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Permanent Income, Hedonic Prices, and Demand for Housing: New Evidence[1]

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Housing demand is examined by looking quite specifically at the income and price variables based on individual household data. Permanent and transitory incomes are computed through instrumental variables related to human and nonhuman wealth. A price is constructed by spatially varying hedonic techniques. Separation of measured income into permanent and transitory components substantially improves the predictive power of the housing demand estimation and leads to demand elasticities of +1 and −1 with respect to permanent income and price. The permanent income elasticity is roughly twice the measured income elasticity.

I. INTRODUCTION

In the past two decades there have been important developments in the study of housing demand. Both improvements in analytical techniques (see [12], for example) and increasing availability of household data have enabled researchers to estimate income and price demand elasticities. Currently Quigley [14] suggests that most studies find values between 0.7 and 0.9 for the former and from −0.5 to −0.7 for the latter.[2]

Neither income nor price is unambiguous for housing demand. First, it is often suggested that use of measured actual income does not yield consistent estimates of the permanent income elasticity due to the errors-in-variables problem [1, 4, 9, 10, 15]. Hence, either an estimation technique that guarantees consistency of the estimators should be adopted or, more directly, permanent income must be placed as an explanatory variable in the demand function. It has been difficult to construct a satisfactory indicator for permanent income and many studies have used either grouped data or multiyear averages of measured income as proxies. Permanent and transitory incomes are computed in this paper using instrumental variables related to human and nonhuman wealth, and the coefficients of the two incomes in the housing demand function are estimated.

[1]We thank Bruce Hamilton, Louis Maccini, and the participants of the Johns Hopkins summer seminar for their comments and critiques. We thank A. Thomas King for providing the unique household data used in this study.

[2] deLeeuw [3] provides an early summary of housing demand studies, and Quigley [14] provides an excellent survey of the current state of the art.

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Second, the unit price of housing is not directly observable; what is seen in the market is the product of price and quantity. As Polinsky [12] points out, estimation of housing demand that omits a price variable may bias the estimated income elasticity. A set of price indices constructed across urban submarkets with hedonic price techniques are employed in this paper (see [5]). These indices allow direct estimation of price elasticity and provide a test of the bias predicted by Polinsky.

We find that the traditional "rule of thumb" elasticities of $+1$ and -1 with respect to permanent income and price appear to be valid. Separation of measured income into permanent and transitory components also produces a reconciliation between studies that use individual observations on permanent income and studies that use group observations to "average out" the transitory component. Both approaches yield higher income elasticities than those obtained from individual measured income data.

The problem of estimation bias in the demand function that can occur through improper specification is discussed in the following section. In Section III determinants of permanent income are developed and instrumental estimates of permanent and transitory income are derived. Housing prices to be used in our demand estimation are described in Section IV. In Section V housing demand is estimated using permanent and transitory incomes and compared with the results obtained from measured income and from other instrumental variables procedures suggested in the literature. In the final section conclusions are summarized.

II. ESTIMATION BIAS IN THE DEMAND FUNCTION

The customary formulation of demand for housing can be written as

$$Q = Q(P, Y, Z)$$

where Q is the quantity of housing services purchased, P the price of housing services (relative to a numeraire good), Y the real income (in terms of the numeraire good), and Z the other variables affecting housing demand such as tastes, household characteristics, and nonhuman wealth.

Within a metropolitan area the price of the numeraire good is generally assumed to be constant, so that nondeflated housing price and nominal income can be represented by P and Y. Z is a set of other exogenous or predetermined variables relevant to the demand function.

Possible estimation biases caused by the omission of P are discussed by Polinsky [12], who claims that since the price systematically falls with distance from a central place and the more affluent are likely to live further out, the income elasticity is underestimated. That is, to the extent that P is correlated with Y, the price variable should not be omitted in consistently estimating income elasticity.

Most analysts agree that some form of long-term income variable is a principal determinant of housing demand. This implies that households look beyond the income of the current period in making demand decisions. With perfect capital markets, consumers could borrow against future incomes to spread out housing consumption over their horizons in ways consistent with their permanent incomes. As a result, random variations in measured actual income should have little (life-cycle model) or no (permanent income model) effects on the amount of the good purchased.[3]

We propose at least two reasons why the random or transitory component of income can have significantly and substantially positive impact on housing demand and, hence, why it should be included in the demand function along with the systematic or permanent component. First, capital markets are not perfect and consumers cannot borrow against their anticipated lifetime earnings. As a result, transitory income may be used to fulfill housing flow demand that could not otherwise be met from permanent income. The second reason is related to the observation of the purchase of housing stock rather than housing flow services. The purchase of a house, on the one hand, is an investment in a durable good from which the purchaser can enjoy a service flow; on the other hand, it is an investment in a portfolio from which he can withdraw his equity when he sells his property. If transitory income in a given year is saved as a source of future consumption, one of many assets into which it might go is the buyer's house. This leads to a positive effect on stock demand. It is unlikely that the "marginal consumption" aspect of transitory income is easily separable from the "marginal savings" aspect. Both are positive and imply that the proper demand function should include transitory income separately from permanent income. Failure to decompose measured income into two separate entities can lead to estimation biases.

To see this point, consider the properly specified linear demand function:

$$Q = \beta_P Y^P + \beta_T Y^T + W\Gamma + U \tag{1}$$

where Y^P and Y^T are permanent and transitory incomes, respectively, W is a $(k-2) \times n$ matrix of other explanatory variables including the constant term and housing price among others, U is the disturbance term uncorrelated with Y^P, Y^T and W, and β_P, β_T, and Γ are coefficients (Γ is a $(k-2) \times 1$ vector) to be estimated. Assume for simplicity that Y^P, Y^T, and W are all pairwise orthogonal.

[3] See Friedman [4], Reid [15], and Mayer [11] for summaries and discussions of such models. Using savings survey data, Attfield [1] concludes that transitory income has a positively significant impact on consumption. His definition of transitory income, however, is not exactly the same as ours.

