each school district and year.[12] In addition, achievement test scores (the sum of math and reading scores from the California Learning Assessment System test) were obtained for 1993 and appear as a cross-sectional control, but do not affect the index over time. While other empirical work has used expenditure data, this would be expected to be of limited value in California, where the 1972 *Serrano v. Priest* decision by the state Supreme Court and passage of Proposition 13 in 1978 have equalized expenditures across districts. (See O'Sullivan, Sexton, and Sheffrin 1995 for details.)

The number of crimes fitting the FBI crime index was obtained from the California Department of Justice for each local jurisdiction in 1990.[13] These crimes were then matched to 1990 populations of those jurisdictions to obtain crime rates per 10,000 people. County-level crime rates were obtained for other years, and percentage changes were applied to each jurisdiction to impute local crime rates for each year. These crime rates were then imputed to each house as an average weighted by the inverse-distance to the jurisdictional centroids. To facilitate the interpretation of each variable as a good with decreasing marginal rates of

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[10] A measure of distance to employment and/or civic centers might also be relevant, but is difficult to pin down in a city such as Los Angeles, which has no well-defined center. However, research by the Texas Transportation Institute indicates that commuting times in the Los Angeles area were relatively flat throughout the period studied. (See their web page at http://tti.tamu.edu.)

[11] For example, according to one real estate agent, roughly half of all clients ask about air quality in the neighborhood of a prospective home (Doheny 1998).

[12] Some missing values were interpolated from adjacent years.

[13] The FBI crime index includes willful homicide, forcible rape, robbery, larceny-theft, burglary, aggravated assault, motor vehicle theft, and arson.

substitution with money, an index of public safety defined as 3,000 minus the crime rate is the actual variable used.

Air quality is represented by ozone, the pollutant that is most commonly in violation of air quality standards, most carefully monitored, and associated with some of the greatest health effects.[14] Ozone data were obtained from the California Air Resources Board. The Los Angeles area is one of the most densely monitored regions in the world: for ozone, an average of 50 monitors are available each year in the study area, plus monitors in neighboring counties that can aid in interpolation. Because epidemiology and toxicology studies have consistently found that acute episodes of high ozone concentrations are behind most damages, the expected number of exceedences of the U.S. one-hour standard are used to represent ozone exposure. This measure has the added advantage of coinciding with the information communicated to residents (for example, on the *Los Angeles Times* weather page) in the form of ozone alerts. These exceedences at the nearest monitor are imputed to each house. Again, the days without an ozone exceedence are then used as a measure of the public good.

The average levels of these three public goods, indexed to 1989, are shown in Figure 2. The figure indicates that air quality improved from 1989 to 1994, with the average number of days without an ozone exceedence increasing from 324 to 343. In contrast, teacher-student ratios improved in the first year and then declined. (The average number of students per teacher declined from 24.5 to 24.2, then increased to 25.8 at the end of the period.) Relative to the other two goods, public safety remained fairly flat throughout the period, improving very slightly overall. Given these changes, one would expect that adjusting the cost-of-living index for public goods would tend to reduce the measure of inflation for the first year of the sample (1989-90), when air quality and teacher-student ratios both improved. In later years (1990-94), the adjustment would have an uncertain effect, depending on the relative weights given to air quality and education.

A final, spatially-differentiated variable included in the analysis is proximity to the southern California coast. Distances were computed from each house to the coastline. Because preliminary analysis suggested that the effect of distance dissipates after a few miles, dummy variables representing houses within one mile of the coast are used in the analysis.

[14] Particulate matter is another pollutant of concern, and has generally been associated with the most severe health effects. The two pollutants are closely correlated over time and space, and preliminary work with particulates led to similar results as those presented here for ozone.

Demographic Data

Demographic characteristics provide one way to introduce heterogeneity in tastes across households. For example, households with children might value educational quality or air quality more than other households. Household income levels are particularly important as they introduce income effects in the demand system for housing.

Unfortunately, the demographic characteristics of individual households cannot be matched to the houses they purchased. Instead, I impute average values of demographic variables obtained from the U.S. Census at each census block-group (the smallest unit) to each household in the block. The demographic variables are median household income among homeowners,[15] the percent of White, Black, and Hispanic households, the percent of households that are married, the percent of households that have children, and the percent of households with a college degree. Table 1 also summarizes the values of these demographic variables by county.

IV. Estimation and Results.

With these data, I estimate environmental cost-of-living indices using definitions (5) and (6). The first stage of this process is estimating the discrete choice models parameterized in (9a) and (9b). The second stage is computing the Hicksian surplus measures and associated price adjustments from these estimated models.

I assume that each household's choice set comprises houses in the entire Los Angeles area that are within its income constraint and that were sold within a three-month window of the date it made its actual purchase (plus or minus six weeks), the average time on the market for Los Angeles houses during the period covered.[16] The sample consists of 25,000 households and

[15] One problem with this measure of income is that some households (about 1%) have imputed incomes that are smaller than the annualized price of the house they occupy. This problem arises because households purchase their houses out of permanent income, whereas I observe current income (with additional error from taking only the median). I make two adjustments to income to overcome these difficulties. First, since I have measured income only in 1989, I appreciate these values for purchases in later years, using income data for U.S. homeowners from the Survey of Consumer Finances (Kennickell, Starr-McCluer, and Sundén 1997). Second, I add an annualized measure of household wealth for homeowners from the same survey. These adjustments account for the majority of cases; remaining cases are dropped from the analysis.

[16] As with previous applications, the estimates can be sensitive to assumptions about the choice set. A sensitivity analysis of these assumptions showed that the qualitative conclusions of this work do not change.

a randomly sampled choice set of 15 alternatives, including the selected house. This sampling scheme satisfies McFadden's (1978) uniform conditioning property.

As noted above, I estimate four models for each year: a linear-in-logs and linear-in-square-roots specification, each with either demographic interactions or random coefficients. The variables are net income, fixed effects for each county, an indicator variable for being within one mile of the coast, the number of days without an ozone exceedence, the index of public safety, the teacher-student ratio, test scores, the number of bathrooms, the square footage of the house, the square footage of the lot, age, and indicators for the presence of a swimming pool and fireplace. In the demographic models, the interactions terms include Black, Hispanic, college education, marital status, and the presence of children. Each of these is interacted with each of the public goods, while Black, Hispanic, and presence of children are interacted with bathrooms, building size and lot size. In the random coefficient models, the coefficients on the public goods, bathrooms, building size, lot size, and age are normally distributed, while the remaining coefficients are held constant. This judgment was made based on a series of likelihood ratio tests and does not appear restrictive. Note that all of the models have income effects. In addition, the models with random coefficients relax the independence of irrelevant alternatives (IIA) property present in the other models.[17]

The estimated models are reported in an appendix. In all cases, the overall model is highly significant based on a Chi-square test, and a likelihood ratio test rejects the hypothesis that public goods can be omitted. Taking the characteristics individually, most of the parameters are of the expected sign and significant. In the case of the random coefficients models, most public goods and housing structural parameters are positive and significant, with the exception of public safety and the number of bathrooms. In the case of the models with demographic characteristics, linear restrictions were tested for the hypothesis that the marginal utility of each characteristic is zero when evaluated at the sample means. A similar pattern emerges, with the hypothesis rejected for most characteristics in most years, the exceptions again being public safety and bathrooms. Finally, the income parameter, crucial for the welfare analysis, also is positive and highly significant in all model-years.

[17] In contrast to the nested logit model, the additive portion of the error remain independent and identically distributed. This assumption is required for welfare analysis with income effects. Recent suggestions for avoiding this problem are either intractable for the large choice sets required for housing (McFadden 1999) or do not apply to changes in the choice set (Karlström 2000). See also Herriges and Kling (1999) for further discussion.

From these estimated parameters, I calculate the required welfare information for the price index. This stage involves four steps. First, a sample of 2,500 households is drawn from the empirical distribution for Los Angeles for each year. This involves sampling an income from an estimated log-normal distribution or, for the models with demographic interactions, from a joint distribution of race, children, marriage, and income.[18] It also involves a draw from the type-I extreme value distribution for the additive errors and, for the models with random coefficients, draws from the distribution of utility parameters. These parameters are censored at zero for all characteristics except age.

Next, for each houshold, its complete choice sets are determined for the three-month period it is in the market and another period one year later (the reference and comparison periods). As noted above, these choice sets are defined as all houses within its budget constraint that sold within a three-month time window around the time the household is observed to purchase its actual house. To avoid attributing welfare effects to spurious changes in the size of the sample, the larger choice set of the two periods is randomly reduced to the size of the smaller. Most choice sets are between 6,000 and 8,000 houses.

In the third step, I compute the compensating and equivalent variations for each household for the change in its choice set. Given the estimated form for the utility function $v(\ )$, these measures are defined implicitly as

$$\max_{\{j\}} v_i(x_j, g_j, y_i\text{-}r_j, \varepsilon_j) = \max_{\{j'\}} v_i(x_{j'}, g_{j'}, y_i\text{-}r_{j'}\text{-CV}, \varepsilon_{j'}) \qquad (11)$$

$$\max_{\{j\}} v_i(x_j, g_j, y_i\text{-}r_j\text{+EV}, \varepsilon_j) = \max_{\{j'\}} v_i(x_{j'}, g_{j'}, y_i\text{-}r_{j'}, \varepsilon_{j'}) \qquad (12)$$

where j indexes the houses in the reference scenario choice set and j' indexes houses in the comparison scenario choice set. CV is the payment that equates realized utility in the comparison scenario with that in the reference scenario, at the house that is chosen after the payment is received. EV is analogously defined at reference period utility. These compensation measures assume that households may freely reoptimize their choice of housing location after the change in prices and public goods. Because household preferences are not quasi-linear in

[18] The income distribution was estimated using a GMM procedure on the income quantiles provided by the U.S. Census. The estimated parameters were $\mu_{\ln(y)}$=10.486, $\sigma_{\ln(y)}$=0.855. The joint demographic distribution was based on the U.S. Census and research by Bishop, Formby, and Smith (1997). It induces correlation between income and the other characteristics while constraining the conditional variance of the income distribution to be constant across groups.

income, there is no closed-form solution to these values. Instead, a numerical bisection is used to estimate the values within \$1.[19]

Fourth, income is adjusted by these values as in the left-hand side of Equations (5) and (6), and the percentage price adjustments that return utility to the appropriate level are determined by a similar simulation routine. These percentage price adjustments are the estimates of λ^* and λ^{**} for each household. These are estimated group sub-indices for housing and public goods that would be components of an augmented Laspeyres or Paasche index, respectively.

Note that this procedure differs in some ways from other applications to quality-adjusted price indices (Trajtenberg 1990, Nevo 2001, Timmins 2001). In particular, price adjustments are computed for weakly complementary market goods, allowing the public goods to enter through existing channels rather than through *ex post* adjustments. In addition, the error terms and non-linear income effects enter the welfare computations in a way that is consistent with the structural model.[20] Finally, the compensating variation is used in computing the adjustment for the Laspeyres index rather than the equivalent variation, since the Laspeyres bound holds at baseline utility levels.

