Housing Price Dynamics and Household Mobility Decisions

by

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Abstract

The first chapter attempts to shed light on the role of housing price dynamics in mobility decisions, asking whether households respond to prices in a forward- or backward-looking manner, and the extent to which high leverage constrains moving behavior. On a broader level, the study tests whether price dynamics dominate non-market shocks as a force governing household mobility, given the importance of housing as an investment good and saving device. Using a 13 year sample from the Panel Study of Income Dynamics, I find that households are largely backward-looking in both their mobility and consumption decisions, and that non-market shocks play a significant role. Households show little or no response to equity constraints, and do not appear to time the market, despite significant forecastability in housing prices. These conclusions lend support to the notion of prices leading trading volume, but do not support the theoretical work of Stein (1995), which attributes mobility behavior to changes in equity constraints brought about by changes in housing prices.

The second chapter uses data from the Retirement History Survey to measure the impact of property tax abatement programs on elderly homeownership decisions. Analysis using a competing risks framework, in which the decision to trade down is treated separately from the decision to end homeownership completely, shows striking differences in the impact of property taxes on each type of failure: for the elderly who choose to trade down, property taxes have a positive effect on the hazard of moving. Alternatively, property taxes have little impact on the tenure decision. Incorporating individual heterogeneity to correct for sample bias, to capture mover-stayer effects, and to account for correlation between property taxes and omitted variables, has little effect on the results. From an "ex post" perspective, the results of the analysis lead to the conclusion that property tax abatement programs have a small impact at best, and may be leading to undesirable redistributional outcomes.

The final chapter employs data from the neighborhood clusters sample of the 1989 American Housing Survey and the wealth supplement of the 1989 Panel Study of Income Dynamics to study to distribution of wealth within US residential neighborhoods. Calculations using the Bourguignon decomposable inequality index show that wealth is more unequally distributed than income, and income more than housing wealth, at all levels of aggregation – neighborhoods, metropolitan areas, census regions, and the entire US.

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Contents

Chapter 1

House Price Dynamics and the Mobility Decisions of Households

1.1 Introduction

In the United States, over two thirds of households own their home. Among these households, the majority use equity as their primary form of saving (Di 2001). Furthermore, the value of owner-occupied housing in the late-1990s totaled close to $5 trillion, accounting for 27% of individual net worth (Smith et al. 1988). Together, these facts reinforce the notion that housing is a very important component of household portfolios, and that housing price dynamics can have a large impact on households' financial situation. In this paper, I try to shed light on the role of price dynamics in moving and housing consumption decisions, asking 1) whether households behave rationally, 2) to what extent high leverage constrains moving behavior, and 3) whether price dynamics dominate non-market "shocks" as a force governing household mobility.

Households may respond to price dynamics in three basic ways. First, they may be forward looking, and thus base mobility decisions on expected prices. Such a response would indicate rational behavior and an understanding of the underlying distribution of returns in the housing market. Second, households may be backward looking. Within this category of behavior, households may base decisions on the belief that returns in the past are good indicators of returns in the future (extrapolation), or on an unwillingness to realize a loss. In the latter case, the household's decision to move is hampered by past price declines not because of any constraint that the loss created, but because of psychological barriers to relating to the loss itself. Finally, households may respond to a change in price that either tightens or relaxes the constraint of being highly leveraged by building or eroding real housing equity[1]. Over the past decade, the housing market literature has put forth several theories attempting to explain the relationship between prices and mobility decisions. So far, much attention has been paid to the work of Stein (1995), which attempts to explain the relationship between prices and trading volume within the context of equity constraints. In the presence of downpayment requirements, one may expect prices to dominate in the decision to move, and thus lead trading volume in the aggregate. For highly leveraged households, declines in market prices may erode equity to the point that they cannot afford the downpayment on a new home, and are constrained from making lateral moves. In contrast, Wheaton (1990) presents the decision to move as a result of "mismatch" between owner and unit, caused by some exogenous demographic or economic shock. The search for a new home, and the resulting process of bargaining between buyer and seller determines prices [2]. As of yet, no empirical work has successfully pinned down the causality in the price-trading volume relationship.

To test for the presence of market based responses, as well as the impact of personal "shocks" on mobility behavior, I employ a variety of econometric models using data from a 13 year sample of households from the Panel Study of Income Dynamics (PSID). In the first stage of analysis, I address the decision to move using a semiparametric hazard specification. I find that equity constraints play an insignificant role in mobility behavior, and that responses to price changes come largely from a backward-looking perspective. Loss aversion cannot be rejected as a factor governing moving decisions. Whether households exhibit any forward-looking behavior is not clear due to measurement and sample selection issues. Economic and demographic "shocks" play a significant role, especially divorce and changes in family size. In the second stage of analysis, I turn to the consumption decision.

[1]This response is independent of whether the household is forward- or backward-looking.

[2]In the strictest sense, trading volume does not "lead" prices in this model, but rather they are co-determined. The "participation" decision clearly comes before the price is set. However, the participation decision is unobservable independently from the decision to move.

Given the fact that individuals have already made the decision to move, and are assumed to be optimizing, measurement error and selection issues no longer bias the results. In the case of trading up, individuals again take past market behavior into strong consideration. Forward-looking behavior can be firmly rejected. In the case of trading down, market-based forces play a much smaller role than demographic factors. Across both stages of analysis, households do not appear to time the market, despite significant forecastability in housing returns.

The remainder of the paper is organized as follows. Section 2 presents a review of the literature relevant to both the moving and consumption decisions. In sections 3, I present a stylized model of the housing consumption decision. In sections 4 and 5, I introduce the data and explain the empirical strategies employed in the paper. Second 6 presents the results, and section 7 makes concluding remarks.

1.2 Literature Review

1.2.1 The Nature of the Housing Market and the Price-Trading Volume Relationship

Although housing is an investment good, making up the greatest part of the wealth portfolio for many Americans, the housing market tends to behave very differently from other asset markets. Prices, to some extent, are driven by fundamentals such as user costs of capital, construction costs, and interest rates (Poterba1984), however strong volatility in housing prices and regular boom-bust cycles in many parts of the United States point to other influencing factors that set housing apart from other forms of investment. The consumption component of housing, transaction costs, tax advantages, and purchase of homes through debt create additional frictions that give rise to the idiosyncrasies observed in the housing market as a whole and in individual mobility behavior.

Hanushek and Quigley (1979) explain mobility decisions as precipitated by "mismatch" through an unanticipated economic or demographic shock. The authors assert that adjustment is not smooth or necessarily symmetric over increases and decreases, but do not attribute the friction to any particular characteristic of the market. In Grossman and Laroque (1990) transactions costs play a major role in households' decision to move. Moves are induced by a deviation of households' actual ratio of housing to total wealth from an "ideal" ratio determined by consumption value, risk aversion, and other factors. As transaction costs increase, the disequilibrium must increase in order to induce a move. Simulations show that small transaction costs can lead to inactivity in the housing market among individual households for periods 20 years or more. Indeed, this is what we observe in reality. Duration dependence in homeownership is very strong, especially among older individuals, occurring as a result of an increasing psychological and economic attachment to the home over time (Venti and Wise, 1990, 2001, Seslen 2002 et al.)