Suppose that either the model is misspecified or data availability restricts estimation so that actual income, $Y = Y^{\mathrm{P}} + Y^{\mathrm{T}}$, is used as a proxy for permanent income:

$$Q = \beta Y + W\Gamma + V \tag{2}$$

where $V = (\beta_{\mathrm{P}} - \beta)Y^{\mathrm{P}} + (\beta_{\mathrm{T}} - \beta)Y^{\mathrm{T}} + U$. The OLS estimators of β and Γ of (2) are

$$\begin{bmatrix} \hat{\beta} \\ \hat{\Gamma} \end{bmatrix} = \begin{bmatrix} \beta \\ \Gamma \end{bmatrix} + \begin{bmatrix} 1/\Sigma Y^2 & 0 \\ 0 & (W'W)^{-1} \end{bmatrix} \begin{bmatrix} \Sigma YV \\ W'V \end{bmatrix}$$

due to the orthogonality property of Y and W. Then the probability limit of $\hat{\beta}$ is

$$\operatorname{plim} \hat{\beta} = \beta + \operatorname{plim} \frac{\Sigma YV}{\Sigma Y^2}.$$

Substituting for V,

$$\operatorname{plim} \hat{\beta} = \frac{\sigma_{\mathrm{P}}^2}{\sigma_{\mathrm{P}}^2 + \sigma_{\mathrm{T}}^2}\beta_{\mathrm{P}} + \frac{\sigma_{\mathrm{T}}^2}{\sigma_{\mathrm{P}}^2 + \sigma_{\mathrm{T}}^2}\beta_{\mathrm{T}} = \theta\beta_{\mathrm{P}} + (1 - \theta)\beta_{\mathrm{T}} \tag{3}$$

where

$$\operatorname{plim} \frac{\Sigma(Y^{\mathrm{P}})^2}{n} = \sigma_{\mathrm{P}}^2; \qquad \operatorname{plim} \frac{\Sigma(Y^{\mathrm{T}})^2}{n} = \sigma_{\mathrm{T}}^2; \qquad \theta = \frac{\sigma_{\mathrm{P}}^2}{\sigma_{\mathrm{P}}^2 + \sigma_{\mathrm{T}}^2}.$$

This indicates that the measured income coefficient β of (2) is the weighted average of the true coefficients β_{P} and β_{T}, the weights being variations in permanent and transitory components relative to the variation in measured income (i.e., θ and $1 - \theta$). $\hat{\Gamma}$ is consistent for Γ. θ is the true (multiple) correlation coefficient R^2 of an income regression equation in which the systematic and nonsystematic components are Y^{P} and Y^{T}, respectively.

If variations in actual income are due totally to variations in transitory income (i.e., $\theta = 0$), $\hat{\beta}$ is consistent for the coefficient of transitory income, β_{T}. On the other hand, if actual income consists only of the permanent component (i.e., $\theta = 1$), then $\hat{\beta}$ is consistent for β_{P}. Since variations in actual income are usually explained by variations in both permanent and transitory incomes (i.e., $0 < \theta < 1$), and permanent income is expected to have a greater impact on housing demand than transitory income at the margin (i.e., $\beta_{\mathrm{P}} > \beta_{\mathrm{T}}$), $\hat{\beta}$ always underestimates β_{P} and overestimates β_{T}:

$$\beta_{\mathrm{T}} < \operatorname{plim} \hat{\beta} < \beta_{\mathrm{P}}. \tag{4}$$

In their tests of the permanent income hypothesis, Friedman [4] and Liviatan [10] argue that the OLS estimate for β is just a fraction of β_P ($\beta = \theta\beta_P$), under the assumption that $\beta_T = 0$. Their argument is a special case of our more general discussion which allows a nonzero β_T. In fact, the procedure to be outlined can consistently estimate not only β_P but also β_T.

To estimate the permanent income coefficient, then, it seems important to include price and correct permanent income in the regression equation. To the extent that the housing price is orthogonal to other explanatory variables in the demand equation, however, its omission should not cause any serious bias to the estimated coefficients. If permanent income is assumed to be uncorrelated with transitory income, omission of Y^T does not bias β_P, but its inclusion in the regression equation should enhance the predictive power. The housing demand equation in its fullest form, therefore, should be specified as

$$Q_i = \alpha + \beta_P Y_i^P + \beta_T Y_i^T + \gamma P_i + \sum_j \delta_j Z_{ji} + U_i, \qquad i = 1,\ldots,n \quad (5)$$

where Z_{ji} are relevant explanatory variables other than income and price, and the i's denote cross-sectional individual households.[4]

III. PERMANENT INCOME AND TRANSITORY INCOME

1. *Determinants of Permanent Income*

The permanent income of an individual may be expressed as the sum of constant fractions of human wealth H and nonhuman wealth vector N:

$$Y^P = \phi H + \psi N$$

where ϕ and ψ are related to the interest rate. Since H and N represent stocks of wealth the individual has accumulated up to his current age

[4] One might argue that since (5) is a demand function, at least two types of simultaneity bias can arise if OLS is applied. The first type is the usual problem of simultaneous determination of quantity and price as a consequence of demand–supply interaction in the housing market. Our procedure solves this in two ways: (i) it is quite legitimate to regard (5) as a microeconomic demand function and hence to use the microeconomic data for estimation; (ii) both our method of constructing the housing price index and its use in the demand function form in essence the two-stage least-squares estimation procedure.

The second type of simultaneity bias concerns the joint decision-making process of the household concerning expenditures on housing (Q) and other durable goods or nonhuman wealth (a part of which may be included in Z). This bias can be potentially serious to the extent that a portion of Z is a function of permanent income. To solve this, a full household expenditure model would have to be developed and tested. Data limitations prevent this alternative, however.

through education, (on-the-job) training, savings, capital gains, or inheritance, for example, they cannot be currently controlled; that is, they should be regarded as predetermined.

If human wealth is defined as the discounted expected value of future labor income streams that grow at some constant rate, and the current labor income depends on education (E), training (T), and age (A), then H and hence Y^{P} can be expressed as functions of E, T, and A:

$$Y^{\mathrm{P}} = \phi H(E, T, A) + \psi N. \tag{6}$$

A fuller argument is developed in Appendix II where it is asserted that

$$\frac{\partial H}{\partial E} \geq 0; \quad \frac{\partial H}{\partial T} \geq 0; \quad \frac{\partial H}{\partial A} \geq 0;$$
$$\frac{\partial^2 H}{\partial E^2} \leq 0; \quad \frac{\partial^2 H}{\partial T^2} \leq 0; \quad \frac{\partial^2 H}{\partial A^2} \leq 0$$

under plausible assumptions.

One way to apply this concept of permanent income to the estimation of housing demand is to include those variables that determine permanent income (such as E, T, A, and N) in the demand regression. This procedure has frequently been taken in the literature (see, e.g., [17]). However, it fails to yield consistent estimate of permanent income elasticity and cannot distinguish between permanent and transitory components of measured income.