The estimated price indices are given in Tables 2a to 2d. Before comparing the models with and without public goods, there are three patterns worth noting in the estimated levels. First, the estimated quality-adjusted housing inflation rates are generally plausible, usually being between +/- 5 percent and with a high and low across model-years of 22% and -21% respectively. Second, the models that do not adjust for public goods tend to reproduce the inflation patterns found in previous research (Case and Shiller 1994). In particular, they predict that Los Angeles housing inflation continued for the 1989-91 period before declining and even turning to deflation. Prices fall the sharpest in the 1991-93 period; in the final year, increases in

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[19] Specifically, guesses at CV and EV are made that are known to bound the true value. The mid-point is calculated as a new guess and subtracted from comparison-period income. Then, the utility-maximizing choice under this budget constraint is found for the period and compared to reference-period utility. If utility is too high, the new guess is a new lower bound; if utility is too low, it is a new upper bound. The process continues until adjustments are within \$1. The initial guesses can be made from closed-form solutions to CV and EV when the household is constrained to its initially observed choices (as in McFadden 1999).

[20] In contrast, most authors have assumed constant marginal utility of income. Nevo (2001) interacts income levels with tastes for characteristics, but ignores this interaction in welfare calculations. Timmons (2001) uses a similar specification to that used here, but ignores the error terms in his welfare computations, solving for the money needed to hold expected utility constant for a hypothetical representative household (compare McFadden 1999, Morey, Rowe, and Watson 1993).

interest rates begin to increase the rate of price change through the effect on user cost. Finally, there is no consistent relationship between the λ^* sub-index that would enter a Laspeyres index and the λ^{**} sub-index that would enter a Paasche index. Reasoning from the intuition that a Laspeyres index is usually (if not always) higher than a Paasche index, one might think that λ^* should exceed λ^{**}. But in the case of the overall price index, the usual bounds arise from the fixed product weights and the possibility of substitution across products. There is nothing that guarantees that an individual sub-index should follow the same pattern.[21]

In all specifications, the models that omit public goods estimate higher housing inflation for 1989-90 than those that include public goods, with differences ranging from 1.7% to 9.2% . This is consistent with the fact that both teacher-student ratios and air quality improved over this period. In the later years, this difference is reversed for most models, which tend to give greater weight to the decline in teacher-student ratios than to the improvement in air quality or public safety. An exception is the square-root specification with demographic interaction effects (Table 2c). Here, including public goods lowers estimated housing inflation throughout the period. This is consistent with the estimated structural model. For example, during the final three years, this model has the lowest average marginal rate of substitution between public safety and teachers of any model and the second-lowest marginal rate of substitution between air quality and teachers. Across the four models, public goods change the sub-index by -1.0 to +8.5 percentage points per year for the final three year period.

Figure 3 illustrates these differences for one model, the Laspeyres sub-index from Table 2b. Figure 4 uses the same data to reconstruct an overall CPI index for Los Angeles. The index is constructed by netting out the BLS's Housing Index for Los Angeles from its Los Angeles CPI and replacing it with the indices from Figure 3. With a weight of 0.28 for housing, including public goods can make a substantial impact on the overall cost-of-living picture, at least in this case. For the model shown, estimated average cost of living increases are 0.5% lower when public goods are included for the first two years of the period, and 0.9% higher for

[21] In fact, *mean* λ^{**} is higher than mean λ^*. This result follows from the logic of equations (5) and (6), and the fact that what is being calculated is a percentage price adjustment that is equivalent to an income adjustment. Consider the case of a decrease in quality. Looking at Equation (6), when quality is changed to the new, lower level, prices may be adjusted to zero and still not compensate some households in the tail of the distribution, suggesting a virtually infinite index for these households. In Equation (5) in contrast, when quality is changed to its original, higher level, a finite percentage adjustment to the vector of housing prices can always be found to return households to the required utility level. Analogous logic holds for a quality improvement.

the remaining three years. For the other models, the estimated average changes are -0.9, -1.3, and -0.3 percentage points for the first two years, and 0.0, -0.5, and +2.5 percentage points for the last three years. These differences are of the same order of magnitude as the quality adjustments suggested by Boskin et al. for market goods.

V. Hedonic Regressions

The approach used in this paper to estimate augmented price indices differs from the much older and more common strategy of hedonic price regressions, which is now used by the BLS for a number of items in the CPI, including computers, other electronics, and apparel. Relative to hedonic indices, the discrete choice models used here are much less restrictive, allowing for heterogeneity in tastes and relaxing the repackaging assumption implicit in hedonic models (see Fisher and Shell 1972, Trajtenberg 1990). Relaxing repackaging is especially important, since it is the only way to value the "filling in" of the product space with new alternatives. Hedonic regressions are much less computation-intensive however, and may be a more pragmatic compromise for a price statistics agency. Accordingly, I also estimate analogous augmented cost-of-living sub-indices for housing and public goods using hedonic regressions. Among other applications, this approach has been used to estimate price indices for automobiles (as in Raff and Trajtenberg 1997), and housing (as in Sieg et al. 2001). It also has been used to recover values for publicly provided goods such as education (in Black 1999) and air quality (in Smith and Huang 1995), and to estimate a "quality of life" index (Blomquist, Berger, and Hoehn 1988). The latter is a similar application to that suggested here, estimating a spatial quantity index of public goods rather than the price index.

In the hedonic framework, prices of quality-differentiated goods are modeled as a continuous function of the underlying characteristics, yielding the relationship $p_j = p(\mathbf{z}_j)$ which can be estimated with standard regression techniques. I estimate "direct" hedonic price indices that decompose the hedonic price equation into two pieces: a quantity index based on characteristics and a temporal (or spatial) price index capturing shifts in the quantity index. For example, a direct hedonic price index for two periods *a* and *b* could be estimated with a hedonic equation of the form

$$\ln(p_j) = \alpha^a D_j^a + \alpha^b D_j^b + f(\mathbf{z}_j) + \eta_j , \qquad (12)$$

where D_j^a and D_j^b are indicator variables for the reference and comparison years respectively (taking a value of one for the year the house is sold and zero otherwise) and the α's are the associated intercepts. Taking the exponent of both sides, it is clear that $e^{\alpha^b}/e^{\alpha^a}$ is a price index corresponding to the quantity index $e^{f(\,)}$. In this approach, omitting pubic goods from *f*( ) causes a standard omitted variable bias in the fixed effects.

With little theory as a guide, the choice of a functional form for hedonic regressions is an empirical matter. Relative to an unrestricted Box-Cox specification, semi-log specifications with these data have the lowest mean squared error of any common specification (when converted to price levels). They also have the advantage of being readily consistent with direct hedonic equations defined by Equation (12). Accordingly, I use semi-log models to estimate direct hedonic regressions.

Table 3 reports the results of three model specifications, each with and without public goods. Model 1 includes a complete list of characteristics, as well as school district fixed effects. Model 2 replaces the school district fixed effects with county fixed effects. Model 3 is the same as Model 2 with the addition of local demographic variables (averaged over census block groups). A case can be made for each specification, and each has drawbacks. The fixed effects in Model 1 have the advantage of controlling for unobserved spatial goods, but depend on intra-community variation to estimate the parameters for public goods, which may be too sensitive to the imputation scheme. The demographic variables in Model 3 clearly have an effect on housing prices, and are included in most empirical work, but are unlikely to be included in an official price index. Model 2 emerges as a preferable compromise. All of the models perform well by the usual statistical criteria. Almost all of the attributes, including public goods, have positive signs and are significant. The negative estimated coefficient on bedrooms in most models is at first surprising, but must be interpreted in light of the fact that square footage is held constant.

The estimated coefficients of the time indicator variables are reported as actual annual price indices in Table 4 (for example, relative to the preceding year), along with 90% confidence intervals. The results of this hedonic methodology generally replicate those of the discrete choice model. Estimated quality-adjusted price indices are at comparable levels and follow a similar pattern, rising the first year before steadily falling throughout the period, with the rate of decline slowing in the last year. Moreover, the difference made by public goods is similar. In all three hedonic models, controlling for public goods again decreases the estimated cost of living in the first two years (with a cumulative difference of -0.6 to -1.8 percentage points) and increases it in the last three years of the period (with a cumulative difference of 0.6 to 2.1 percentage points).

These results are generally robust to the specification of the model and to the assumption of constant parameter values across years. In addition, using an alternative "imputation approach" by estimating separate models for each year and taking the average ratio of predicted prices does not change these findings. Thus, although it is more restrictive, the simpler hedonic approach may be sufficient for incorporating public goods in a cost of living framework. Further research is warranted to see if this pattern continues in other contexts before drawing conclusions.

VI. Conclusions

This research suggests that including public goods in a cost-of-living index is feasible for a large class of important public goods. When differentiated spatially, public goods may be linked to housing as a weak complement to create a sub-index of housing and public goods. The sub-index can be estimated with a discrete choice or hedonic model and can be incorporated into a modified Laspeyres index.

Moreover, in the test case of Los Angeles from 1989-1994, the effect of public goods appears to be substantial. In the first year of the period, when both public goods are improving, including public goods reduces the estimated cost of living. Using the CPI housing weight of 0.28 and the λ^* index consistent with a Laspeyres index, this reduction is estimated to be between 0.5 and 2.6 percentage points, depending on the model. In the final three years, the effect of including public goods depends on the relative estimated values for air quality and education. The average annual effect of including public goods during this period is between -0.5 and +2.5 percentage points.

Taken together, these results support the importance of public goods in a true cost-of-living index. While more work and considerable judgment would have to go into any official price indices incorporating public goods, this research demonstrates that it may be feasible to estimate augmented indices that are released alongside the CPI. At a minimum, such an index would be useful in deflating incomes for quality of life comparisons across regions of the country. In the future, such an index also would arguably be a better way to determine cost-of-living adjustments for government expenditures: since these adjustments are designed to offset the costs of achieving a standard of living, they should reflect the supply of public goods that are substitutes for private goods in the achievement of that standard of living. The estimates in this paper suggest incorporating public goods would make a significant difference to such cost-of-living adjustments. (Compare them, for example, with the savings estimated by Boskin et al., 1996, for a 1.1 percentage point adjustment to the CPI for market goods.)

One important question would be how many other types of public goods, other than those that vary within metropolitan areas, could be included in such an index. Potentially, other spatial goods may be similarly linked if one is willing to broaden the geographic extent of the housing market. Other public goods may be linked to other markets. Drinking-water quality, for example, may be linked to expenditures on water filters and other substitutes. More pure public goods may only be included as a final adjustment to the index using stated preferences. While perhaps not all of them could ever be included, an index of spatially differentiated goods would be a first step in answering the call of a number of economists to think of the modern economy in broader terms (e.g. Fogel 1999).