Within the empirical literature, numerous studies have confirmed a positive correlation between housing prices and trading volume. Among studies using aggregate data, trading volume tends to lead prices, lending support for "mismatch" models a la Wheaton (1990). Ortalo-Magne and Rady (1998), Leung et al. (2002), and Andrew and Meen (2003) present empirical evidence in support of the Wheaton model for the US, UK and Hong Kong, respectively. But it should be noted that studies of aggregate data can only go so far in establishing causality between correlated series. Without controlling for the demographic and economic factors that come up frequently in the literature as influencing mobility decisions, aggregate results suffer from significant omitted variable bias.

In support of the Stein (1995) model of downpayment effects, Lamont and Stein (1999) show that house prices react more sensitively to city-specific shocks (such as changes in per-capita income) in cities with a larger fraction of highly leveraged homeowners.

With the development of the field of behavioral economics, including the prospect theory of Kahneman and Tversky, economists have made an attempt to explain the reluctance to move in down markets through loss aversion, as opposed to equity constraints. In Englehardt (2003), the author uses interactions between initial period loan-to-value ratio and nominal gains and losses in housing value to shed light on the role of loss aversion. The results indicate that losses among the most leveraged households do not lead to a statistically significant decrease in the probability of moving above and beyond the impact of a loss in general. In other words, the loss itself lowers mobility, not the tightening of equity constraints due to declining prices. These results should be interpreted with care, given that the study focuses only on the young, and does not account for individual heterogeneity in mobility behavior. Perhaps more compelling evidence of loss aversion can be found in studies of sales data from Boston condominium market. Genesove and Mayer (2001) find that sellers experiencing nominal losses tend to set higher list prices and keep properties on the market longer as compared to those experiencing nominal gains in hopes of attenuating the loss. In a follow up paper with the same source of data, the authors conclude that only one quarter of seller behavior can be explained by equity constraints, three-quarters by loss aversion.

1.2.2 The Housing Consumption Decision

In order to fully understand the role of house price dynamics on mobility decisions, we must not only analyze households' decision to move, but the amount of housing the choose to consume as well. Generally speaking, the literature on the price-trading volume relationship has not addressed the consumption decision. Moves are assumed to be lateral, and the concept of match/mismatch reflects an abstract set of taste preferences that do not affect the value of the dwelling (house color, for instance). Although the factors influencing the decisions of "When?" and "How much?" may be very different, these questions are inseparable from one another in household decisionmaking. The added benefit of looking at the consumption decision comes from the fact that in choosing to move, the household signals that they were in a non-optimal state, and the new consumption choice reflects an optimizing decision. For households that do not move, we cannot know whether they made their decision based on the fact that they were already consuming their optimal level of housing, or whether market frictions were forcing the household to remain in a non-optimized state. And as long as the household is optimizing, we can be sure that the observed price variables are a true reflection of the values on which households are basing their decisionmaking.

A vast body of literature has been produced over the years in the area of housing consumption decisions, beginning in the late 1970s with analysis of the impact of inflation on housing demand. According to Wheaton (1983), the substantial inflation experienced over the previous decade had three competing effects. It raised mortgage interest payments through higher interest rates, but caused the payments to fall over time in real terms, since the dollars borrowed were worth far more than those being used to repay the loan. In addition, it raised real equity through appreciation in home values. The model presented in the paper demonstrates that as long as individuals can borrow against their home to stay on the life-cycle consumption path, and their individual rates of time preference are not higher than the real interest rate, the combination of the three effects will lead to higher demand for housing.

The early analysis of the effects of inflation gave rise to a broader analysis of the consumption decision as it related to user costs. Broadly speaking, user costs of housing include components of housing expenditures such as interest rates, maintenance, depreciation, and taxes. Their relationship to housing consumption is straightforward: the lower the user costs of housing, the more housing an individual should want to consume. Much of the work in the area of user costs has focused on measurement issues, and how the tax code affects user costs for various types of individuals[3]. Looking back at the inflationary period of the 1970s, user costs were potentially very low for itemizing households, who were able to deduct their mortgage interest payments from their Federal income taxes. This component of the tax code softened the main negative impact of inflation – higher interest rates – and increased demand for housing considerably. According to Poterba (1984), despite record-breaking rates of new construction in 1977 and 1978, the increased demand for housing associated with a lowering of user costs pushed up the real price of owner-occupied housing by as much as 30%.

1.2.3 Predictability of Prices in the Housing Market

According to the efficient markets model, prices of assets are fully flexible and reflect all available information. In efficient markets, price changes must follow random patterns, for if past prices or trading volume played any role in the formation of future prices, buyers and sellers would discover the patterns and act on their findings. Prices would adjust and the pattern would disappear. In financial markets, where transaction costs are low, opportunities for earning excess returns are arbitraged away quickly. Generally speaking,

[3]See Hendershott and Slemrod (1983), Poterba (1984), Dynarski and Sheffrin (1984).

prices are a random walk. In the housing market however, which is rife with frictions that make transactions costly, one can observe patterns that persist over time. Poterba (1984) attributes much of the predictability in housing prices to supply lags. Given that houses are physical assets that take time to be built or torn down, idiosyncratic shocks to the market cannot be responded to instantaneously through changes in supply. In the case of a positive demand shock, housing prices will rise, and remain high as long as the supply of housing is unaltered. Homebuilders will eventually see the opportunity for excess profits, and respond by constructing more housing. As the supply begins to meet demand, the price of housing will fall. Hence, housing prices exhibit both autocorrelation and mean reversion. Every rise (fall) in price persists as long as supply lags behind demand, and is followed by a fall (rise) as supply catches up. Even if individuals correctly anticipate the changes in housing prices following a shock, the patterns do not disappear. Furthermore, according to Wheaton (1999), irrational formation of prices (via extrapolation, loss aversion, or some other mechanism) is not sufficient in and of itself to create real estate cycles. Only in the presence of asset durability, supply lags, and specific demand and supply elasticities does irrational behavior contribute to predictable oscillations in prices.

In Shiller and Case (1989,1990) the authors use sale prices and other administrative data about single-family homes four major metropolitan areas to show strong evidence of positive correlation in housing prices over short intervals. An increase in the price of housing in the current period predicted an increase one-half to one-quarter as big the following period. Both prices and excess returns are forecastable, however, the authors believe that the forecastability in prices is largely a result of forecastability of interest rates over the time period of the sample (1970 to 1986). Of course, serial dependence in and of itself does not necessarily imply inefficient markets if there is no way of exploiting the opportunities for earning excess returns. Indeed, the idiosyncrasies of the housing market make it difficult to do so. Among other things, there are no opportunities for short-selling on primary residence in the event of a market downturn. Likewise, homebuyers face high search costs, and sellers face brokerage fees of five percent or more, moving costs and potential capital gains taxes. As the authors conclude, "If excess returns are expected to be positive because of appreciation, there is nothing to preclude a buy-and-hold strategy" (p. 132). The owneroccupier is, in essence, limited to timing the market in his decision to trade up or cash out.