The procedure developed here solves these two problems and remains consistent with the human–capital determination of permanent income. Measured income of an individual Y consists of permanent and transitory components:

$$Y = Y^{\mathrm{P}} + Y^{\mathrm{T}} \tag{7}$$

where permanent and transitory incomes Y^{P} and Y^{T}, respectively, are assumed to be orthogonal.[5] Combining (6) and (7),

$$Y = \phi H(E, T, A) + \psi N + Y^{\mathrm{T}}.$$

To construct the permanent and transitory components of the measured

[5] If Y^{P} and Y^{T} are not orthogonal, Y^{T} cannot be considered as transitory because that part of Y^{T} that is correlated with Y^{P} can be systematically predicted. To the extent that an income component is systematically captured through a theoretically well founded model, it should be included in the permanent component.

income, we estimate

$$Y_i = \phi_0 + \phi_1 E_i + \phi_2 E_i^2 + \phi_3 T_i + \phi_4 T_i^2 + \phi_5 A_i + \phi_6 A_i^2 + \sum_j \psi_j N_{ji} + U_i, \quad i = 1, \ldots, n \qquad (8)$$

where N_{ji} is the jth type of nonhuman wealth the individual i has accumulated. E_i^2, T_i^2, and A_i^2 are included to capture nonlinear effects of these variables on permanent income. U_i is the disturbance term uncorrelated with the explanatory variables so that the OLS estimation procedure provides consistent and efficient estimators.[6] The signs of coefficients are expected to be $\phi_1 \geq 0$, $\phi_2 \leq 0$, $\phi_3 \geq 0$, $\phi_4 \leq 0$, $\phi_5 \geq 0$, $\phi_6 \leq 0$, $\psi_j \geq 0$. (The negative signs of ϕ_2, ϕ_4, and ϕ_6 represent, of course, the diminishing returns to E, T, and A.) $\hat{Y}_i$, the predicted value of Y_i, and $\hat{U}_i$, the predicted value of U_i, can be naturally interpreted as the estimates for permanent and transitory incomes, respectively.

In (8), log Y_i may also be placed on the left-hand side (with E, T, A, and N's in nonlogarithmic forms). This may mitigate possible heteroscedasticity of the disturbance term. Here U_i must be interpreted as $\log(1 + Y_i^{\mathrm{T}}/Y_i^{\mathrm{P}})$, which, for small values of $Y_i^{\mathrm{T}}/Y_i^{\mathrm{P}}$, is approximately equal to $Y_i^{\mathrm{T}}/Y_i^{\mathrm{P}}$.

Various measured incomes can be estimated by using different sets of instrumental variables. We choose, as the best combination of instruments, that regression that yields the smallest standard error of the regression (SER).

2. Estimation of Permanent and Transitory Income

Permanent and transitory income (and the subsequent housing demand functions) are estimated from a sample of 633 home buyers in the New Haven SMSA from 1967 through 1969. All households with incomes over \$25,000 in any of the 3 years are omitted, as this category was open-ended on the questionnaire. The variables used in this and the following sections are listed and explained in Appendix I[7]. All variables refer to the head of the household.

Table 1 displays the best estimated equations for various measured incomes. CY is current income (income the year the house was purchased), AY is 3-year average income, and Y68 is measured 1968 income. LCY, LAY, and LY68 are the corresponding logarithmic measured incomes. The results are plausible and consistent with the hypotheses. The age and education variables have the expected signs and reflect the diminishing

[6] The exogeneity assumption of the E, T, A, and N variables is clearly important for (8).

[7] King [7] documents the data collection procedures. Goodman [5] adds neighborhood variables and computes price indices.

TABLE 1
Estimation of Various Measured Incomes

	Linear				Logarithmic			
	CY	AY	Y68	Y68[a]	LCY	LAY	LY68	LY68[b]
EDUC	0.985	0.943	0.942	—	0.084	0.084	0.084	—
	(0.102)	(0.088)	(0.094)		(0.010)	(0.008)	(0.009)	
AGE	0.112	0.108	0.112	—	0.016	0.016	0.016	—
	(0.035)	(0.031)	(0.032)		(0.003)	(0.003)	(0.003)	
AGESQ	−0.0006	−0.0006	−0.0005	—	−0.0002	−0.0002	−0.0001	—
	(0.0005)	(0.0004)	(0.0005)		(0.0001)	(0.0000)	(0.0000)	
EQUITY	0.064	0.040	0.059	—	0.005	0.004	0.004	—
	(0.022)	(0.025)	(0.020)		(0.002)	(0.002)	(0.002)	
CAR	1.499	1.314	1.249	—	0.160	0.150	0.143	—
	(0.271)	(0.233)	(0.250)		(0.025)	(0.022)	(0.024)	
WD	—	0.508	—	—	—	—	—	—
		(0.418)						
Y67 (LY67)	—	—	—	0.517	—	—	—	0.444
				(0.025)				(0.021)
Y69 (LY69)	—	—	—	0.456	—	—	—	0.522
				(0.021)				(0.023)
CONSTANT	0.809	1.217	1.224	0.460	1.302	1.329	1.317	0.086
$\bar{R}^2$	0.220	0.257	0.228	0.851	0.223	0.268	0.233	0.849
SER	3.839	3.301	3.531	1.549	0.361	0.312	0.340	0.151

Note. Numbers in parentheses are the estimated standard errors.
[a, b] The linear and logarithmic estimation based on the Liviatan–Lee method.

marginal returns posited above, although some coefficients of AGESQ ($= A^2$) are insignificantly different from zero, and all coefficients of E^2 are negative but have the absolute values of t statistics less than unity. (Since the inclusion of E^2 raises the SER, it is discarded from the regression equation according to the minimum SER criterion.) Level of education instead of number of years is used in the recognition that there are certain steps in the educational process, rather than its absolute duration, that are important.[8] The number of years in the present job is used as a proxy for on-the-job training or job tenure, but its coefficients are always insignificant and less than one in their t ratios; hence the training variable is excluded from the regression equation. The number of years in the present job may not represent (on-the-job) training—this is particularly so when the training is industry rather than firm specific.[9]

[8] It has been suggested that a set of dummy variables for the individual educational levels might be appropriate, given the restrictions of linear or quadratic forms. This is being incorporated into further work investigating the precise functional forms of the equations.

[9] Worker occupation should also improve the prediction of measured income. Although some occupational data are available, their use has not, thus far, been fruitful.