Figure 1.
Housing Observations in the Los Angeles Area.

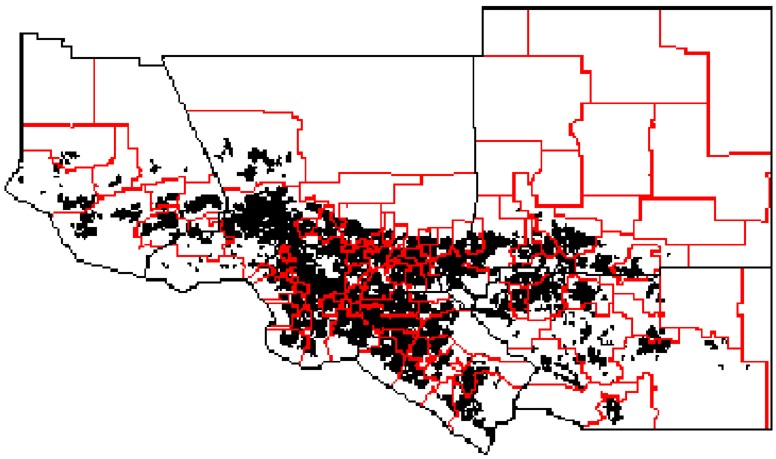

Figure 2.
Plot of Public Goods Over Time
(three-year moving average over households, 1989=100)

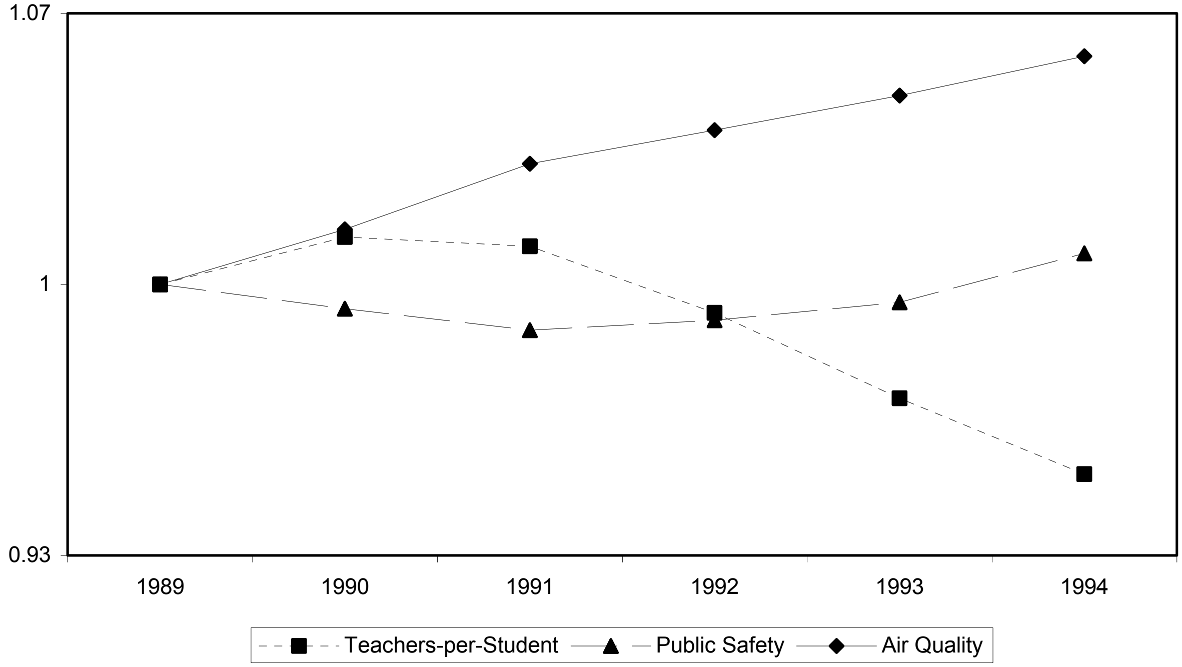

Figure 3
Housing Price Indices With and Without Public Goods
(λ^* from Logarithmic Model With Random Coefficients)

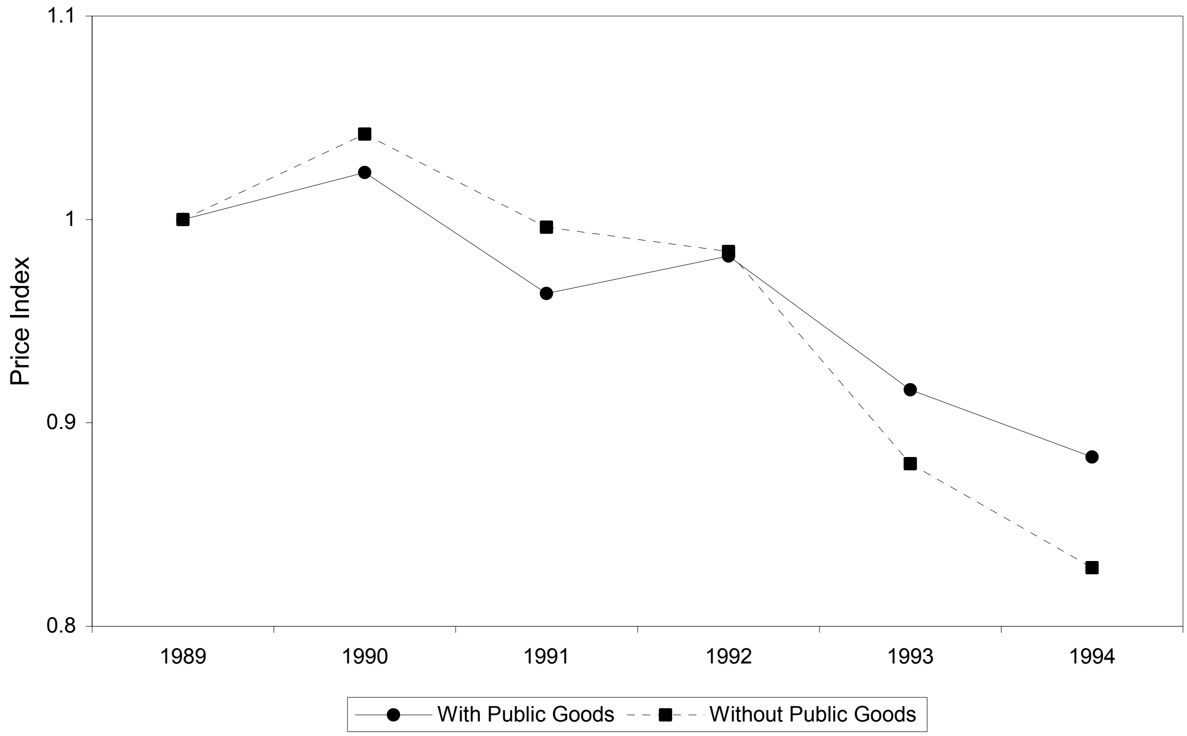

Figure 4
Overall Laspeyres Indices With and Without Public Goods
(λ^* from Logarithmic Model with Random Coefficients)

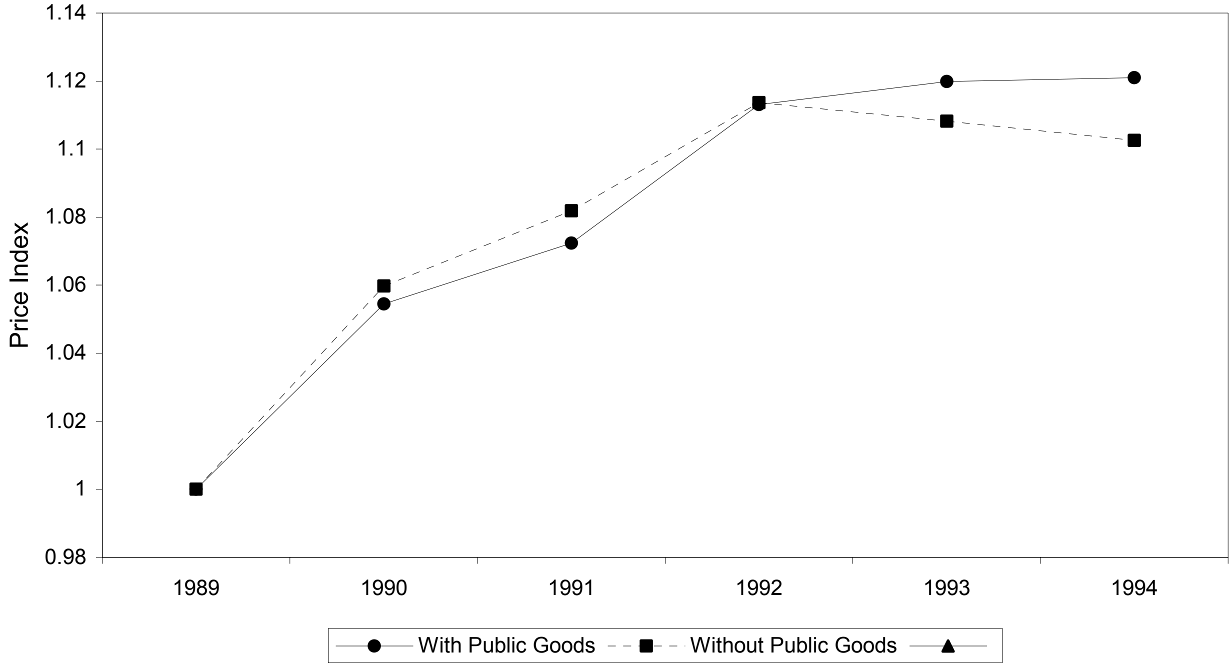

Table 1.
Number of Observations and Means of Housing Variables by County, 1989-1994.