At the level of individual housing units, the evidence of predictability in prices is not as conclusive. As might be expected, the current period's change in price is most responsive to the most recent lagged change in price, however, the standard errors on the coefficients are quite large. The authors attribute the results to inadequacy of individual housing data as compared to an aggregate weighted repeat-sales index that was used in the MSA-level regressions.

Picking up where Shiller and Case left off, with a sample of weighted repeat-sales indices from over 200 MSAs between 1983 and 2002, I estimate similar patterns to those found in their research. For one- and two-year intervals, there is significant inertia in housing prices. Regressing the (real) current period's log change in housing prices against the previous period's log change in housing prices for non-overlapping intervals, an increase in housing prices in the current period forecasts an increase just over half as big in the subsequent period. If I extend the interval to five years, a pattern of negative autocorrelation emerges from the data. The full results can be found in Table 1-1a. Incorporation of the housing price level serves as a test of series stationarity. For all regressions, the coefficient on housing price level is negative and near zero, indicating that although housing prices may be predictable, the predictability is not being exploited in such a way that prices are spiraling off to infinity or zero. Figure 1-1 shows graphically the trends in housing prices for 12 different metropolitan areas over the same interval. The autocorrelation in housing prices is even clearer here, due to long and distinct peak-to-trough intervals. As can be seen in Table 1-1b, rarely did prices spike or decline over intervals of less than 5 years, which would have given homeowners substantial time to incorporate that inertia into their mobility and consumption decisions. Whether they actually did so or not is a question that remains to be answered.

From the perspective of the individual, rational behavior typically implies that only the expected value of future returns is taken into consideration in the mobility decision, and not past returns. Consequently, in a regression of the mobility or consumption decision on expected (future) and past returns, expected returns should have the greater impact. Past returns may not have a coefficient of zero, given the presence of supply-side effects that may influence individuals' decisions[4]. Of course, the model does not require that all individuals have the same expectation, only that they be distributed around the true expected value of the variable to be forecasted. Divergence from the actual value must only come from unpredictable uncertainty in the mobility/consumption model.

1.3 A Stylized Model of the Housing Consumption Decision

In this section, I present a very stylized model of housing consumption and investment behavior under uncertainty and autocorrelation of returns. The model is a simple utility maximization program over two periods with two forms of consumption – housing (a durable, h) and a numeraire (non-durable, c) – and a riskless asset b. In the first period, the the individual observes the realization of the price of housing and chooses his optimal allocation of goods and assets based on endowment W_0, and his beliefs about the autocorrelation of returns over time. The only constraint is that he may not borrow more than the value of his allocation to housing. Returns on housing an the riskless bond from the first period provide income in the second period. In this framework, the individual has preferences represented by the CARA utility function with no intermediate consumption. Returns on housing are normally distributed with mean μ_H and variance σ_H^2. The individual maximizes:

$$U(c,h) = -e^{-ac-\alpha h}$$

[4]In this analysis, we only have realized future returns, as opposed to expected returns. Any difference between the two emerges in the results as classical measurement error, and will be picked up by the coefficient on lagged returns due to the correlation between the returns. So where realized future returns does not equal expected returns, we will get a coefficient on future returns that is biased toward zero and a nonzero coefficient on lagged returns. Using a bootstrap method of turning realized subsequent returns into an expected value may help to alleviate some of this error. See section 5 of the paper for further details on how this procedure was carried out.

subject to

$$
\begin{aligned}
W_0 &= p_h h + b \\
c &= p_h h H + bR
\end{aligned}
$$

Solving the maximization

$$\max E[-e^{-ac-\alpha h}] = \max E[-e^{-a(p_h hH+bR)-\alpha h}]$$

we get optimal housing expenditure

$$p_h h^* = \frac{\mu_H - R + \frac{\alpha}{a}}{a\sigma_H^2}$$

With no autocorrelation of returns, optimal housing expenditure increases the greater the investment or consumption gain, and decreases the greater the risk associated with home-ownership. It is purely a function of the moments of housing returns, and wealth effects do not come into play. One particular advantage of the CARA framework is that the model produces an intuitive regression setup for analyzing rationality in the housing market.

Adding serial correlation of housing returns into the model is straightforward in that it only effects housing expenditure to the extent that it affects the moments of housing returns.

We assume

$$
\begin{aligned}
H_t &= \gamma H_{t-1} + \varepsilon_t \qquad (1.1) \\
\varepsilon_t &= \gamma \varepsilon_{t-1} + u_t.
\end{aligned}
$$

The variance of H_t remains unchanged, since it is a function of (non-stochastic) past returns and a stochastic error component.

From before, $E[H_t] = E[H_t|H_{t-1}] = \mu_H$. Now, with serial correlation

$$
\begin{aligned}
E[H_t|H_{t-1}] &= \gamma H_{t-1} \\
&= \mu'_H
\end{aligned}
$$

Note that $E[\varepsilon_t|H_{t-1}] \neq 0$ if the error term in equation (#) has an AR(1) form. If we regress

$$p_h h = \beta_{0h} + \beta_{1h} H_t + \beta_{2h} H_{t-1} + \ldots$$

we get (from the optimization solution):

$$\begin{aligned} \beta_{1h} &= \frac{1}{a\sigma_H^2} \\ \beta_{2h} &= \frac{\gamma}{a\sigma_H^2} \\ \gamma &= \frac{\beta_2}{\beta_1} \end{aligned} \tag{1.2}$$

The "expectations" effect of $\gamma \neq \mu_H$ spurs investment when prices are on the upswing and depresses investment when prices are on the downswing. The manipulation in (2) implies that in perfectly frictionless housing and capital markets, we can extrapolate the average belief about autocorrelation in the sample of households based on the parameter estimates attached to future and lagged housing returns and the μ_H obtained from the data. Without frictionless markets, the model still provides a useful tool for understanding housing consumption and investment decisions at the micro level.

1.4 Data

The primary data used in the analysis are from a 13 year unbalanced sample from the Panel Study of Income Dynamics household survey. The panel was supplemented with data from three additional sources: Geocodes containing the MSA of residence for each household were obtained with special permission for the purpose of matching MSA-level information from other sources on to the main dataset. Using the matched geocodes, I merged onto each household observation the weighted repeat-sales housing price index for the corresponding interview year and quarter. These data come from the Office of Federal Housing Enterprise and Oversight (OFHEO), and are available for all MSAs, states, and the nation as a whole. The length of the series varies depending on the MSA. For larger MSAs such as Los Angeles-Long Beach and New York, the indices were calculated as far back as 1975, for smaller MSAs, the series may only go back a decade or less. In this study, I limit the sample to individuals in the 155 MSAs with non-missing indices going back to 1983 (which permits a measure of two-year lagged return to be calculated for households in the 1985 survey). Although indices exist for all states as far back as 1975, state indices are population-weighted, and do not provide a good representation of housing price changes in less populated (and typically less expensive) rural areas. As a result, non-MSA residents were left out of the sample. This accounted for about 26% of all survey respondents. To round out the variables used in the analysis, I merged on a measure of price *level* based on estimation from the 5% Public Use Microsample from the 1990 Census[5]. This variable represents the price in dollars of a three bedroom, single family home with full kitchen and plumbing facilities built after 1940[6]. Given that the census data only reports housing prices in bracketed form and not actual values, I used the ordered probit specification to expand the brackets for each MSA into a continuous lognormal distribution. After data cleaning, 4579 households remained, representing 6469 homeownership spells and 28722 total observations. The final dataset covers the period 1985-1997, a time in which there was significant volatility in housing prices as well as variation in returns across markets.