Three types of nonhuman wealth are included. EQUITY represents the accumulated equity from the previous residence of the household. WD is a wealth dummy variable and takes the value 0 if the owner has no previous equity, and 1 otherwise. CAR represents the number of automobiles owned by the household. The magnitude of their coefficients is also plausible. Increases in equity yield increases in permanent income of from 4.0 to 6.4%. This is comparable with the mean yield for 3-month Treasury bills over the same 3-year period of 5.4%. The coefficient of CAR implies that the permanent incomes of households rise by $1200 to $1500 per car.[10]

Liviatan [10] and Lee [9] assert that lagged and/or future incomes meet the criteria for successful instrumental variables estimators of permanent income elasticity. Accordingly we estimate $Y68$ ($LY68$) using $Y67$ and $Y69$ ($LY67$ and $LY69$) as instruments, to allow comparison with our procedure. From Table 1 it appears that the use of lagged and future incomes yields a substantially lower SER and a higher $\bar{R}^2$ (multiple correlation coefficient adjusted for degrees of freedom) than those of other regressions.

IV. HOUSING PRICE

Two basic methods have been used to derive unit housing prices for individual households. Polinsky and Ellwood [13] estimate a production function for housing and then calculate a corresponding cost function. After substituting the appropriate factor prices, they are able to deflate the expenditures per house by this unit valuation at factor costs. Perfect competition in all markets must be assumed for this procedure to be valid. In addition, it is not clear how neighborhood variables are capitalized into the land prices in their study.

Other authors such as Kain and Quigley [6] and Straszheim [18] estimate hedonic prices allowing the equations to vary spatially. Letting the resulting coefficients imply differing component prices, they estimate component demands. King [7] and Witte et al. [19] attempt to estimate systems of demand for characteristics following Lancaster's analysis [7]. Both studies depend on a linear approximation to what Rosen [16] contends is a generally nonlinear function. The resulting inferences about demand require strong assumptions about the combination of housing components into utility-giving characteristics.

The price series used in this paper is the one derived in Goodman [5] for the New Haven SMSA. It involves estimation of hedonic price regressions allowing for submarket segmentation both by space and by time. The

[10] The coefficient of CAR may be too large and at least two explanations can be provided. First, we may have left out other variables that are positively correlated with CAR, so that this variable may pick up their effects. Second, to the extent that CAR is an increasing function of permanent income, the estimated CAR coefficient is biased upwards.

functional form is determined through the Box–Cox transformation:

$$\frac{S_i^{\lambda} - 1}{\lambda} = \nu_0 + \sum_j \nu_j X_{ji} + U_i, \qquad i = 1,\ldots,n \tag{9}$$

where the X_{ji}'s are the jth components that determine the house sales price S_i that the individual i faces, U_i is the disturbance, and λ and ν are the parameters to be estimated. Fifteen submarkets are obtained (five areas over 3-years) for estimation. The maximum likelihood estimators for λ and ν are computed by constraining the functional form to be the same across the 15 submarkets. The best estimate λ under this constraint is 0.6, rejecting the hypothesis of either linearity or log-linearity in the hedonic price function.[11] The price index P is formed by evaluating a "market basket" house, including neighborhood and public service components, according to the structure of hedonic prices in a given submarket at a given time. Distance from the central business district (CBD) is allowed to vary within submarkets. The value of the market basket in New Haven in 1967, at a distance of 3.5 miles, $30,370, is normalized at 100.0. (See Appendix III for a detailed description of market basket components.) The market sales price of each house is divided by its price index to determine Q, the number of units of "housing" that have been purchased.

Means and standard deviations of housing price indices P and housing quantities Q are reported in Table 2 for different municipalities. The table shows that both housing price indices and quantities vary substantially across municipalities. The mean price of all municipalities is 92.02 but the town means (3 years averages) vary from 83.35 in Hamden to 102.34 in New Haven. East Haven, a community of small houses with a small public service package, has a mean of 2.08 units of housing, whereas Woodbridge, with large houses and better public services, has a mean of 5.45 units. The null hypotheses of equal prices and equal quantities across municipalities are rejected, each at the 1% significance level. (The F_{9859} values are 83.02 and 37.72, respectively.)

V. ESTIMATION OF HOUSING DEMAND

1. Price and Income Elasticities

The estimation of housing demand using both measured and permanent/transitory incomes is discussed in this section. The primary finding is that permanent income derived through instrumental variable methods provides better estimates in terms of predictive power (SER and

[11] It is well known that this form, developed by Box and Cox [2], in which λ and ν are estimated by maximum likelihood methods, reduces to linear form when $\lambda = 1$ and semilog form when $\lambda = 0$.

TABLE 2
Price Index and Housing Quantity by Municipality
(Standard Deviations in Parentheses)

	Price index	Quantity	Number of observations
Branford	91.43	3.22	26
	(10.79)[a]	(1.31)	
Cheshire	95.71	3.02	96
	(3.59)	(1.09)	
East Haven	90.62	2.08	72
	(10.56)	(0.39)	
Hamden	83.35	3.34	213
	(5.69)	(1.31)	
New Haven	102.34	2.51	143
	(6.19)	(1.11)	
North Haven	92.81	3.16	110
	(9.92)	(1.11)	
Orange	89.73	3.95	54
	(5.21)	(0.64)	
Wallingford	96.27	2.37	58
	(3.27)	(0.69)	
West Haven	90.55	2.13	75
	(5.31)	(0.44)	
Woodbridge	93.44	5.45	22
	(3.32)	(1.71)	
Total	92.02	2.96	869
	(6.78)	(1.06)	
F_{9859}	83.02*	37.72*	

[a]Parentheses indicate standard deviations.
*F statistics significant at the 1% level.

$\bar{R}^2$), as well as substantially higher income elasticities, than do measured income or instrumental variables derived from the Liviatan–Lee method. In fact, in linear regressions the income and price demand elasticities are very close to $+1$ and -1, respectively.

In Table 3, the demand function is estimated using various measured incomes—income of the year the house was purchased (CY), the 3-year average household income (AY), and the 1968 income (Y68). The equation is estimated both linearly and logarithmically. As shown in the table, the linear income elasticities at the means are 0.50, 0.53, and 0.50, whereas the logarithmic elasticities are 0.41, 0.44, and 0.40. Price elasticities are -1.04, -0.80, and -0.77 for the linear equation and -1.03, -0.84, and -0.82 for the logarithmic equation. Kain and Quigley [6] suggest that 3-year average income is a more appropriate proxy for permanent income than is single-year income. In fact, AY and LAY yield higher income elasticities than CY (and LCY) or Y68 (and LY68). Since CY or LCY represents the