Variable	Los Angeles	Orange	Riverside	S. Bernrdino	Ventura
N	144,731	71,147	43,588	37,686	22,489
Price	234,674	262,891	138,025	150,236	235,151
Lot Size (acres)	0.18	0.16	0.24	0.21	0.22
Building (sqft)	1,568	1,766	1,629	1,619	1,831
Bathrooms	1.92	2.17	2.07	2.11	2.24
Bedrooms	3.03	3.33	3.26	3.29	3.47
Firepl (0/1)	0.54	0.20	0.84	0.80	0.80
Pool (0/1)	0.16	0.13	0.12	0.13	0.15
Age	39.2	25.7	10.9	17.3	19.1
Test Score	4.79	5.68	4.80	4.82	5.04
Teachers per Student	0.040	0.040	0.040	0.040	0.039
Public Safety Index	2388	2470	2285	2349	2599
Ozone-free days	329.8	354.5	307.0	281.0	358.9
1 Mi of Coast (0/1)	0.03	0.06	0	0	0.04
Median Income	47,027	59,166	40,444	44,054	51,325
Pct White	0.65	0.82	0.81	0.74	0.84
Pct Black	0.09	0.01	0.05	0.07	0.02
Pct Hispanic	0.28	0.14	0.19	0.25	0.18
Pct Married	0.60	0.68	0.68	0.67	0.70
Pct w/ Children	0.38	0.40	0.43	0.46	0.43
Pct College Grad.	0.17	0.22	0.10	0.12	0.17

Table 2a
Logarithmic Model With Demographic Interactions: Estimated Price Indices

Year	λ^{*} With Public Goods	λ^{*} Without Public Goods	λ^{**} With Public Goods	λ^{**} Without Public Goods
1989-90	1.091	1.140	1.084	1.135
1990-91	1.021	1.032	1.023	1.033
1991-92	0.948	0.957	0.952	0.957
1992-93	0.981	0.979	0.982	0.980
1993-94	0.995	0.990	0.994	0.990

Table 2b
Logarithmic Model With Random Coefficients: Estimated Price Indices

Year	λ^{*} With Public Goods	λ^{*} Without Public Goods	λ^{**} With Public Goods	λ^{**} Without Public Goods
1989-90	1.023	1.042	1.022	1.039
1990-91	0.942	0.956	0.943	0.954
1991-92	1.019	0.988	1.022	0.988
1992-93	0.933	0.894	0.937	0.890
1993-94	0.964	0.942	0.964	0.944

Table 2c
Square Root Model With Demographic Interactions: Estimated Price Indices

	λ^{*}		λ^{**}	
Year	With Public Goods	Without Public Goods	With Public Goods	Without Public Goods
1989-90	1.132	1.224	1.110	1.146
1990-91	1.011	1.010	1.013	1.009
1991-92	0.926	0.940	0.905	0.911
1992-93	1.001	1.020	1.001	1.018
1993-94	1.015	1.029	1.013	1.021

Table 2d
Square Root Model With Random Coefficients: Estimated Price Indices

	λ^{*}		λ^{**}	
Year	With Public Goods	Without Public Goods	With Public Goods	Without Public Goods
1989-90	0.990	1.018	0.983	1.021
1990-91	0.920	0.913	0.895	0.869
1991-92	1.078	0.979	1.062	0.979
1992-93	0.951	0.827	0.933	0.785
1993-94	1.0002	0.964	1.0002	0.959

Table 3
Direct Hedonic Price Regressions

	Model 1		Model 2		Model 3	
Variable	With public goods	Without public goods	With public goods	Without public goods	With public goods	Without public goods
Year 1990	0.0405	0.0452	0.0290	0.0395	0.0337	0.0447
	(0.0018)	(0.0017)	(0.0019)	(0.0020)	(0.0017)	(0.0017)
Year 1991	0.0256	0.0314	0.0166	0.0324	0.0081	0.0259
	(0.0018)	(0.0017)	(0.0019)	(0.0019)	(0.0016)	(0.0016)
Year 1992	-0.0050	-0.0009†	-0.0094	-0.0008†	-0.0257	-0.0091
	(0.0018)	(0.0016)	(0.0018)	(0.0019)	(0.0016)	(0.0016)
Year 1993	-0.0744	-0.0733	-0.0700	-0.0722	-0.0973	-0.0841
	(0.0019)	(0.0016)	(0.0018)	(0.0018)	(0.0016)	(0.0016)
Year 1994	-0.1123	-0.1124	-0.1046	-0.1114	-0.1367	-0.1242
	(0.0021)	(0.0016)	(0.0019)	(0.0018)	(0.0017)	(0.0015)
Orange Co.			-0.0706	0.0307	-0.0930	-0.0436
			(0.0017)	(0.0014)	(0.0016)	(0.0013)
Sanbern Co.			-0.4040	-0.4583	-0.3340	-0.3890
			(0.0018)	(0.0017)	(0.0017)	(0.0016)
Riversd. Co.			-0.4904	-0.5472	-0.4389	-0.4731
			(0.0018)	(0.0018)	(0.0018)	(0.0018)
Ventura Co.			-0.1701	-0.1213	-0.1512	-0.1118
			(0.0021)	(0.0020)	(0.0019)	(0.0018)
1 Mi. of Coast	0.1737	0.1747	0.1951	0.2365	0.1063	0.1160
	(0.0052)	(0.0052)	(0.0054)	(0.0054)	(0.0047)	(0.0047)
3 Mi. of Coast	0.1526	0.1536	0.1844	0.2314	0.1160	0.1472
	(0.0029)	(0.0029)	(0.0027)	(0.0028)	(0.0023)	(0.0023)
Ozn Free Days	0.0004		0.0007		0.0011	
	(3.81E-5)		(1.92E-5)		(1.69E-5)	
Test Score			0.1180		0.0424	
			(0.0012)		(0.0011)	
Tchrs to Stdnts	0.0524		0.1731		0.0815	
	(0.0049)		(0.0030)		(0.0028)	
Safety	4.40E-5		0.0002		5.09E-5	
	(5.15E-6)		(3.92E-6)		(3.56E-6)	
Bathrooms	0.0322	0.0317	0.0454	0.0484	0.0257	0.0240
	(0.0013)	(0.0013)	(0.0014)	(0.0015)	(0.0012)	(0.0013)
Bedrooms	-0.0185	-0.0183	-0.0263	-0.0292	0.0025	0.0017**
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)
Bldg Size (sqft)	0.0003	0.0003	0.0004	0.0004	0.0003	0.0003
	(1.73E-6)	(1.73E-6)	(1.81E-6)	(1.87E-6)	(1.68E-6)	(1.70E-6)
Lot Size (sqft)	6.34E-6	6.36E-6	5.66E-6	5.79E-6	5.26E-6	4.83E-6
	(1.14E-7)	(1.14E-7)	(1.16E-7)	(1.18E-7)	(1.07E-7)	(1.06E-7)
Fireplace	0.0829	0.0828	0.1018	0.1095	0.0582	0.0557
	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0010)	(0.0010)
Swimming	0.0564	0.0560	0.0557	0.0575	0.0397	0.0358

Pool	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0012)	(0.0013)
Age	-0.0038	-0.0038	-0.0011	-0.0016	-0.0027	-0.0029
	(9.26E-5)	(9.27E-5)	(9.27E-5)	(9.59E-5)	(0.0001)	(8.48E-5)
Age^2	1.06E-5	1.07E-5	5.36E-7†	1.09E-6†	2.96E-5	0.0000
	(1.24E-6)	(1.23E-6)	(1.28E-6)	(1.31E-6)	(1.15E-6)	(1.15E-6)
Pct Black					-0.3360	-0.3446
					(0.0037)	(0.0036)
Pct Hispanic					-0.0611	-0.0995
					(0.0031)	(0.0030)
Pct College					1.2319	1.2604
					(0.0077)	(0.0077)
Pct Married					0.0758	0.0797
					(0.0038)	(0.0038)
Constant	9.0773	9.5181	7.5149	9.3851	8.3391	9.3557
	(0.0256)	(0.0042)	(0.0152)	(0.0040)	(0.0152)	(0.0044)
School Fixed Effects	Yes	Yes	No	No	No	No
N	294,683	294,683	294,683	294,683	292,153	292,153
R2	0.75	0.75	0.70	0.68	0.77	0.76

Dependent variable: log of sales price in current dollars.
Standard Errors in Parentheses.
All variables significant at 1% level unless otherwise noted.
**Significant at 5 percent level. †Not significant at 10 percent level.

Table 4
Annual Direct Hedonic Housing Price Indices, 1989-1994

	Model 1		Model 2		Model 3	
Year	With public goods	Without public goods	With public goods	Without public goods	With public goods	Without public goods
1989-90	1.041	1.046	1.029	1.040	1.034	1.046
	(1.038-1.044)	(1.043-1.049)	(1.026-1.033)	(1.037-1.044)	(1.031-1.037)	(1.043-1.049)
1990-91	0.985	0.986	0.988	0.993	0.975	0.981
	(0.983-0.988)	(0.984-0.989)	(0.985-0.991)	(0.99-0.996)	(0.972-0.977)	(0.979-0.984)
1991-92	0.970	0.968	0.974	0.967	0.967	0.966
	(0.967-0.972)	(0.966-0.971)	(0.972-0.977)	(0.965-0.97)	(0.964-0.969)	(0.963-0.968)
1992-93	0.933	0.930	0.941	0.931	0.931	0.928
	(0.931-0.935)	(0.928-0.932)	(0.939-0.944)	(0.929-0.933)	(0.929-0.933)	(0.926-0.930)
1993-94	0.963	0.962	0.966	0.962	0.961	0.961
	(0.961-0.965)	(0.960-0.964)	(0.964-0.968)	(0.959-0.964)	(0.959-0.963)	(0.959-0.963)

Ninety percent confidence intervals shown in parentheses, based on White-corrected standard errors.

VII. References

Banzhaf, H. Spencer. 2002. "Green Price Indices." RFF Discussion Paper 02-09. Washington, DC: Resources for the Future.

Berry, Steven, and Ariel Pakes. 1999. "Estimating the Pure Hedonic Discrete Choice Model." Mimeo. New Haven, CT: Yale University.

Bishop, John A., John P. Formby, and W. James Smith. 1997. "Demographic Change and Income Inequality in the United States, 1976-1989." *Southern Economic Journal* 64(1): 34-44.

Black, Sandra. 1999. "Do Better Schools Matter? Parental Valuation of Elementary Education." *Quarterly Journal of Economics* 114: 577-599.

Blackley, Paul, and Jan Ondrich. 1988. "A Limiting Joint-Choice Model for Discrete and Continuous Housing Characteristics." *Review of Economics and Statistics* 70: 266-74.

Blomquist, Glenn, Mark C. Berger, and John P. Hoehn. 1988. "New Estimates of the Quality if Life in Urban Areas." *American Economic Review* 78: 89-107.

Boskin, Michael J., E. Dulberger, R. Gordon, Z. Griliches, and D. Jorgenson. 1996. *Toward a More Accurate Measure of the Cost of Living*. Final Report to the U.S. Senate Finance Committee, Dec. 4.

Bresnahan, Timothy F., and Robert J. Gordon, Eds. 1997. *The Economics of New Goods*. Chicago: The University of Chicago Press.

Case, Karl E., and Robert J. Shiller. 1994. "A Decade of Boom and Bust in the Prices of Single-Family Homes: Boston and Los Angeles, 1983 to 1993." *New England Economic Review*, March/April: 40-51.

Chattopadhyay, Sudip. 2000. "The Effectiveness of McFaddens's [*sic*] Nested Logit Model in Valuing Amenity Improvements." *Regional Science and Urban Economics* 30: 23-43.

Cutler, David M., Mark McClellan, Joseph P. Newhouse, Dahlia Remler. 1998. "Are Medical Prices Declining?" *Quarterly Journal of Economics* 11: 991-1024.