In summary, the construction of the dataset led to the creation of four price variables integral to the analysis of mobility decisions: expected returns, past returns, price index, and price level. Expected and past returns allow for the testing of whether individuals understand the patterns that exist in housing prices, whether they are loss-averse or merely extrapolative, and the extent to which prices affect mobility decisions relative to other economic and behavioral forces. The price index is, in essence, a time-series effect, designed to capture the impact of the position of housing prices in the business cycle. Analyzing the effects of the price index together with the effects of lagged returns, we can get a sense of whether individuals are able to time the market. The price index, by itself, gives no indication of whether the market arrived at that price from above or below; by adding in lagged returns, we can ask, "Where is the price, and how did it get there?" to determine whether

[5]House values are self reported, however, there is no reason to believe that measurement error due to self-reporting is likely to be more or less severe in cheap versus expensive markets.

[6]Number of bathrooms was not included in the 1990 census questionnaire, although number of bathrooms is known to have a substantial impact on home value.

mobility decisions take place at the peak of the business cycle, at the trough, or somewhere in between. If indeed the PSID represents a random sample of households, we should not expect market timing to occur, as this would indicate an exploitation of the predictability in prices, in which case the patterns would necessarily disappear. In addition, given a fixed supply of housing in the short run, households cannot *all* time the market, since for the set of households that are trading up (down) at a valley (peak), the same number of households must be trading down (up). The final variable, the 1990 price level, is designed to capture the effects of living in an expensive versus cheap market, and takes the place of standard MSA fixed-effects. Ortalo-Magne and Rady (1999) have suggested that the more expensive the market, the lower the mobility of the residents due to more severe "straddling costs" that come as a result of being unable to sell one's old home prior to purchasing a new one. With regard to the consumption decision, the price level (as it relates to straddling costs) should not play a significant role, since the decision to move has already been undertaken. Research by Davidoff (2003) suggests that the price level does indeed matter in the housing consumption decision, but not in ways that relate to the expensiveness of the market. Individuals use their homes as a hedge against fluctuations in labor income, purchasing less housing in areas where housing prices covary positively with labor income and more housing in areas where prices covary negatively with income. Given that the measure of price level is a cross-sectional measure only, and the fact that there is no subsetting of occupations in the sample, we should not see any hedging effect coming through in the price level variable.

Table 1-2 reports summary statistics for the full sample. Over the period 1985-1997, the U.S. experienced several boom-bust cycles – From 1985 until 1989 the economy experienced a strong increase in real house prices, resulting from a lowering of interest rates, a reduction in inflation. From 1989 to 1994, the economy flagged, bringing the housing market down with it. The economic recovery of the mid-90s, and a reduction of interest rates to 40-year lows brought with it another boom in the housing market that has yet to turn around. As a result, average real returns over the sample period are quite small – 0.27% over a one-year interval and 0.52% over a two-year interval. Graphs of the real price index in a variety of metropolitan markets can be found in Figure 1-2. The average 15-year fixed mortgage interest rate was 9.6%, while the average price of a home, as estimated above, was approximately \$95,600. At the household level, 5.6% of homeowners moved during the 13-year interval. With the average age of the household head being nearly 48, this statistic is not particularly surprising. Given that older individuals are more established in their careers and may be less concerned about school choice for younger children, we would expect an older sample to demonstrate lower mobility relative to a younger sample[7].

With regard to household leverage, 14.4% fall into a category that might be considered "constrained"; 7.8% have a loan-to-value ratio of between eighty and ninety percent, 2.5% have a loan-to-value ratio between ninety and ninety-five percent, and 4.1 percent have a loan to value ratio over ninety-five percent. Such high leverage may be explained in two ways: 1) The individual recently secured a mortgage requiring very little downpayment and prices did not change much between the securing of the mortgage and the interview date and 2) the individual purchased their home with a larger downpayment at a peak in the market, and then experienced an erosion in real home prices. The reader should note that The loan-to-value ratio is measured in the period prior to when a move might have occurred to avoid endogeneity bias.

Looking at demographics, we find that divorce and job loss are the two most common lifestyle shocks experiences by the sample population. Families are still growing over the time interval, gaining around 3 individuals per 20 households on average. Real income changed little, falling by 0.2% over the 13 year interval.

1.5 Empirical Strategies

To shed further light on the price-trading-volume relationship, I employ two specifications, a standard probit model with spell-period fixed effects, and the Han-Hausman-Meyer (HHM) semi-parametric duration estimator.. Each specification measures the probability of failure (a within-MSA move) in period t given survival through period $t-1$. The benefits of the HHM estimation strategy is twofold: 1) it allows for non-monotonic duration dependence in homeownership 2) it successfully incorporates left- and right- censoring of homeownership

[7]The mobility rate in Englehardt (2003), which employs the National Longitudinal Survey of Youth, is around 11%. At the other end of the spectrum, studies of the elderly (Venti and Wise 1990, Seslen 2002) show mobility rates of 3% or less.

durations

The baseline hazard is incorporated as a set of constants, estimated simultaneously with the beta parameters in the model. This process of estimating a separate hazard for each time interval allows for a much more flexible shape than parametric hazard models, thereby minimizing the possibility of specification bias.

In the HHM model, the probability of failure in period t by household i is:

$$\int_{\delta_{t-1}-X_i\beta}^{\delta_t-X_i\beta} f(\varepsilon)d\varepsilon$$

where

$$\delta_t = \log \int_0^t \lambda_0(\tau)d\tau$$

is the log of the integrated hazard. Then the log likelihood function, assuming no censoring, is:

$$\log L = \sum_i \sum_t y_{it} \log \int_{\delta_{t-1}-X_i\beta}^{\delta_t-X_i\beta} f(\varepsilon)d\varepsilon$$

where $y_{it} = 1$ if individual i failed in period t, and 0 otherwise. The basic HHM model resembles an ordered probit, with the ordering based upon the time until failure.

The first set of regressions focuses on the moving decision, irrespective of whether the household chooses to trade up, trade down, or move laterally. The regressors can be divided into three categories: market characteristics, household economic characteristics, and demographic characteristics/changes. One- and two-year lagged real return are calculated as the percent change in the housing price index over the one- or two-year interval prior to a possible move, or

$$\ln(I_t/I_{t-i}), \quad i = 1, 2.$$

Where included, subsequent returns are calculated via a simulation process[8]. We run into

[8]To create a simulated value of subsequent returns, I estimated an AR(1) model of future on lagged housing returns for the mover and tradeup/trade-down samples. Residuals from the regression were collected for each sample. For each value of lagged returns, fifty residuals were randomly selected. The mean of the

trouble in the interpretation of lagged returns with the direct inclusion of subsequent returns because the *ceteris paribus* requirement no longer holds. Given that subsequent returns are a function of lagged returns, a change in lagged returns necessarily implies a change in subsequent returns. Simulation of subsequent returns through a bootstrap method creates independence between the two series.