TABLE 3

Estimation of Housing Demand with Measured Income

	Linear			Logarithmic		
	CY	AY	Y68	LCY	LAY	LY68
P (LP)	−0.031	−0.024	−0.023	−1.031	−0.844	−0.823
	(0.003)	(0.003)	(0.003)	(0.101)	(0.101)	(0.102)
Y (LY)	0.114	0.124	0.116	0.409	0.439	0.404
	(0.006)	(0.007)	(0.007)	(0.024)	(0.027)	(0.026)
CONSTANT	4.188	3.436	3.445	4.629	3.710	3.699
$\bar{R}^2$	0.390	0.368	0.355	0.357	0.338	0.327
SER	0.655	0.667	0.674	0.245	0.249	0.251
Price elasticity	−1.04	−0.80	−0.77	−1.03	−0.84	−0.82
				(0.10)	(0.10)	(0.10)
Measured income elasticity	0.50	0.53	0.50	0.41	0.44	0.40
				(0.02)	(0.03)	(0.03)

Note. Numbers in parentheses are the estimated standard errors; elasticities for the linear regression are evaluated at the means.

income of the year the house is purchased (rather than a multiyear average), housing demand might be expected to be more sensitive to the housing price when CY or LCY is used. Price elasticities are indeed higher with current income (CY or LCY) than with other measured incomes. In terms of the predictive power of housing demand (the size of SER and $\bar{R}^2$), CY or LCY performs best.

Regression results are reported in Table 4 using the different pairs of permanent and transitory incomes estimated in Table 1. Decomposition of the income term into its permanent and transitory components produces substantial changes in the explanatory power of the regression and in the estimates of the income elasticity. The SER is reduced from 0.66, 0.67, and 0.67 (with measured income) to 0.60, 0.62, and 0.62 (with decomposed incomes) when CY, AY and Y68 are used. The $\bar{R}^2$ for the linear equation with the decomposed income terms increases to 0.49, 0.46, and 0.46 when CY, AY, and Y68 are used, from 0.39, 0.37, and 0.35 for the previous linear regression with measured income. Comparable increases in the explanatory power are achieved in the logarithmic estimation as well. The linear regression yields permanent income elasticities of 0.98, 1.01, and 1.02 when CY, AY, and Y68 are used, respectively, as opposed to 0.50, 0.53, 0.50 for the measured income variables. The logarithmic regressions present comparable increases, but the estimated elasticities are about 0.8, or smaller than the linear estimates.

This result concerning permanent income elasticity supports the hypothesis that our method is similar to the grouping technique often employed to

TABLE 4

Estimation of Housing Demand with Permanent and Transitory Income

	Linear				Logarithmic			
	CY	AY	$Y68$	$Y68^a$	LCY	LAY	$LY68$	$LY68^b$
P (LP)	−0.030	−0.024	−0.024	−0.023	−1.024	−0.891	−0.879	−0.837
	(0.003)	(0.003)	(0.003)	(0.003)	(0.094)	(0.095)	(0.095)	(0.102)
Y^P (LY^P)	0.226	0.236	0.239	0.126	0.812	0.825	0.834	0.435
	(0.012)	(0.012)	(0.013)	(0.007)	(0.046)	(0.049)	(0.049)	(0.028)
Y^T (LY^T)	0.081	0.084	0.078	0.057	0.288	0.295	0.269	0.230
	(0.006)	(0.007)	(0.007)	(0.017)	(0.025)	(0.030)	(0.027)	(0.066)
CONSTANT	2.764	2.201	2.111	3.390	3.635	3.002	2.926	3.691
$\bar{R}^2$	0.487	0.461	0.460	0.368	0.443	0.416	0.420	0.335
SER	0.601	0.616	0.617	0.667	0.228	0.234	0.233	0.250
Price elasticity	−1.00	−0.82	−0.81	−0.79	−1.02	−0.89	−0.88	−0.84
					(0.09)	(0.10)	(0.10)	(0.10)
Permanent income elasticity	0.98	1.01	1.02	0.54	0.81	0.82	0.83	0.43
					(0.05)	(0.05)	(0.05)	(0.03)

Note. Numbers in parentheses are the estimated standard errors; elasticities for the linear regression are evaluated at the means.

[a, b] The linear and logarithmic estimation based on the Liviatan–Lee method.

TABLE 5

Biases in Permanent Income and Price Elasticities from Omission of Transitory Income

Transitory	Linear				Logarithmic			
income	CY	AY	$Y68$	$Y68^a$	LCY	LAY	$LY68$	$LY68^b$
(i) Estimates of permanent income elasticity								
Y^T Included	0.98	1.01	1.02	0.54	0.81	0.82	0.83	0.43
					(0.05)	(0.05)	(0.05)	(0.03)
Y^T Excluded	0.97	1.01	1.02	0.54	0.81	0.83	0.83	0.44
					(0.05)	(0.05)	(0.05)	(0.03)
(ii) Estimates of price elasticity								
Y^T Included	−1.00	−0.82	−0.81	−0.79	−1.02	−0.89	−0.88	−0.84
					(0.09)	(0.10)	(0.10)	(0.10)
Y^T Excluded	−0.80	−0.80	−0.80	−0.81	−0.90	−0.90	−0.90	−0.85
					(0.10)	(0.10)	(0.10)	(0.10)

Note. Numbers in parentheses are the estimated standard errors; elasticities for the linear regression are evaluated at the means.

[a, b] The linear and logarithmic estimation based on the Liviatan–Lee method.

construct permanent income. For example, Polinsky and Ellwood [13] report that income elasticities estimated by the grouping of observations are from 46 to 75% higher than those representing individual measured incomes. Similar increases are observed in our case by inserting the computed individual permanent (and transitory) income in the demand function.[12]

The coefficient of the transitory income term is always significantly positive and generally about one-third the size of the permanent income coefficient. For the linear regression a \$1000 increase in permanent income leads to an increased purchase of 0.24 units of housing, whereas an identical increase in transitory income leads to an increased purchase of only 0.08 units. As the mean value of transitory income is zero, an elasticity concept is not meaningful. The significantly positive transitory income coefficient leads to rejection of the hypothesis that transitory income should have no impact in a demand function. However, exclusion of transitory income does not cause biases to the permanent income coefficients due to the orthogonality property (see Table 5). The estimation results clearly confirm our earlier contention that, if measured income is used, the estimated income coefficient underestimates the effect of permanent income and overestimates the transitory income coefficient.

[12] There are at least two reasons to believe that our method is preferable to the grouping procedure. First, grouping leads to the possible simultaneity bias by including supply effects. Second, nonhuman wealth variables that might be useful in estimating grouped demand equations are almost certainly not available above the individual level.