Doheny, Kathleen. 1998. "Nothing to Sneeze At." *Los Angeles Times*, Sept. 27, K1.

Fisher, Franklin M, and Karl Shell. 1972. *The Economic Theory of Price Indices: Two Essays on the Effects of Taste, Quality, and Technical Change*. New York: Academic Press.

Fogel, Robert W. 1999. "Catching Up with the Economy." *American Economic Review* 89: 1-21.

Gillingham, Robert. 1983. "Measuring the Cost of Shelter for Homeowners: Theoretical and Empirical Considerations." *Review of Economics and Statistics* 65(2): 254-265.

Hausman, Jerry A. 1999. "Cellular Telephone, New Products and the CPI." *Journal of Business and Economic Statistics* 17: 188-194.

Hazilla, Michael, and Raymond J. Kopp. 1990. "Social Cost of Environmental Quality Regulations: A General Equilibrium Analysis." *Journal of Political Economy* 98: 853-873.

Herriges, Joseph A., and Catherine Kling. 1999. "Nonlinear Income Effects in Random Utility Models." *Review of Economics and Statistics* 81(1): 62-72.

Karlström, Anders. 2001. "Hicksian Welfare Measures in a Nonlinear Random Utility Framework." Mimeo. Stockholm: Royal Institute of Technology.

McFadden, Daniel. 1978. "Modeling the Choice of Residential Location." In *Spatial Interaction Theory and Planning Models*, ed. by Anders Karlqvist, Lars Lundqvist, Folke Snickars, and Jörgen W. Weibull. Amsterdam: North-Holland.

McFadden, Daniel. 1999. "Computing Willingness-to-Pay in Random Utility Models." In *Theory and Econometrics: Essays in Honour of John S. Chipman*, ed. by J. Moore, R. Riezman, and J. Melvin. London: Routledge.

Meyers, Laura. 1997. "Is it buying time again?" *Los Angeles Magazine* 42(January): 76-81.

Morey, Edward R., Robert D. Rowe, and Michael Watson. 1993. "A Repeated Nested Logit Model of Atlantic Salmon Fishing." *American Journal of Agricultural Economics* 75: 578-592."

Neary, J.P., and K.W.S. Roberts. 1980. "The Theory of Household Behaviour Under Rationing." *European Economic Review* 13: 25-42.

Nechyba, Thomas, and Robert P. Strauss. 1998. "Community Choice and Local Public Services: A Discrete Choice Approach." *Regional Science and Urban Economics* 28: 51-73.

Nevo, Aviv. 2001. "New Products, Quality Changes, and Welfare Measures Computed from Estimated Demand Systems." *Review of Economic Statistics,* forthcoming.

Nordhaus, William D. 1999. "Beyond the CPI: An Augmented Cost-of-Living Index." *Journal of Business and Economic Statistics* 17: 182-187.

Nordhaus, William D., and Edward C. Kokkelenberg, Eds. 1999. *Nature's Numbers: Expanding the National Economic Accounts to Include the Environment*. Report from the Panel on Integrated Environmental and Economic Accounting, National Research Council. Washington, DC: National Academy Press.

O'Sullivan, Arthur, Teri A. Sexton, and Steven M. Sheffrin. 1995. *Property Taxes and Tax Revolts: The Legacy of Proposition 13*. Cambridge, UK: Cambridge University Press.

Palmquist, Raymond B., and Adis Israngkura. 1999. "Valuing Air Quality with Hedonic and Discrete Choice Models." *American Journal of Agricultural Economics* 81: 1128-33.

Petrin, Amil. 2001. "Quantifying the Benefits of New Products: The Case of the Minivan." NBER Working Paper 8227. Cambridge, MA: National Bureau of Economic Research.

Pollak, Robert A. 1989. *The Theory of the Cost-of-Living Index*. New York: Oxford University Press.

Ptacek, Frank, and Robert M. Baskin. 1996. "Revision of the CPI Housing Sample and Estimators." *Monthly Labor Review* 119(12): 31-39.

Quigley, John M. 1985. "Consumer Choice of Dwelling, Neighborhood, and Public Services." *Regional Science and Urban Economics* 15(1): 1-23.

Raff, Daniel M.G., and Manuel Trajtenberg. 1997. "Quality-Adjusted Prices for the American Automobile Industry, 1906-1940." In *The Economics of New Goods,* ed. by Timothy F. Bresnahan and Robert J. Gordon. Chicago: The University of Chicago Press.

Revelt, David, and Kenneth Train. 1998. "Mixed Logit with Repeated Choice: Households' Choice of Appliance Efficiency Level." *Review of Economics and Statistics* 80(4): 647-657.

Sieg, Holger, V. Kerry Smith, H. Spencer Banzhaf, and Randy Walsh. 2001. "Using Locational Equilibrium Models to Evaluate Housing Price Indexes." *Journal of Urban Economics*, forthcoming.

Smith, V. Kerry, and Ju-Chin Huang. 1995. "Can Markets Value Air Quality? A Meta-Analysis of Hedonic Property Value Models." *Journal of Political Economy* 103(1): 209-227.

Stigler, George, Dorothy S. Brady, Edward Denison, Irving B. Kravis, Philip J. McCarthy, Albert Rees, Richard Ruggles, and Boris C. Swerling. 1961. *The Price Statistics of the Federal Government*. National Bureau of Economic Research.

Timmins, Christopher. 2001. "A True Spatial Cost-of-Living Index with Developing-Country Data." Mimeo. New Haven, CT: Yale University.

Trajtenberg, Manuel. 1990. *Economic Analysis of Product Innovation: The Case of CT Scanners*. Cambridge, MA: Harvard University Press.

Triplett, Jack E. (ed). 1999. *Measuring the Prices of Medical Treatments*. Washington, DC: Brookings Institution Press.

U.S. Department of Justice. 2001. www/ojp.usdoj.gov/bjs/dataonline.

U.S. Environmental Protection Agency. 2000. *National Air Quality and Emissions Trends Report, 1998*. Report no. 454/R-00-003. Research Triangle Park, NC: Office of Air Quality Planning and Standards.

Willig, Robert D. 1978. "Incremental Consumer's Surplus and Hedonic Price Adjustment." *Journal of Economic Theory* 17: 227-253.

Appendix

Table A.1
Annual Logarithmic Utility With Demographic Interactions, With Public Goods, 1989-1993

	1989	1990	1991	1992	1993
Net Income	1.3448	2.1038	2.4004	2.4626	2.2864
	(0.0264)	(0.0418)	(0.0478)	(0.0490)	(0.0465)
Orange Co.	-0.2820	-0.2145	-0.2145	-0.2018	-0.1455
	(0.0249)	(0.0231)	(0.0218)	(0.0219)	(0.0221)
Sanbernardino Co.	-0.3805	-0.3383	-0.2967	-0.2779	-0.2717
	(0.0256)	(0.0249)	(0.0245)	(0.0239)	(0.0244)
Riverside Co.	-0.4443	-0.4213	-0.4118	-0.4463	-0.4315
	(0.0259)	(0.0262)	(0.0262)	(0.0256)	(0.0261)
Ventura Co.	-0.0735	-0.1069	-0.2075	-0.2099	-0.1617
	(0.0273)	(0.0292)	(0.0279)	(0.0269)	(0.0248)
Coast	0.1655	0.2843	0.2753	0.2746	0.2536
	(0.0485)	(0.0456)	(0.0417)	(0.0403)	(0.0375)
Ozone-Free Days	-0.0072	0.0301	-0.1558	0.2067	-0.2879
	(0.2665)	(0.2759)	(0.3187)	(0.3399)	(0.3561)
Teacher-Studnt Ratio	-1.0299	-0.9475	0.8904	0.0414	0.1936
	(0.8166)	(0.7348)	(0.6845)	(0.7394)	(0.8355)
Test Score	-0.4068	-0.4568	-0.4320	-0.0528	-0.2040
	(0.3673)	(0.3650)	(0.3561)	(0.3651)	(0.3577)
Public Safety	0.1319	0.2334	0.1180	-0.4167	-0.1847
	(0.2485)	(0.2527)	(0.2716)	(0.2948)	(0.3053)
Black*Ozone-Free	-0.2512	-0.3180	-0.8034	-0.9167	0.4583
	(0.4772)	(0.5181)	(0.6272)	(0.6850)	(0.7475)
Black*Teachers	-0.4000	0.5669	0.8460	0.7457	0.8346
	(1.2325)	(1.1515)	(1.2065)	(1.3498)	(1.6516)
Black*Test Score	0.1208	-0.2798	-1.2028	-1.0744	-1.0683
	(0.8430)	(0.9329)	(0.9851)	(1.0401)	(1.1017)
Black*Safety	0.8491	0.6564	1.1288	1.3693	0.1326
	(0.4376)	(0.4711)	(0.5509)	(0.5968)	(0.6581)
Hisp.*Ozone-Free	-0.1295	0.2180	0.6069	0.3250	0.4549
	(0.3137)	(0.3199)	(0.3855)	(0.4128)	(0.4267)
Hispanic*Teachers	0.1383	0.9183	-0.2781	1.0332	0.9440
	(0.8570)	(0.7817)	(0.7748)	(0.8215)	(0.9259)
Hispanic*Test Score	1.8475	2.3482	2.2403	1.4863	1.7718
	(0.4840)	(0.4690)	(0.4826)	(0.4902)	(0.4868)
Hispanic*Safety	0.5998	0.1255	0.0652	0.3151	0.1765
	(0.2968)	(0.3009)	(0.3346)	(0.3618)	(0.3812)
Child*Ozone-Free	0.1778	0.0377	-0.0888	-0.1328	-0.1602
	(0.4711)	(0.4858)	(0.5824)	(0.6150)	(0.6417)
Child*Teachers	2.6235	1.3008	0.8839	-0.9790	0.4751
	(1.4417)	(1.3054)	(1.1843)	(1.3194)	(1.4726)
Child*Test Score	-0.8065	-1.5114	-1.4056	-0.9594	-1.0074
	(0.6115)	(0.5900)	(0.5820)	(0.5915)	(0.5925)
Child*Safety	-0.3277	0.0243	0.1894	0.7739	0.4903
	(0.4330)	(0.4553)	(0.5035)	(0.5391)	(0.5569)