Among household economic characteristics, the variables of greatest interest are a set of dummies for the loan-to-value ratio. Inclusion of these variables is designed to test the Stein hypothesis of whether prices drive trading volume through their impact on leverage. The change in real household income is also included. Presumably, a negative shock in income would generate constraints that would inhibit household mobility. Demographic characteristics include age, race, and sex; the changes track whether the individual got married, became widowed or divorced, started a new job, became unemployed, retired, or experienced a change in family size independent of the change associated with a new marital status.

In each of the econometric specifications, the covariates are from the survey period prior to the one in which a move might have occurred. The dependent variable in the first stage of analysis is a binary variable equal to one if the household moved regardless of the type of move – up, down, or lateral. I include households that moved and traded down to rentership. Households that moved from ownership to non-ownership, non-rentership situations were excluded from the sample. In the second stage of analysis, I focus on the type of household mobility decision – whether the household chooses to trade up or trade down. The analysis is carried out using a probit specification. The dependent variable is equal to one if the household traded up (down) in consumption terms by 15% or more. To create this measure, the self reported house value was deflated by the housing price index for the MSA of residence in the period prior to a potential move and compared to a similar measure calculated for the period one year prior. By deflating with the housing price index, I capture whether the family is actually consuming more housing, not just whether housing expenditure has increased. Although housing values in the PSID are self-reported, measurement error should not play a significant role. According to DiPasquale

selected residuals was calculated, and added to the corresponding value of lagged returns.

and Somerville (1995), households tend to misreport the value of their home by less than 10%. If indeed there were measurement error on the left hand side – that is, misclassification of a household as a trader up/trader down when indeed they were not, or vice versa – it would lead to biased and inconsistent coefficient estimates. Techniques have been developed to deal with such non-classical measurement error [Hausman and Abrevaya (2001)], but are inapplicable to the current analysis due to the strong time-varying nature of the data.

1.6 Results

1.6.1 The Mobility Decision

In the first set of regressions, found in Table 1-3, the dependent variable is equal to one if the household moved since the last survey and zero if they did not. The results from the two specifications – the probit with spell period fixed effects and semi-parametric hazard with a normally distributed error term – are extremely similar for each set of included regressors. The impact of the one year lagged real return is consistently greater in magnitude and more statistically significant than the lagged two year return. Interpreting the coefficient as an odds ratio, where

$$\begin{aligned} \Pr(move_t &= 1|move_{t-j} = 0) = e^{\beta} - 1 \\ & j = 1..t-1, \end{aligned}$$

a 1-percentage point increase in real returns raises the probability (hazard) of moving by between 140 and 440 percent. As the interval stretches to five years, all explanatory power of real returns is lost[9]. Individuals appear to make moving decisions based on recent data over short time intervals. As the data from the time series analysis shows, correlation of returns increases as the interval length decreases, suggesting that individuals would have the least difficulty predicting what the housing market will do in the near future based on what has happened in the recent past. At an interval of five years, correlation of housing

[9]Regressions containing five year lagged returns are not included in the table, but may be requested directly from the author. Incorporation of this variable results in a much smaller sample size due to a steeply shrinking number of MSAs with complete housing price indices going back to 1980.

returns between 1983 and 2002 are clearly negative; the boom-bust cycles in the largest, most highly represented markets occur with surprising regularity. Yet, individuals do not respond accordingly with their mobility decisions. Whether they fail to see the pattern or do not believe the pattern will continue is unclear. Adding simulated subsequent returns to each specification, we see that individuals generally extrapolate information about the future based on past returns and do not "forecast" in the strictest rational expectations sense of the term. The coefficient on housing price index is generally positive and insignificant, suggesting that households care only whether housing returns were positive in the near past, not whether those returns came near the bottom or the top of a cycle. The coefficient on housing price index is generally negative and significant, indicating that individuals are less likely to move in expensive versus cheap markets. As suggested earlier, this result can largely be attributed to "straddling costs" associated with the ownership of two homes. If circumstances prevent an individual from selling his old home at the time that he purchases his new home, he will be stuck paying two mortgages, which is typically a much more severe strain in expensive markets. If the cost of holding two homes simultaneously, even if for a few months, is high enough, the individual may be discouraged from moving completely.

A high loan to value ratio clearly has no effect on its own. Two interrelated scenarios may explain this result. First, if the length of time over which prices are falling is particularly large, forward-looking households may increase savings in hopes of making up for the equity that was eroded by the price decline. In this case, equity constraints would not bind because the extra savings would enable the household to cover the downpayment requirement for a lateral move. Along similar lines, given that the PSID is an older sample of individuals, households may, on average, have more savings already built up outside the home than a younger sample, many of whom may be first time homebuyers According to Englehardt (2003), at the time of first home purchase, the median household has over 90 percent of their wealth tied up in the home at the time of first purchase, and 25 percent of individuals have no other wealth to speak of[10]. One problem with this approach is that we do not know if the household arrived at a high current loan to value position through an

[10]Unfortunately, the infrequency with which the PSID collects wealth data does not allow for the construction of a similar measure at the time of a new home purchase for households in my sample.

initial position of high leverage with little change in housing prices over time, or through a higher initial loan-to-value position that was eroded away by falling house prices. Only in the latter instance could one could make a case for the individual being truly constrained. Taking this into consideration, a better approach would include interactions between the initial equity position and the growth in housing prices from the initial period to the present. In Table 1-4, I present two specifications that test for the presence of equity constraints using this approach: an IV linear probability model, in which housing returns at the MSA level instruments for actual housing returns, and a reduced-form hazard model, which incorporates MSA-level housing returns directly. The IV approach takes account of the fact that the housing values used to calculate returns are self-reported, and may be tainted by measurement error. These regressions are a replication of Englehardt (2003) using slightly different demographic controls. With a broader demographic sample of households, the results continue to show no effect of equity constraints.

Looking at the demographic coefficients, age, not surprisingly, has a strong effect on mobility behavior. A 10-year decrease in the age of the household head leads to a 31.3% increase in the probability of moving. Marriage, divorce, and changes in family size also have a positive impact on mobility. Nonwhite status lowers the probability of moving. This result is most likely a reflection of unobserved cultural and income-related factors. Households appear to be generally insensitive to interest rates, although the sign on the coefficient is correct. Finally, estimation of the hazard function shows positive duration dependence in ownership of one's current residence; in other words, the longer a household has gone without a move, the less likely they are to move in the next observed period. A graph of the hazard function for the one- and two-year HHM specifications can be found in Figure 1-2.