It is instructive to compare the results in Table 4 with those obtained from the Liviatan–Lee instrumental variable method, summarized in the last columns for the linear and logarithmic regression. According to their suggestion, we include in the demand function the permanent and transitory components of *Y*68 (or L*Y*68) that are estimated with lagged and future measured incomes. (The regression results of *Y*68 against *Y*67 and *Y*69, and L*Y*68 against L*Y*67 and L*Y*69, are shown in the last columns of Table 1). As noted in Table 4, our three regression results are roughly comparable, and perform substantially better than Liviatan–Lee's method in terms of predictive power. Although the Liviatan–Lee method finds both permanent and transitory incomes to be important, the estimated permanent income elasticity is 0.54 in the linear form and only 0.43 in the logarithmic form, roughly half of our other estimates.

These differences in parameters stem largely from the efficacy of the instruments. Use of lagged and/or future variables is essentially a statistical construct. Comparison of values from Table 4 (permanent and transitory incomes) with those from Table 3 (measured income) shows that the parameter estimates using the Liviatan–Lee method are almost identical to those using measured income. Our method is more thoroughly based on economic theory, and data availability allows estimation of the parameters of (8). The improvement in explanatory power demonstrates the importance of constructing permanent income through human and nonhuman wealth, where data permit.

The price elasticities vary between −0.81 (linear regression with *Y*68) and −1.02 (logarithmic estimation with LC*Y*). The absolute values of the price elasticities approach unity in regressions using decomposed income terms (Table 4), in comparison with those using measured income (Table 3). Also the price elasticity obtained from the Liviatan–Lee method is persistently less than those obtained by our method. The price variables appear to be almost completely orthogonal to all of the permanent income variables and their omission does not seriously bias the estimated permanent income elasticities (see Table 6). Thus, Polinsky's assertion that omission of a price variable causes a bias in the income elasticity does not apply to our sample data if permanent income is properly used. It does apply, however, to transitory income. Exclusion of price reduces the transitory income coefficient (confirming results not reported here but available upon request from the authors) and, conversely, exclusion of transitory income leads to downward biases in the estimated price elasticity (see Table 5) in regressions using the permanent component of C*Y* or LC*Y*, our best regressions. C*Y* or LC*Y* is the income of year the house is purchased, so it is more correlated with price than any other income.

Our procedure of demand estimation based on permanent and transitory incomes substantially outperforms a simple demand estimation using mea-

TABLE 6

Income Elasticity Bias from Omission of Price

	Linear			Logarithmic		
Price	CY	AY	$Y68$	LCY	LAY	L$Y68$
(i) Estimates of measured income elasticity						
P Included	0.50	0.53	0.50	0.41	0.44	0.40
				(0.02)	(0.03)	(0.03)
P Excluded	0.45	0.52	0.49	0.38	0.43	0.40
				(0.03)	(0.03)	(0.03)

(ii) Estimates of permanent income elasticity								
	CY	AY	$Y68$	$Y68^a$	LCY	LAY	L$Y68$	L$Y68^b$
P Included	0.98	1.01	1.02	0.54	0.81	0.82	0.83	0.43
					(0.05)	(0.05)	(0.05)	(0.05)
P Excluded	0.96	0.99	1.00	0.53	0.78	0.80	0.81	0.43
					(0.05)	(0.05)	(0.05)	(0.03)

Note. Numbers in parentheses are the estimated standard errors; elasticities for the linear regression are evaluated at the means.

[a, b] The linear and logarithmic estimation based on the Liviatan–Lee method.

sured income or the Liviatan–Lee method. In addition, the best regression equation (in the sense of the smallest SER and the highest $\bar{R}^2$), using CY, yields the estimated income and price elasticities $+1$ and -1, respectively. This conclusion remains essentially intact (except for a slight change in the permanent income elasticity) when other relevant explanatory variables are included in the demand function.

One might conjecture that the omission of relevant explanatory variables (occupation, for example) in computing permanent and transitory incomes may lead to biased estimates of the income elasticities. It can be shown, however, that the estimators are consistent if the omitted variables are uncorrelated with the explanatory variables included in the income regression equation.[13]

2. *Other Characteristics in the Demand Function*

Demand for housing is determined not only by income and housing price but also by other household characteristics—such as the number of household members (NHM), the presence or absence of children in school

[13] Suppose the true model is $Y = \phi_1 A + \phi_2 E + U$, $Q = \beta_P Y^P + \beta_T Y^T + V$. Y^P is represented by the systematic component $\phi_1 A + \phi_2 E$, and Y^T by U. Also suppose that instead of $\phi_1 A + \phi_2 E$, only $\phi_1 A$ is used as Y^P in estimating Q. It is easily shown under the assumption of orthogonality among A, E, U, and V, that plim $\hat{\beta}_P = \beta_P$, plim $\hat{\beta}_T = \beta_T$.

TABLE 7

Estimation of Housing Demand with Permanent and Transitory Income and Other Household Characteristics

	Linear				Logarithmic			
	CY	AY	$Y68$	$Y68^a$	LCY	LAY	L$Y68$	L$Y68^b$
P (LP)	−0.029	−0.024	−0.023	−0.023	−1.014	−0.881	−0.867	−0.831
	(0.003)	(0.003)	(0.003)	(0.003)	(0.089)	(0.091)	(0.091)	(0.095)
Y^P (LY^P)	0.213	0.221	0.216	0.108	0.807	0.809	0.800	0.381
	(0.014)	(0.016)	(0.015)	(0.007)	(0.059)	(0.060)	(0.060)	(0.027)
Y^T (LY^T)	0.082	0.084	0.078	0.055	0.289	0.298	0.273	0.217
	(0.006)	(0.007)	(0.007)	(0.016)	(0.024)	(0.028)	(0.026)	(0.062)
NHM	0.053	0.044	0.041	0.020	0.009	—	—	—
	(0.019)	(0.020)	(0.020)	(0.017)	(0.007)			
CHD	−0.108	−0.119	−0.116	—	−0.039	−0.032	−0.031	—
	(0.058)	(0.060)	(0.060)		(0.022)	(0.019)	(0.019)	
RACE	−0.213	−0.207	−0.221	−0.197	−0.089	−0.087	−0.093	−0.085
	(0.095)	(0.097)	(0.098)	(0.102)	(0.036)	(0.036)	(0.037)	(0.038)
EQUITY	0.020	0.025	0.020	0.029	0.008	0.009	0.009	0.011
	(0.003)	(0.004)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
CAR	−0.105	−0.074	−0.051	0.107	−0.047	−0.038	−0.031	0.041
	(0.047)	(0.048)	(0.047)	(0.045)	(0.019)	(0.019)	(0.019)	(0.017)
WD	—	−0.110	—	—	—	—	—	—
		(0.076)						
CONSTANT	3.057	2.527	2.479	3.387	3.725	3.130	3.085	3.766
$\bar{R}^2$	0.531	0.503	0.499	0.454	0.497	0.474	0.473	0.424
SER	0.575	0.591	0.594	0.620	0.217	0.222	0.222	0.232
Price elasticity	−0.99	−0.81	−0.79	−0.78	−1.01	−0.88	−0.87	−0.83
					(0.09)	(0.09)	(0.09)	(0.09)
Permanent income elasticity	0.91	0.94	0.93	0.46	0.81	0.81	0.80	0.38
					(0.06)	(0.06)	(0.06)	(0.03)

Note. Numbers in parentheses are the estimated standard errors; elasticities for the linear regression are evaluated at the means.