Married*Ozone-Free	-0.1417	0.0429	0.2246	0.0596	0.2127
	(0.4236)	(0.4458)	(0.5166)	(0.5513)	(0.5785)
Married*Teachers	-1.7112	-1.2581	-2.8914	-1.8710	-2.7078
	(1.2468)	(1.1097)	(1.0598)	(1.1100)	(1.2242)
Married*Test Score	0.2829	0.6235	0.6584	-0.0819	-0.0939
	(0.5603)	(0.5444)	(0.5240)	(0.5378)	(0.5341)
Married*Safety	0.3394	0.0566	0.2040	0.3062	0.3290
	(0.3472)	(0.3735)	(0.4119)	(0.4508)	(0.4716)
College*Ozone-Free	3.5384	2.7022	3.7078	3.2712	3.9661
	(0.5574)	(0.6027)	(0.6756)	(0.7082)	(0.7210)
College*Teachers	11.4752	12.4609	6.4970	8.8458	7.3169
	(1.6453)	(1.6429)	(1.3321)	(1.4036)	(1.5073)
College*Test Score	3.3766	3.1049	3.3747	3.8550	4.2620
	(0.7367)	(0.7414)	(0.7160)	(0.7276)	(0.7023)
College*Safety	-5.1060	-4.6724	-4.3990	-4.6061	-4.9150
	(0.4559)	(0.4915)	(0.5213)	(0.5658)	(0.5731)
Bathrooms	0.0517	-0.0217	0.0103	0.0132	0.0760
	(0.0740)	(0.0735)	(0.0734)	(0.0750)	(0.0731)
Building Size	0.6964	0.7437	0.6495	0.8083	0.7176
	(0.0882)	(0.0868)	(0.0866)	(0.0883)	(0.0856)
Lot Size	0.2452	0.2365	0.2501	0.2916	0.2995
	(0.0410)	(0.0392)	(0.0401)	(0.0391)	(0.0388)
Fireplace	0.0194	-0.0125	-0.0099	-0.0047	-0.0171
	(0.0138)	(0.0137)	(0.0133)	(0.0134)	(0.0139)
Swimming Pool	0.0575	0.0454	0.0473	0.0688	0.0534
	(0.0166)	(0.0171)	(0.0168)	(0.0162)	(0.0161)
Age	-0.0022	-0.0278	-0.0293	-0.0270	-0.0445
	(0.0064)	(0.0069)	(0.0072)	(0.0077)	(0.0080)
Child*Bathrooms	-0.0512	0.0831	0.0793	0.0552	-0.1299
	(0.1761)	(0.1750)	(0.1793)	(0.1844)	(0.1815)
Child*Building Size	0.2451	0.1761	0.1685	-0.0040	0.0465
	(0.2103)	(0.2061)	(0.2083)	(0.2115)	(0.2078)
Child*Lot Size	-0.2740	-0.1165	-0.1255	-0.2607	-0.2391
	(0.1025)	(0.0998)	(0.1025)	(0.1014)	(0.1002)
Black*Building Size	-0.3800	-0.4210	-0.3715	-0.2759	-0.3521
	(0.1333)	(0.1312)	(0.1350)	(0.1435)	(0.1516)
Black*Lot Size	-0.2812	-0.1112	-0.1254	-0.3435	-0.1057
	(0.1386)	(0.1296)	(0.1347)	(0.1423)	(0.1548)
Hispanic*Bldg. Size	-0.9698	-0.9045	-0.7530	-0.9500	-0.9250
	(0.1021)	(0.0992)	(0.1022)	(0.1054)	(0.1079)
Hispanic*Lot Size	-0.0181	-0.0850	-0.1949	-0.1501	-0.1589
	(0.0788)	(0.0756)	(0.0808)	(0.0824)	(0.0811)
N	524,919	524,438	523,879	524,575	524,824
Log Likelihood	-92,835	-93,051	-93,006	-93,441	-93,003

Table A.2
Annual Logarithmic Utility With Demographic Interactions,
Without Public Goods, 1989-1993

	1989	1990	1991	1992	1993
Net Income	1.1284	1.7146	1.9414	1.9930	1.8534
	(0.0250)	(0.0390)	(0.0445)	(0.0452)	(0.0426)
Orange Co.	-0.1568	-0.1337	-0.1142	-0.1122	-0.0850
	(0.0206)	(0.0182)	(0.0169)	(0.0170)	(0.0174)
Sanbernardino Co.	-0.4615	-0.4161	-0.3778	-0.3559	-0.3317
	(0.0216)	(0.0209)	(0.0211)	(0.0212)	(0.0212)
Riverside Co.	-0.5356	-0.4770	-0.4824	-0.4797	-0.4694
	(0.0220)	(0.0230)	(0.0237)	(0.0237)	(0.0239)
Ventura Co.	-0.0993	-0.1339	-0.2004	-0.1880	-0.1691
	(0.0239)	(0.0259)	(0.0248)	(0.0236)	(0.0219)
Coast	0.5605	0.6054	0.5472	0.5261	0.4923
	(0.0438)	(0.0413)	(0.0381)	(0.0370)	(0.0344)
Bathrooms	0.2033	0.1288	0.0886	0.1916	0.2523
	(0.0602)	(0.0590)	(0.0591)	(0.0591)	(0.0585)
Building Size	0.6229	0.6544	0.6134	0.6215	0.5392
	(0.0563)	(0.0550)	(0.0552)	(0.0546)	(0.0538)
Lot Size	0.0945	0.0996	0.0960	0.1144	0.1555
	(0.0389)	(0.0372)	(0.0375)	(0.0367)	(0.0367)
Fireplace	0.0307	-0.0032	-0.0008	-4.32E-05	-0.0115
	(0.0135)	(0.0134)	(0.0131)	(0.0132)	(0.0137)
Swimming Pool	0.0497	0.0341	0.0347	0.0568	0.0435
	(0.0164)	(0.0169)	(0.0166)	(0.0161)	(0.0160)
Age	0.0036	-0.0134	-0.0153	-0.0124	-0.0287
	(0.0063)	(0.0067)	(0.0070)	(0.0075)	(0.0078)
Child*Bathrooms	-0.4935	-0.3568	-0.1951	-0.4672	-0.6343
	(0.1403)	(0.1371)	(0.1411)	(0.1425)	(0.1418)
Child*Building Size	0.4145	0.2615	0.1892	0.3227	0.3472
	(0.1202)	(0.1164)	(0.1178)	(0.1173)	(0.1167)
Child*Lot Size	-0.3094	-0.1949	-0.1483	-0.2403	-0.2528
	(0.0952)	(0.0922)	(0.0933)	(0.0928)	(0.0923)
Black*Building Size	-0.1811	-0.2851	-0.2309	-0.0488	-0.1654
	(0.1162)	(0.1112)	(0.1132)	(0.1213)	(0.1302)
Black*Lot Size	0.0864	0.1836	0.1466	-0.0043	0.1044
	(0.0958)	(0.0915)	(0.0932)	(0.1001)	(0.1073)
Hispanic*Bldg. Size	-0.7036	-0.5508	-0.4605	-0.5612	-0.4992
	(0.0781)	(0.0755)	(0.0798)	(0.0814)	(0.0815)
Hispanic*Lot Size	0.5062	0.3976	0.3274	0.4063	0.3653
	(0.0637)	(0.0615)	(0.0652)	(0.0665)	(0.0664)
N	524,919	524,438	523,879	524,575	524,824
Log Likelihood	-93320	-93470	-93411	-93441	-93382

Table A.3
Annual Square-Root Utility With Demographic Interactions, With Public Goods, 1989-1993

	1989	1990	1991	1992	1993
Net Income	0.0091	0.0114	0.0121	0.0133	0.0134
	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0004)
Orange Co.	-0.2200	-0.1608	-0.1510	-0.1390	-0.1021
	(0.0247)	(0.0230)	(0.0217)	(0.0218)	(0.0220)
Sanbernardino Co.	-0.2454	-0.1952	-0.1606	-0.1555	-0.1657
	(0.0258)	(0.0250)	(0.0246)	(0.0240)	(0.0244)
Riverside Co.	-0.2718	-0.2143	-0.2126	-0.2491	-0.2566
	(0.0263)	(0.0264)	(0.0264)	(0.0256)	(0.0259)
Ventura Co.	-0.0504	-0.0794	-0.1420	-0.1315	-0.0998
	(0.0282)	(0.0301)	(0.0288)	(0.0276)	(0.0254)
Coast	0.1801	0.2430	0.2192	0.2311	0.2045
	(0.0474)	(0.0444)	(0.0408)	(0.0393)	(0.0367)
Ozone-Free Days	-0.0228	0.0033	-0.0124	0.0261	-0.0286
	(0.0315)	(0.0327)	(0.0379)	(0.0406)	(0.0422)
Teacher-Studnt Ratio	0.9068	0.5377	0.6862	-0.0433	0.4374
	(0.5233)	(0.4542)	(0.4462)	(0.4728)	(0.5184)
Test Score	-0.0842	-0.1276	-0.4807	-0.1727	-0.2348
	(0.3221)	(0.3133)	(0.3080)	(0.3136)	(0.3166)
Public Safety	-0.0082	0.0117	0.0160	0.0022	-0.0006
	(0.0197)	(0.0183)	(0.0188)	(0.0199)	(0.0205)
Black*Ozone-Free	-0.0012	-0.0297	-0.0566	-0.0772	0.0635
	(0.0537)	(0.0563)	(0.0667)	(0.0728)	(0.0798)
Black*Teachers	-0.7765	0.0470	0.8765	0.2767	-0.0721
	(1.2093)	(1.0989)	(1.1381)	(1.2751)	(1.5364)
Black*Test Score	-0.0316	-0.4772	-0.7269	-0.7082	-0.7104
	(0.8018)	(0.8679)	(0.9117)	(0.9720)	(1.0316)
Black*Safety	0.0501	0.0410	0.0257	0.0638	0.0179
	(0.0370)	(0.0344)	(0.0384)	(0.0405)	(0.0446)
Hisp.*Ozone-Free	-0.0066	-0.0082	0.0223	0.0023	-0.0074
	(0.0374)	(0.0381)	(0.0464)	(0.0493)	(0.0511)
Hispanic*Teachers	-1.3126	-0.4663	-0.6917	0.0143	-0.2508
	(0.6082)	(0.5313)	(0.5443)	(0.5733)	(0.6231)
Hispanic*Test Score	1.3283	1.6453	1.7337	0.9804	1.3007
	(0.4157)	(0.4006)	(0.4109)	(0.4236)	(0.4241)
Hispanic*Safety	0.0264	-0.0230	-0.0313	-0.0172	-0.0136
	(0.0225)	(0.0209)	(0.0219)	(0.0232)	(0.0238)
Child*Ozone-Free	-0.0138	-0.0175	-0.0494	-0.0401	-0.0081
	(0.0565)	(0.0575)	(0.0681)	(0.0723)	(0.0757)
Child*Teachers	2.4755	1.9744	1.4675	0.6396	0.7432
	(0.8314)	(0.7540)	(0.7517)	(0.8254)	(0.9051)
Child*Test Score	-0.3027	-0.7430	-0.7659	-0.3281	-0.6761
	(0.5617)	(0.5424)	(0.5375)	(0.5520)	(0.5599)
Child*Safety	-0.0690	-0.0375	-0.0018	0.0183	0.0199