From this set of regressions, we cannot conclude that individuals successfully time the market. Although equity constraints, through either low initial equity or a decline in housing prices, do not appear to have an effect, behavioral factors such as loss aversion cannot be ruled out as a factor affecting housing investment decisions. Demographic shocks clearly play an important role. All in all, the basic regression setup suffers from two potential shortcomings. First of all, one- and two-year future returns may be biased as a result of measurement error. Although the return – the growth rate in the housing price index over the specified interval for a given MSA – is not in itself measured improperly, it may not be a true reflection of the return on which non-mover households are basing their consumption decisions because of frictions in the market that prevent the household from fully optimizing their consumption of housing. Let us assume for a moment that household moving behavior can be explained by the Grossman-Laroque model, in which transaction costs create a band of inactivity around a target ratio of housing- to total wealth. In times of negative expected returns where a move is not induced, individuals are consuming too much housing, and in times of positive returns, households are consuming too little. This implies that the measurement error – the deviation between the growth rate in the housing price index and the growth rate reflected by the household's decision not to move – is negatively correlated with the return itself. As a result, the coefficient on subsequent return suffers from an additional negative bias on top of the typical attenuation bias that results from measurement error in which there is no correlation between the true value of the variable in question and the error term.

Given

$$\begin{aligned} X &= X^* + \eta \\ \widehat{\beta} &= \frac{cov\left((X^* + \eta), Y\right)}{Var(X^* + \eta)}, \end{aligned}$$

if $cov(X^*, \eta) \neq 0$, then

$$\begin{aligned} \widehat{\beta} &= \frac{cov(X^*, Y)}{Var(X^* + \eta)} + \frac{cov(\eta, Y)}{Var(X^* + \eta)} \\ &= \frac{cov(X^*, Y)}{Var(X^* + \eta)} + \frac{cov(\eta, X^*\beta + \varepsilon)}{Var(X^* + \eta)}. \end{aligned}$$

Consequently, if the true relationship between expected returns and mobility is positive, and market frictions create a strong negative correlation between the actual return and the measurement error, we may estimate a negative coefficient for subsequent returns. Indeed, this is what we observe in the results. This non-typical measurement error is the most likely explanation. Based on the theoretical model presented above, we would not expect individuals to have a lower hazard of moving in times of positive expected returns.

The second shortcoming of the price-trading volume specification is that it suffers from sample selection bias. As stated earlier, households who moved across MSAs were dropped from the sample (censored) the period in which the move occurred. If the decision to move within or across MSAs is random, then there is no bias. But there little reason to believe such is the case. Job transfers, new employment and retirement often induce cross-MSA moves; within-MSA moves may be influenced by investment motives, education concerns, and neighborhood quality changes as well. The problem is that there is no systematic way of separating the potential cross-MSA movers from within-MSA movers. In periods where cross-MSA movers do not move, we cannot assume that the decision being made was between staying and moving to another MSA versus staying and moving within the same MSA, so it would be incorrect to remove the "stayer" observations. But censoring implies that the potential for a within-MSA move exists and has not happened yet. Throwing away the knowledge that the within-MSA move, in reality, did not occur will also produce misleading results.

1.6.2 The Consumption Decision

In the second stage of the analysis, I attempt to address the aforementioned shortcomings by examining the decision to trade up or trade down among the sample of within-MSA movers over the 14-year interval. As in the basic trading volume analysis, lagged one-year real return has the largest impact on the decision to increase housing consumption. The magnitude of both one- and two-year returns has increased significantly, while the impact of future returns has remained relatively small and insignificant. Homeowners continue to base investment decisions on past returns rather than an understanding of the distribution of future returns. The reader can now feel confident about this result: by focusing only on those who move, I virtually eliminate the possibility of measurement error in subsequent returns since, presumably, by moving, individuals are able to perfectly optimize their housing consumption. In other words, the returns on which their actions are based is the true return observed in the data.

Given that individuals do not appear to base consumption decisions on expected returns, I include two additional specifications that exclude future returns from the model and replace it with the price index. In doing so, we still see no indication that individuals are successful in timing the market. The coefficient on price index is positive, but not statistically different from zero, suggesting that while they are more likely to trade up when prices have been on the upswing, they do so without consideration for where prices are in the business cycle. The only thing that matters is that prices have been rising, not whether the rise started recently or had persisted for a long time.

As expected, once the household has decided to move, the expensiveness of the market no longer matters. The coefficient on housing price level is near zero and insignificant. Although the possibility of straddling two homes still exists in this scenario, the moving decision has already been made, so the severity of those costs in expensive versus cheap markets should not matter. Unlike before, loan-to-value ratio has a large, positive effect. Household that are highly leveraged are between 36 and 44% less likely to trade up relative to households with at least 20% equity in their home. This result is most likely a consequence of 1) significant downpayment requirements and 2) the fact that individuals have the majority of their wealth tied up in their home. Households may have the desire to move to a larger property, but they don't have the liquid assets to cover the higher downpayment.

With regard to demographics, age is no longer an influencing factor; however, male-headed households are 1.5 times more likely to trade up than female-headed households. As before, nonwhite status, a recent divorce, and a change in family size have a strong impact on the decision to trade up, decreasing the probability by 22%, 74%, and 32%, respectively. Complete results can be found in Table 1-6.

Turning to traders down, I examine two different samples: those who remain homeowners and movers that trade down to any homeownership status (Tables 1-7 and 1-8). This strategy will determine whether there are systematic differences between those who choose to end homeownership and those that do not. Yet again, returns have a strong impact; the higher the lagged real return, the lower the probability of trading down, given the decision to move. There is no clear indication of what point in the cycle individuals are most or least likely to move. As expected, newly divorced individuals have a much higher probability of trading down. Finally, the larger one's family becomes, the more likely they are to trade down. One possible explanation for this phenomenon is that the families' resources are constrained, and in order to provide for additional member's needs such as food and clothing, consumption of housing must be cut back. If we take into consideration movers who enter into a non-ownership situation, the sample size increases by nearly half, and the coefficient estimates change substantially. Although significant, the impact of one- and two-year returns is not nearly as strong as in earlier analyses. All in all, demographic controls are the dominating factor in the decision to trade down irrespective of tenure status. Individuals do not appear to be "cashing out," and attempting to maximize returns or minimize losses in their housing investment, but rather responding to lifestyle changes. These results are consistent with the idea put forth by Hanushek and Quigley (1979) that decisions to alter the amount of housing consumed are typically asymmetric. In times of positive returns, low interest rates, positive changes in income and the like, individuals will readily trade up, perhaps using their home as an opportunity to raise consumption through higher leverage. In "bad" times, individuals are less likely to trade up, but not necessarily more likely to trade down.

1.7 Conclusion

The analysis in this study has provided significant evidence that behavioral mechanisms dominate individuals' actions in housing market transactions. Although housing is a very important investment tool and savings vehicles, the response to growth in housing prices is not forward-looking. Individuals do not appear to understand the underlying distribution of housing returns, nor do they time the market. Generally speaking, the results provide evidence in support of the notion that prices lead trading volume, however, this relationship is not created through a mechanism of equity constraints. Falling house prices do not greatly affect the mobility behavior of highly leveraged households, and high leverage among movers does not increase the probability of decreasing housing consumption.