[a, b] The linear and logarithmic estimation based on the Liviatan–Lee method.

(CHD), and race (RACE)—and nonhuman wealth variables. Table 7 reports the results with these variables included.

It is plausible that larger households would prefer more housing, whereas households with children in school would prefer less housing for a given number of household members. This is verified by the positive coefficients for the variable NHM and negative coefficients for the variable CHD (1 if there is at least one child in school and 0 otherwise), though the coefficients are not always significant. The dummy variable RACE (1 if black and 0

TABLE 8
Sensitivity of Price and Income Elasticities to the Inclusion of Wealth Variables

	Linear				Logarithmic			
	CY	AY	Y68	Y68[a]	LCY	LAY	LY68	LY68[b]
(i) Estimation with measured income								
Price elasticity	−1.03	−0.79	−0.76	—	−1.02	−0.84	−0.81	—
					(0.10)	(0.10)	(0.10)	
Measured income elasticity	0.49	0.53	0.49	—	0.41	0.44	0.40	—
(wealth variables excluded)					(0.02)	(0.03)	(0.03)	
Price elasticity	−1.00	−0.79	−0.76	—	−1.00	−0.84	−0.82	—
					(0.09)	(0.09)	(0.10)	
Measured income elasticity	0.44	0.46	0.43	—	0.36	0.39	0.35	—
(wealth variables included)					(0.02)	(0.03)	(0.03)	
(ii) Estimation with permanent and transitory income								
Price elasticity	−0.99	−0.82	−0.80	−0.78	−1.02	−0.88	−0.87	−0.83
					(0.09)	(0.09)	(0.09)	(0.10)
Permanent income elasticity	0.97	1.02	1.03	0.53	0.82	0.83	0.83	0.44
(wealth variables excluded)					(0.05)	(0.05)	(0.05)	(0.03)
Price elasticity	−0.99	−0.81	−0.79	−0.78	−1.01	−0.88	−0.87	−0.83
					(0.09)	(0.09)	(0.09)	(0.09)
Permanent income elasticity	0.91	0.94	0.93	0.46	0.81	0.81	0.80	0.38
(wealth variables included)					(0.06)	(0.06)	(0.06)	(0.03)

Note Numbers in parentheses are the estimated standard errors; elasticities for the linear regression are evaluated at the means.
[a, b] The linear and logarithmic estimation based on the Livitan–Lee method.

otherwise) indirectly allows one type of test for housing market discrimination; black families, with all other variables constant, purchase approximately 9% less housing than do comparable white families.[14]

It might be suggested that certain nonhuman wealth variables directly affect demand through a liquidity effect apart from permanent income. Demand for housing can be expected to be higher for those who own more liquid nonhuman wealth, for a given permanent income, since this relaxes their liquidity constraint with an imperfect capital market. In Table 7 such an effect is clearly found for the EQUITY variable. However, the CAR variable should, holding all other variables constant, negatively affect

[14] Yinger [20] notes that through restrictions on the quantity of housing supplied, blacks may consume less housing than whites in similar circumstances. In order to examine whether blacks and whites with the same characteristics consume different quantities of housing, he suggests estimation of a demand function by controlling housing price, income, family size, and life-cycle status.

housing demand, because the opportunity cost of owning an additional automobile should reduce demand for all durable goods, one of which is a house. Since permanent income, by its construction, includes nonhuman wealth components, the inclusion of EQUITY, CAR, and WD reduces the effect of permanent income.[15]

Even so, as noted in Table 7, the estimated permanent income elasticities for CY fall only to 0.91 and 0.81 in the linear and logarithmic forms, respectively. The price elasticity, as expected, is virtually unchanged. It would be disturbing if permanent income elasticities were more sensitive to the inclusion of nonhuman wealth variables (EQUITY, CAR, and WD) than are measured income elasticities. Table 8 summarizes price and income elasticities with and without the nonhuman wealth variables in the regression equation. In all cases in the table, permanent income elasticities are, in percentage terms, less sensitive than measured income elasticities. Price elasticities are not affected.

VI. CONCLUSION

Housing demand was reexamined in this paper by looking quite specifically at income and price variables based on individual household data. The income elasticities suggest that many common proxies for permanent income are inappropriate compared to a model relating to the accumulation of human and nonhuman wealth. Estimates using measured current, 3-year average or midperiod income yield elasticities of 0.4 to 0.5. Division of measured income into permanent and transitory components improves the predictive power of the regression considerably, and leads to permanent income elasticities of 0.8 to 1.0. Similar increases in the elasticities are observed by the grouping procedure, although our estimates seem to be closer to unity than most of those studies. In the "best" equation, the permanent income elasticity is very close to $+1$.

A price series is created by spatially varying hedonic techniques. In the New Haven case prices are nearly orthogonal to permanent incomes, and their omission results in almost no bias in the permanent income elasticities. The price elasticities are insignificantly different from -1 for the "best" equation, which is slightly more elastic than has been recently reported. Proper specification of the regression equation with both permanent and transitory incomes accounts for this high price elasticity.

The validity of this finding depends on the effectiveness of the instruments used to estimate permanent income. Instrumental regressions of income from the Liviatan–Lee procedure have a smaller SER and a higher $\bar{R}^2$ than our method; the demand estimation, however, is substantially

[15] The full regression results without nonhuman wealth variables are not reported in the paper but they and other regression summaries are available from the authors upon request.

inferior to ours which uses the age, education, and nonhuman wealth variables. Recent studies have used income variables comparable with current or 3-year average income and arrived at elasticities much smaller than those reported in our best estimation equation. It is plausible that these studies would have yielded higher income elasticities if estimated with the instruments suggested in the paper. One might argue that our decomposition of measured income into the two income terms is subject to error due to omitted variables in the income regression equation. Even if this is the case, our estimate of the permanent income coefficient is consistent so long as the omitted variables are orthogonal to the instruments used.