	(0.0328)	(0.0330)	(0.0353)	(0.0382)	(0.0392)
Married*Ozone-Free	0.0291	0.0361	0.0697	0.0443	0.0581
	(0.0499)	(0.0519)	(0.0607)	(0.0648)	(0.0679)
Married*Teachers	-1.8087	-1.4981	-1.8672	-0.9196	-1.1840
	(0.7684)	(0.6932)	(0.7010)	(0.7257)	(0.7785)
Married*Test Score	-0.1232	0.0698	0.4584	-0.0453	0.0095
	(0.4950)	(0.4788)	(0.4689)	(0.4834)	(0.4884)
Married*Safety	0.0687	0.0448	0.0286	0.0237	0.0251
	(0.0304)	(0.0301)	(0.0309)	(0.0325)	(0.0331)
College*Ozone-Free	0.3053	0.1548	0.1906	0.1025	0.1781
	(0.0673)	(0.0729)	(0.0812)	(0.0845)	(0.0862)
College*Teachers	1.3280	2.8104	2.0019	3.4247	1.6739
	(1.0743)	(1.0183)	(0.9042)	(0.9412)	(0.9962)
College*Test Score	1.8417	1.5674	2.5075	2.5021	2.9249
	(0.6700)	(0.6666)	(0.6404)	(0.6504)	(0.6421)
College*Safety	-0.2164	-0.2202	-0.2435	-0.2712	-0.2440
	(0.0427)	(0.0430)	(0.0403)	(0.0423)	(0.0416)
Bathrooms	0.0469	-0.0965	0.0067	-0.0212	0.1001
	(0.1134)	(0.1130)	(0.1126)	(0.1136)	(0.1110)
Building Size	0.0333	0.0337	0.0267	0.0351	0.0297
	(0.0045)	(0.0045)	(0.0044)	(0.0044)	(0.0043)
Lot Size	0.0033	0.0027	0.0036	0.0036	0.0040
	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0008)
Fireplace	0.0131	-0.0096	-0.0119	-0.0026	-0.0090
	(0.0137)	(0.0135)	(0.0132)	(0.0133)	(0.0138)
Swimming Pool	0.0374	0.0217	0.0214	0.0474	0.0322
	(0.0165)	(0.0170)	(0.0167)	(0.0161)	(0.0160)
Age	0.0061	-0.0034	-0.0019	-0.0009	-0.0078
	(0.0041)	(0.0043)	(0.0043)	(0.0045)	(0.0046)
Child*Bathrooms	0.0439	0.3169	0.2196	0.2547	-0.1079
	(0.2691)	(0.2698)	(0.2748)	(0.2783)	(0.2749)
Child*Building Size	-0.0065	-0.0113	-0.0064	-0.0176	-0.0066
	(0.0106)	(0.0104)	(0.0104)	(0.0104)	(0.0101)
Child*Lot Size	-0.0047	-0.0016	-0.0028	-0.0039	-0.0040
	(0.0020)	(0.0020)	(0.0021)	(0.0020)	(0.0019)
Black*Building Size	-0.0205	-0.0193	-0.0160	-0.0108	-0.0146
	(0.0069)	(0.0069)	(0.0070)	(0.0075)	(0.0077)
Black*Lot Size	-0.0037	-0.0003	-0.0004	-0.0060	0.0002
	(0.0031)	(0.0029)	(0.0029)	(0.0032)	(0.0031)
Hispanic*Bldg. Size	-0.0412	-0.0352	-0.0269	-0.0355	-0.0361
	(0.0054)	(0.0053)	(0.0054)	(0.0056)	(0.0057)
Hispanic*Lot Size	0.0005	-0.0011	-0.0031	-0.0013	-0.0022
	(0.0016)	(0.0016)	(0.0018)	(0.0018)	(0.0017)
N	524,919	524,438	523,879	524,575	524,824
Log Likelihood	-94,119	-94,243	-9,4164	-94,210	-94,150

Table A.4
Annual Square-Root Utility With Demographic Interactions, Without Public Goods, 1989-1993

	1989	1990	1991	1992	1993
Net Income	0.0067	0.0084	0.0089	0.0100	0.0103
	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Orange Co.	-0.1197	-0.0980	-0.0763	-0.0745	-0.0603
	(0.0203)	(0.0180)	(0.0168)	(0.0169)	(0.0173)
Sanbernardino Co.	-0.2660	-0.2258	-0.1951	-0.1906	-0.1910
	(0.0221)	(0.0212)	(0.0212)	(0.0214)	(0.0213)
Riverside Co.	-0.3055	-0.2384	-0.2440	-0.2525	-0.2727
	(0.0225)	(0.0231)	(0.0238)	(0.0237)	(0.0238)
Ventura Co.	-0.0728	-0.0858	-0.1277	-0.1152	-0.1007
	(0.0240)	(0.0260)	(0.0250)	(0.0238)	(0.0221)
Coast	0.4250	0.4048	0.3662	0.3497	0.3293
	(0.0432)	(0.0411)	(0.0379)	(0.0367)	(0.0341)
Bathrooms	-0.1556	-0.2097	-0.1023	-0.1724	-0.0664
	(0.1076)	(0.1079)	(0.1068)	(0.1078)	(0.1047)
Building Size	0.0333	0.0325	0.0265	0.0319	0.0261
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0041)
Lot Size	0.0007	0.0006	0.0013	0.0010	0.0018
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)
Fireplace	0.0149	-0.0078	-0.0104	-0.0035	-0.0102
	(0.0134)	(0.0132)	(0.0129)	(0.0130)	(0.0135)
Swimming Pool	0.0287	0.0123	0.0094	0.0366	0.0234
	(0.0164)	(0.0169)	(0.0166)	(0.0160)	(0.0159)
Age	0.0140	0.0066	0.0072	0.0087	0.0031
	(0.0040)	(0.0041)	(0.0042)	(0.0043)	(0.0044)
Child*Bathrooms	0.5273	0.5672	0.4538	0.6196	0.3164
	(0.2501)	(0.2522)	(0.2550)	(0.2576)	(0.2527)
Child*Building Size	-0.0143	-0.0199	-0.0140	-0.0205	-0.0090
	(0.0099)	(0.0099)	(0.0099)	(0.0100)	(0.0097)
Child*Lot Size	-0.0025	-0.0005	-0.0013	-0.0013	-0.0021
	(0.0019)	(0.0018)	(0.0019)	(0.0019)	(0.0018)
Black*Building Size	-0.0084	-0.0120	-0.0089	-0.0012	-0.0067
	(0.0053)	(0.0051)	(0.0050)	(0.0055)	(0.0056)
Black*Lot Size	-0.0008	0.0021	0.0013	-0.0027	0.0008
	(0.0024)	(0.0023)	(0.0023)	(0.0026)	(0.0026)
Hispanic*Bldg. Size	-0.0231	-0.0149	-0.0117	-0.0160	-0.0134
	(0.0033)	(0.0032)	(0.0036)	(0.0035)	(0.0035)
Hispanic*Lot Size	0.0054	0.0033	0.0020	0.0036	0.0031
	(0.0014)	(0.0014)	(0.0015)	(0.0015)	(0.0015)
N	524,919	524,438	523,879	524,575	524,824
Log Likelihood	-94,365	-94,412	-94,335	-94,381	-94,331

Table A.5
Annual Logarithmic Utility With Random Coefficients, With Public Goods, 1989-1993

	1989	1990	1991	1992	1993
Net Income	1.0514	1.6386	1.7856	1.9574	1.818
	(0.0284)	(0.0451)	(0.0490)	(0.0529)	(0.0576)
Orange Co.	-0.177	-0.137	-0.178	-0.143	-0.079
	(0.0290)	(0.0270)	(0.0250)	(0.0260)	(0.0260)
Sanbernardino Co.	-0.354	-0.322	-0.28	-0.271	-0.251
	(0.0290)	(0.0280)	(0.0280)	(0.0270)	(0.0280)
Riverside Co.	-0.374	-0.345	-0.377	-0.395	-0.361
	(0.0290)	(0.0300)	(0.0290)	(0.0290)	(0.0300)
Ventura Co.	-0.074	-0.069	-0.188	-0.182	-0.124
	(0.0320)	(0.0350)	(0.0330)	(0.0320)	(0.0290)
Coast	0.52	0.49	0.49	0.49	0.41
	(0.0500)	(0.0500)	(0.0500)	(0.0400)	(0.0400)
Ozone-Free: μ	0.2703	0.3371	0.4138	0.476	0.4253
	(0.0703)	(0.0786)	(0.0930)	(0.1028)	(0.1026)
Ozone-Free: σ	0.0198	0.2697	0.0201	-0.5444	0.0108
	(0.0522)	(0.2458)	(0.0740)	(0.9616)	(0.1149)
Teacher-Stud.: μ	1.3092	1.6941	0.8942	1.1627	1.2106
	(0.1683)	(0.1793)	(0.1496)	(0.1790)	(0.1974)
Teacher-Stud.: σ	4.8426	5.6713	4.8663	5.1134	4.809
	(0.4856)	(0.4955)	(0.4333)	(0.4525)	(0.5110)
Test Score: μ	0.9138	0.7827	0.8593	0.6667	0.5809
	(0.0855)	(0.0885)	(0.0860)	(0.0871)	(0.0871)
Test Score: σ	0.0853	0.111	0.0689	0.6473	0.7268
	(0.0653)	(0.1027)	(0.0645)	(0.8530)	(0.5538)
Public Safety: μ	0.1715	0.0506	0.1309	0.0098	-0.0322
	(0.1373)	(0.1279)	(0.1312)	(0.1120)	(0.1299)
Public Safety: σ	0.3486	0.4945	0.6921	0.0642	0.2422
	(0.7265)	(0.4358)	(0.3607)	(0.0888)	(0.8057)
Bathrooms: μ	0.056	0.028	0.033	0.048	0.073
	(0.0300)	(0.0300)	(0.0300)	(0.0300)	(0.0340)
Bathrooms: σ	0.046	0.015	0.035	0.038	0.199
	(0.0740)	(0.0300)	(0.0890)	(0.0780)	(0.2450)
Building Size: μ	0.5684	0.5801	0.5716	0.6146	0.5327
	(0.0362)	(0.0366)	(0.0364)	(0.0364)	(0.0375)
Building Size: σ	0.6099	0.7959	0.671	0.6957	0.5982
	(0.0945)	(0.0733)	(0.0864)	(0.0828)	(0.1008)
Lot Size: μ	0.1074	0.147	0.1331	0.1264	0.1415
	(0.0162)	(0.0164)	(0.0165)	(0.0168)	(0.0169)
Lot Size: σ	0.0746	0.0436	0.1398	0.1803	0.2092
	(0.0724)	(0.2120)	(0.1074)	(0.0697)	(0.0637)
Fireplace	0.077	0.034	0.03	0.032	0.02
	(0.0160)	(0.0160)	(0.0160)	(0.0160)	(0.0170)
Pool	0.078	0.054	0.06	0.071	0.046
	(0.0190)	(0.0200)	(0.0200)	(0.0190)	(0.0190)