A natural place to turn next is the question of why individuals do not, on average, exploit the clear patterns of housing returns. Do transaction costs and other market frictions prevent such actions, or do individuals simply not understand that a pattern exists? Although this study provides substantial insight into the role of price dynamics, additional research is needed to fully understand the mechanisms that drive household mobility decisions.

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Figure 1-1: Real Housing Prices 1983-2002

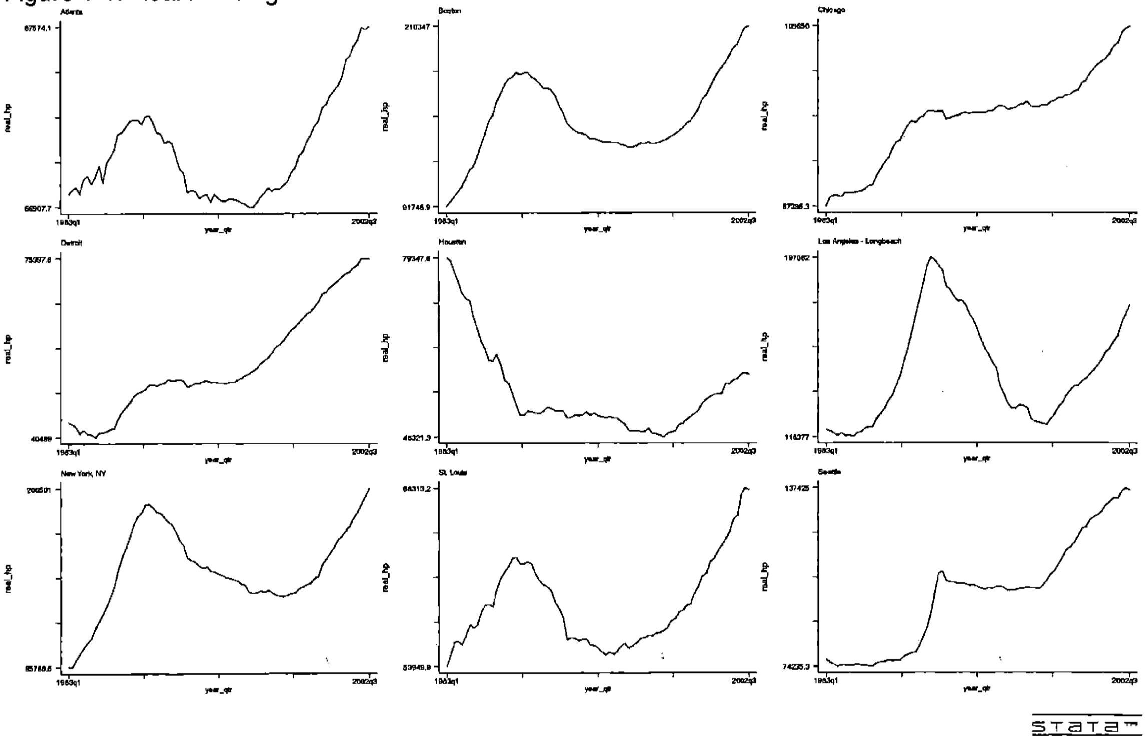


Table 1-1a: Autocorrelation of housing returns

	AR(1) non-overlapping		
	(1)	(2)	(3)
lagged one year real return	0.548***		
	(0.027)		
lagged two year real return		0.457***	
		(0.040)	
lagged five year real return			-0.182***
			(0.017)
housing price level (log)	-.005***	-.004	-0.007***
	(0.001)	(0.007)	(-.001)
R-squared	0.3142	0.21	0.2013
N	2664	1184	1184

Robust standard errors in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 1-1b: Peak/trough price behavior for a selection of MSAs

	peak/trough transition #1		peak/trough transition #2		peak/trough transition #3	
	interval	% change	interval	% change	interval	% change
Atlanta	83:1 to 88:2	13.1	88:2 to 94:3	-13.1	94:3 to 02:3	64.4
Boston	83:1 to 88:2	100.9	88:2 to 93:4	-26.3	93:4 to 02:3	59.3
Chicago	83:1 to 88:3	29.5	97:2 to 02:3	20.6		
Houston	83:1 to 90:4	-37.2	97:1 to 02:3	24.9		
LA-Longbeach	83:4 to 89:4	65.8	89:4 to 97:4	-37.3	97:4 to 02:3	42.4
Minneapolis	93:2 to 02:3	54.7				
New York, NY	83:1 to 88:2	105.3	88:2 to 97:1	29.1	97:1 to 02:3	47.7
Seattle	83:3 to 90:3	43.8	96:4 to 02:2	35.1		
St. Louis	83:1 to 87:3	16.3	87:3 to 93:4	-12.3	93:4 to 02:2	24.4

Table 1-2: Summary statistics

	mean	std. deviation
moved	0.056	0.229
lagged one year real return	0.0027	0.049
lagged two year real return	0.0052	0.091
housing price index	4.224	0.1163
housing price level (log)	11.468	0.433
loan-to-value >.95	0.041	0.199
loan-to-value .90 to .95	0.025	0.158
loan-to-value .80 to .90	0.078	0.269
percent change in real income	-0.002	0.715
age	47.91	14.9
sex	0.807	0.394
newly married	0.007	0.083
newly widowed	0.009	0.095
newly divorced	0.017	0.13
nonwhite	0.292	0.455
lose job	0.066	0.248
become employed	0.026	0.157
newly retired	0.016	0.124
change in family size	0.157	0.364
real 15-year mortgage interest rate	0.096	0.019
N	28722	

Table 1-3: Mobility hazards

	(1) Probit	(2) Probit	(3) Hazard	(4) Hazard	(5) Probit	(6) Probit	(7) Hazard	(8) Hazard
future one year real return	--	--	--	--	-0.231	--	-0.727	--
					(0.347)		(0.464)	
future two year real return	--	--	--	--	.	-0.015		-0.075
						(0.176)		(0.237)
lagged one year real return	0.86***	--	0.922**	--	1.076**	--	1.68**	--
	(0.26)		(0.358)		(0.432)		(0.619)	
lagged two year real return	--	0.392***	--	0.344		0.403		0.465
		(0.114)		(0.193)		(0.224)		(0.320)
housing price index	0.03	-0.012	-0.016	-0.026	--		--	
	(0.11)	(0.111)	(0.136)	(0.136)				
housing price level (log)	-0.06**	-0.063**	-0.075*	-0.074*	-0.057*	-0.063**	-0.039	-0.049
	(0.03)	(0.031)	(0.041)	(0.041)	(0.030)	(0.030)	(0.041)	(0.041)
loan-to-value >.95	0.002	0.003	-0.034	-0.033	0.0032	0.006	-0.041	-0.038
	(0.057)	(0.057)	(0.070)	(0.070)	(0.057)	(0.057)	(0.070)	(0.070)
loan-to-value .90 to .95	0.088	0.091	-0.1	0.103	0.091	0.094	0.104	0.109
	(0.067)	(0.067)	(0.081)	(0.080)	(0.067)	(0.067)	(0.081)	(0.081)
loan-to-value .80 to .90	0.003	0.004	-0.03	-0.03	0.0035	0.005	-0.016	-0.016
	(0.043)	(0.043)	(0.056)	(0.056)	(0.043)	(0.043)	(0.055)	(0.056)
change in real income	0.008		-0.024					
	(0.018)		(0.025)					
age	-0.051***		-0.052***					
	(0.006)		(0.007)					
age squared	0.0003***		0.0003***					
	(0.00006)		(0.00007)					
sex	-0.015		-0.014					
	(0.045)		(0.046)					
newly married	0.414***		0.421***					
	(0.115)		(0.145)					
newly widowed	-0.186		-0.467					
	(0.210)		(0.455)					
newly divorced	0.864***		1.148***					
	(0.069)		(0.090)					
nonwhite	-0.205***		0.263***					
	(0.030)		(0.040)					
lose job	-0.002		0.011					
	(0.053)		(0.077)					
become employed	0.107		0.145					
	(0.075)		(0.98)					
newly retired	0.127		0.237					
	(0.116)		(0.163)					
change in family size	0.354***		0.447***					
	(0.031)		(0.043)					
real 15-year mortgage interest rate	-0.009		-0.017*					
	(0.007)		(0.009)					
Log Likelihood	-5698.78		-5745.54					
N				28722				