Our method can be readily extended to the estimation of any demand function, particularly that of durable goods, and the estimation of the saving function. In addition, while data collection efforts should stress variables that determine human capital, multiyear data may be unnecessary, as current year's income appears to outperform other incomes (averaged and midperiod) in the estimation of housing demand through price, permanent income, and transitory income.

APPENDIX I: LIST OF VARIABLES

Q (LQ)	Quantity of housing purchased (natural logarithm)
P (LP)	Housing price index (natural logarithm)
Y (LY)	Measured income (natural logarithm)
Y^P (LY^P)	Permanent income (natural logarithm)
Y^T (LY^T)	Transitory income ($LY^T = LY - LY^P$)
Y67 (LY67)	Measured 1967 income (natural logarithm)
Y68 (LY68)	Measured 1968 income (natural logarithm)
Y69 (LY69)	Measured 1969 income (natural logarithm)
AY (LAY)	Three-year average income (natural logarithm)
CY (LCY)	Current income = Income of the year the house was purchased (natural logarithm)
EDUC	Education level per highest grade completed

Grade completed	Code
0–6	1
7–8	2
9–11	3
12	4
13–15	5
16	6
16 +	7

AGE	Age of head of household
AGESQ	AGE*AGE
WD	1, if family owned a house prior to purchase; 0, otherwise
EQUITY	Sales price less amount remaining on mortgage for previous house
CAR	Number of automobiles owned by household
RACE	1, if black; 0, otherwise

NHM	Household size (the number of household members)
CHD	1, if one or more household members are attending school; 0, otherwise

APPENDIX II: DERIVATION OF PERMANENT INCOME

An individual's permanent income can be expressed as the sum of fractions of human wealth and nonhuman wealth:

$$Y^{P} = \phi H + \psi N$$

where Y^{P}, H, and N are permanent income, human wealth, and nonhuman wealth, respectively, and ϕ and ψ are positive constants. (Theoretically ϕ and ψ should depend on market interest rates.) Since H and N represent stocks of wealth accumulated up to one's present age through education, (on-the-job) training, savings, capital gains, and inheritance, they cannot be currently controlled (but they can in previous periods); that is, they should be regarded as exogenous or predetermined.

Human wealth H is the discounted expected value of future labor income flows:

$$H = \int_{A}^{\bar{A}} e^{-r(t-A)} w_t \, dt$$

where A and $\bar{A}$ are the current age and the age of retirement or death, respectively, r is the discount rate, and w_t is nonwealth (labor) income expected at age t as of age A. Assuming that w_t grows at a constant rate g, one can rewrite H as

$$H = \int_{A}^{\bar{A}} e^{-r(t-A)} w_A e^{g(t-A)} \, dt = w_A \int_{A}^{\bar{A}} e^{-(r-g)(t-A)} \, dt.$$

Assume that w_A is a function of education (E) and (on-the-job) training (T), each acquired up to the present, and the current age (A):

$$w_A = w(E, T, A)$$

with the properties that

$$\frac{\partial w}{\partial E}, \frac{\partial w}{\partial T}, \frac{\partial w}{\partial A} \geq 0; \qquad \frac{\partial^2 w}{\partial E^2}, \frac{\partial^2 w}{\partial T^2}, \frac{\partial^2 w}{\partial A^2} \leq 0$$

where the negative second derivatives indicate diminishing returns to scale. The function $w(\cdot)$ may not be monotone in A but can be assumed to be monotonically increasing in A for certain age groups, young and middle-aged, that represent our sample data. We can easily show that

$$\frac{\partial H}{\partial E} = \frac{H}{w_A}\frac{\partial w}{\partial E} \geq 0; \qquad \frac{\partial^2 H}{\partial E^2} = \frac{H}{w_A}\frac{\partial^2 w}{\partial E^2} \leq 0;$$

$$\frac{\partial H}{\partial T} = \frac{H}{w_A}\frac{\partial w}{\partial T} \geq 0; \qquad \frac{\partial^2 H}{\partial T^2} = \frac{H}{w_A}\frac{\partial^2 w}{\partial T^2} \leq 0$$

but the signs of $\partial H/\partial A$ and $\partial^2 H/\partial A^2$ are indeterminate without further assumptions. H is

$$H\begin{cases} = \dfrac{w_A}{r-g}\left[1 - e^{-(r-g)(\bar{A}-A)}\right] & \text{if } r \neq g \\ = (\bar{A} - A)w_A & \text{if } r = g \end{cases}$$

so that

$$\frac{\partial H}{\partial A}\begin{cases} = \dfrac{1}{r-g}\left[1 - e^{-(r-g)(\bar{A}-A)}\right]\dfrac{\partial w}{\partial A} - w_A e^{-(r-g)(\bar{A}-A)} & \text{if } r \neq g \\ = (\bar{A} - A)\dfrac{\partial w}{\partial A} - w_A & \text{if } r = g \end{cases}$$

$$\frac{\partial^2 H}{\partial A^2}\begin{cases} = \dfrac{1}{r-g}\left[1 - e^{-(r-g)(\bar{A}-A)}\right]\dfrac{\partial^2 w}{\partial A^2} - 2e^{-(r-g)(\bar{A}-A)}\dfrac{\partial w}{\partial A} & \\ \quad - w_A(r-g)e^{-(r-g)(\bar{A}-A)} & \text{if } r \neq g \\ = (\bar{A} - A)\dfrac{\partial^2 w}{\partial A^2} - 2\dfrac{\partial w}{\partial A} & \text{if } r = g. \end{cases}$$

If $\bar{A}$ tends to be very large, say infinite, then $r - g$ must be positive for the convergence of H. In this case $\partial H/\partial A \geq 0$ and $\partial^2 H/\partial A^2 \leq 0$. Since the mean age of individuals in the sample is approximately 35, this appears to be a reasonable assumption.

APPENDIX III: HOUSING MARKET BASKET

The "market" house used to compute the price index P is described. It is evaluated according to the hedonic price regression (9) in the text for a given submarket in a given year. Distance from the CBD is allowed to vary in the estimation. The price of the market house in New Haven in 1967, at a distance of 3.5 miles from the CBD is \$30,370. This is normalized to be 100.0.

Components of Market Basket

Structure	
Lot size (sq ft)	22,000
Living space (sq ft)	1,440
Age (years)	30
Rooms	7
Bathrooms	1
Lavatories	1
Garage spaces	1
Fireplaces	1
Hardwood floors (dummy variable; 1 if yes and 0 otherwise)	
Neighborhood	
Percent black—block group	4
Percent incomes under $5000—block group	8
Percent with some college education—block group	30
School reading score (percentile)	75
Neighborhood service Index	0.3

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