Age: μ	-0.0059	-0.0229	-0.012	-0.013	0.0014
	(0.0075)	(0.0080)	(0.0093)	(0.0090)	(0.0139)
Age: σ	0.0321	0.0014	0.0544	0.0338	0.1636
	(0.0464)	(0.0175)	(0.0491)	(0.0282)	(0.0388)
N	375,000	375,000	375,000	375,000	375,000
Log Likelihood	-66,745	-66,833	-66,817	-66,796	-66,756

Table A.6
Annual Logarithmic Utility With Random Coefficients, Without Public Goods, 1989-1993

	1989	1990	1991	1992	1993
Net Income	0.9558	1.4999	1.6454	1.8207	1.7008
	(0.0272)	(0.0432)	(0.0469)	(0.0507)	(0.0544)
Orange Co.	0.0110	0.0038	-0.0145	-0.0297	0.0188
	(0.0233)	(0.0205)	(0.0190)	(0.0193)	(0.0205)
Sanbernardino Co.	-0.3876	-0.3757	-0.3430	-0.3333	-0.2981
	(0.0249)	(0.0240)	(0.0243)	(0.0244)	(0.0250)
Riverside Co.	-0.4133	-0.3810	-0.3956	-0.4133	-0.3817
	(0.0256)	(0.0267)	(0.0275)	(0.0275)	(0.0288)
Ventura Co.	-0.0197	-0.0541	-0.1417	-0.1514	-0.0954
	(0.0278)	(0.0300)	(0.0287)	(0.0275)	(0.0258)
Coast	0.6133	0.5802	0.5773	0.5733	0.4859
	(0.0514)	(0.0491)	(0.0445)	(0.0432)	(0.0405)
Bathrooms: μ	0.0673	0.0265	0.0423	0.0458	0.0737
	(0.0297)	(0.0295)	(0.0298)	(0.0296)	(0.0340)
Bathrooms: σ	0.0098	0.0127	0.0681	0.0033	0.2322
	(0.0322)	(0.0117)	(0.0637)	(0.0283)	(0.2361)
Building Size: μ	0.5661	0.5869	0.5659	0.6219	0.5352
	(0.0361)	(0.0364)	(0.0362)	(0.0362)	(0.0374)
Building Size: σ	0.6643	0.8253	0.7009	0.7504	0.6385
	(0.0835)	(0.0693)	(0.0812)	(0.0758)	(0.0987)
Lot Size: μ	0.0926	0.1191	0.1148	0.1013	0.1230
	(0.0160)	(0.0160)	(0.0160)	(0.0163)	(0.0167)
Lot Size: σ	0.0694	0.1329	0.1827	0.1866	0.1953
	(0.1138)	(0.0885)	(0.0756)	(0.0721)	(0.0763)
Fireplace	0.0805	0.0410	0.0394	0.0383	0.0243
	(0.0163)	(0.0162)	(0.0157)	(0.0159)	(0.0165)
Pool	0.0742	0.0446	0.0550	0.0649	0.0388
	(0.0194)	(0.0200)	(0.0196)	(0.0190)	(0.0191)
Age: μ	-0.0042	-0.0142	-0.0096	-0.0048	0.0084
	(0.0072)	(0.0079)	(0.0082)	(0.0087)	(0.0136)
Age: σ	0.0128	0.0028	0.0070	0.0056	0.1632
	(0.0188)	(0.0088)	(0.0249)	(0.0179)	(0.0379)
N	375,000	375,000	375,000	375,000	375,000
Log Likelihood	-66,858	-66,933	-66,900	-66,867	-66,817

Table A.7
Annual Square-Root Utility With Random Coefficients, With Public Goods, 1989-1993

	1989	1990	1991	1992	1993
Net Income	0.0058	0.0795	0.0870	0.0967	0.1015
	(0.0003)	(0.0045)	(0.0047)	(0.0048)	(0.0044)
Orange Co.	-0.1430	-0.1063	-0.1279	-0.0985	-0.0411
	(0.0287)	(0.0265)	(0.0252)	(0.0256)	(0.0259)
Sanbernardino Co.	-0.1993	-0.1790	-0.1439	-0.1427	-0.1424
	(0.0290)	(0.0285)	(0.0280)	(0.0277)	(0.0279)
Riverside Co.	-0.2075	-0.1734	-0.1945	-0.2168	-0.2095
	(0.0292)	(0.0300)	(0.0298)	(0.0290)	(0.0295)
Ventura Co.	-0.0531	-0.0320	-0.1221	-0.1086	-0.0604
	(0.0327)	(0.0350)	(0.0333)	(0.0326)	(0.0293)
Coast	3.8336	2.9771	3.1553	3.2671	2.7362
	(0.5123)	(0.4950)	(0.4505)	(0.4416)	(0.4055)
Ozone-Free: μ	0.0195	0.2542	0.2824	0.3292	0.3084
	(0.0081)	(0.0906)	(0.1039)	(0.1270)	(0.1132)
Ozone-Free: σ	0.0016	0.5737	0.0533	0.9844	0.0129
	(0.0088)	(0.5867)	(0.1763)	(1.4550)	(0.1690)
Teacher-Stud.: μ	0.9915	1.2934	0.5670	0.8770	0.8852
	(0.1633)	(0.1720)	(0.1448)	(0.1738)	(0.1906)
Teacher-Stud.: σ	4.5196	5.1788	4.4275	4.6821	4.0784
	(0.4678)	(0.5148)	(0.4487)	(0.4704)	(0.5678)
Test Score: μ	0.5294	0.4106	0.4956	0.3151	0.2926
	(0.0761)	(0.0786)	(0.0754)	(0.0785)	(0.0784)
Test Score: σ	0.0617	0.3411	0.1821	1.0885	0.9655
	(0.0785)	(0.4706)	(0.1782)	(0.4149)	(0.4423)
Public Safety: μ	0.0022	-0.0172	0.0282	-0.0273	-0.0213
	(0.0058)	(0.0531)	(0.0550)	(0.0495)	(0.0528)
Public Safety: σ	0.0245	0.1989	0.4003	0.0616	0.1271
	(0.0298)	(0.2420)	(0.1779)	(0.0789)	(0.2649)
Bathrooms: μ	0.7910	0.2589	0.5974	0.6962	1.1581
	(0.4760)	(0.4737)	(0.4777)	(0.4743)	(0.4775)
Bathrooms: σ	2.6202	0.4553	4.1379	1.2907	5.4103
	(3.9001)	(0.8024)	(2.6478)	(10.2526)	(2.1391)
Building Size: μ	0.0190	0.0182	0.0176	0.0195	0.0176
	(0.0019)	(0.0020)	(0.0019)	(0.0019)	(0.0019)
Building Size: σ	0.0157	0.0303	0.0177	0.0227	0.0159
	(0.0086)	(0.0043)	(0.0082)	(0.0066)	(0.0090)
Lot Size: μ	0.0011	0.0016	0.0015	0.0014	0.0018
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Lot Size: σ	0.0004	0.0001	0.0001	0.0003	0.0008
	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0005)
Fireplace	0.0499	0.0201	0.0132	0.0189	0.0157
	(0.0163)	(0.0163)	(0.0158)	(0.0160)	(0.0165)
Pool	0.0507	0.0246	0.0321	0.0492	0.0261
	(0.0193)	(0.0200)	(0.0196)	(0.0190)	(0.0192)

Age: μ	0.0027	-0.0036	0.0031	0.0012	0.0057
	(0.0046)	(0.0048)	(0.0049)	(0.0050)	(0.0054)
Age: σ	0.0096	0.0058	0.0402	0.0127	0.0704
	(0.0180)	(0.0122)	(0.0235)	(0.0161)	(0.0242)
N	375,000	375,000	375,000	375,000	375,000
Log Likelihood	-67,445		-67,478	-67,452	-67,401

Table A.8
Annual Square Root Utility With Random Coefficients, Without Public Goods, 1989-1993

	1989	1990	1991	1992	1993
Net Income	0.0048	0.0069	0.0077	0.0087	0.0093
	(0.0003)	(0.0004)	(0.0005)	(0.0005)	(0.0004)
Orange Co.	-0.0153	-0.0168	-0.0203	-0.0349	0.0171
	(0.0234)	(0.0203)	(0.0191)	(0.0194)	(0.0204)
Sanbernardino Co.	-0.2117	-0.2131	-0.1819	-0.1840	-0.1755
	(0.0256)	(0.0245)	(0.0248)	(0.0249)	(0.0248)
Riverside Co.	-0.2241	-0.1921	-0.2000	-0.2275	-0.2250
	(0.0261)	(0.0268)	(0.0278)	(0.0276)	(0.0279)
Ventura Co.	-0.0276	-0.0376	-0.0963	-0.1038	-0.0475
	(0.0281)	(0.0303)	(0.0291)	(0.0279)	(0.0259)
Coast	0.4369	0.3608	0.3705	0.3835	0.3230
	(0.0505)	(0.0485)	(0.0441)	(0.0426)	(0.0396)
Bathrooms: μ	0.0916	0.0244	0.0668	0.0675	0.1147
	(0.0477)	(0.0470)	(0.0473)	(0.0470)	(0.0475)
Bathrooms: σ	0.3163	0.0288	0.4228	0.1487	0.5607
	(0.3894)	(0.0335)	(0.2545)	(0.7097)	(0.2077)
Building Size: μ	0.0178	0.0177	0.0167	0.0191	0.0172
	(0.0019)	(0.0020)	(0.0019)	(0.0019)	(0.0019)
Building Size: σ	0.0167	0.0314	0.0193	0.0245	0.0168
	(0.0079)	(0.0041)	(0.0077)	(0.0056)	(0.0088)
Lot Size: μ	0.0010	0.0013	0.0137	0.0114	0.0161
	(0.0003)	(0.0003)	(0.0030)	(0.0030)	(0.0029)
Lot Size: σ	0.0002	0.0002	0.0011	0.0013	0.0019
	(0.0002)	(0.0002)	(0.0014)	(0.0018)	(0.0019)
Fireplace	0.0520	0.0253	0.0183	0.0219	0.0181
	(0.0163)	(0.0161)	(0.0157)	(0.0159)	(0.0164)
Pool	0.0466	0.0163	0.0275	0.0433	0.0205
	(0.0192)	(0.0199)	(0.0195)	(0.0188)	(0.0190)
Age: μ	0.0037	0.0007	0.0033	0.0049	0.0085
	(0.0045)	(0.0047)	(0.0047)	(0.0049)	(0.0052)
Age: σ	0.0030	0.0015	0.0018	0.0054	0.0732
	(0.0100)	(0.0071)	(0.0287)	(0.0110)	(0.0220)
N	375,000	375,000	375,000	375,000	375,000
Log Likelihood	-67,504	-67,526	-67,518	-67,487	-67,430