Robust standard errors in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.
Probit regressions include spell-period fixed effects.
All regressors listed were included in all regressions. Output for demographic variables was suppressed in columns (2) and (4)-(8) for visual clarity.

Table 1-4: Replication of Englehardt (2003), evidence of loss aversion

	(1) 2SLS	(2) Reduced form hazard
dummy for real loss x real loss	-0.221*	-4.055*
	(0.115)	(2.128)
dummy for real gain x real gain	-0.019	-0.385
	(0.012)	(0.220)
dummy for real loss x real loss x initial LTV > 0.95	1.081	12.81
	(1.474)	(14.83)
dummy for real loss x real loss x initial LTV 0.90-0.95	-0.912	-3.627
	(0.667)	(8.51)
dummy for real loss x real loss x initial LTV 0.80-0.90	0.855*	9.301*
	(0.488)	(3.38)
dummy for real gain x real gain x initial LTV > 0.95	0.159	1.272**
	(0.110)	(0.561)
dummy for real gain x real gain x initial LTV 0.90-0.95	-0.031	-0.147
	(0.047)	(0.758)
dummy for real gain x real gain x initial LTV 0.80-0.90	-0.039	0.578
	(0.196)	(0.419)
initial LTV > 0.95	-0.065	-0.047
	(0.067)	(0.150)
initial LTV 0.90 to 0.95	0.021	0.256
	(0.022)	(0.186)
initial LTV 0.80 to 0.90	0.039**	-0.102
	(0.020)	(0.126)
housing price level (log)	-0.007	-0.113
	(0.004)	(0.088)
Log Likelihood	--	-3610.5
N	22292	

Robust standard errors in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Other regressors include: change in real income, age, age squared, sex, newly married, newly widowed, newly divorced, nonwhite, lose job, become employed, newly retired, change in family size, real 15-year interest rate, and spell periiod dummies (IV only)

Table 1-5: Moving hazard rates[a]

period	censored	failed	percent failed
1	1043	131	0.02
2	770	125	0.023
3	895	128	0.029
4	300	133	0.039
5	232	120	0.041
6	206	122	0.047
7	198	152	0.067
8	158	141	0.073
9	160	152	0.093
10	152	131	0.099
11	119	122	0.117
12	221	98	0.124
13	409	68	0.143

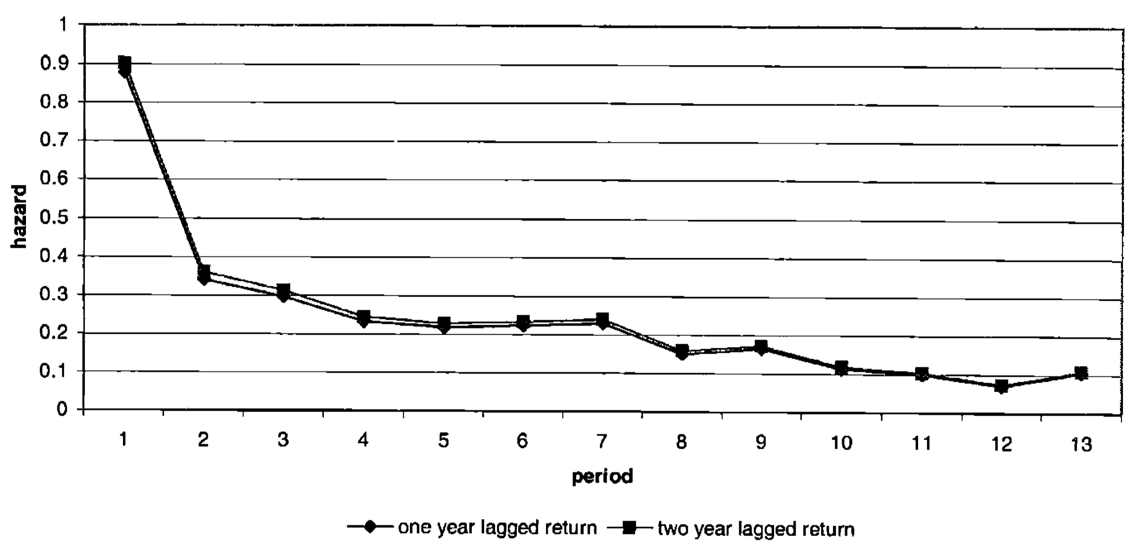
N=6476

Estimated hazards from HHM duration specifications

period	one year hazard	two year hazard
1	0.8783	0.9024
2	0.3406	0.3594
3	0.2967	0.3124
4	0.2325	0.2441
5	0.2178	0.2281
6	0.2224	0.2328
7	0.2295	0.2389
8	0.1512	0.1593
9	0.1645	0.1723
10	0.1128	0.1186
11	0.0991	0.1036
12	0.07	0.0744
13	0.1043	0.1087

N=28722

Figure 1-2: Semi-parametric hazard estimates for movers



[a] Hazard rates may be misleading to to the criteria under which data are censored from the sample. Not only are observations censored due to missing data and interview non-response, but due to cross-MSA moves as well. The implications of the latter are discussed in the text.

Table 1-6: Traders up

	(1) Probit	(2) Probit	(3) Probit	(4) Probit
future one year real return	--	--	0.815	--
			(.866)	
future two year real return	--	--	--	0.157
				(0.435)
lagged one year real return	2.58***	--	2.02**	--
	(0.692)		(.887)	
lagged two year real return	--	1.65***	--	1.588***
		(0.457)		(0.423)
housing price index	0.152	0.017	--	--
	(0.281)	(0.282)		
housing price level (log)	0.052	0.04	0.063	0.042
	(0.082)	(0.082)	(0.079)	(0.080)
loan-to-value >.95	-0.500***	-0.483***	-0.505***	-0.485***
	(0.151)	(0.151)	(0.150)	(0.151)
loan-to-value .90 to .95	-0.568***	-0.554***	-0.564***	-0.553***
	(0.167)	(0.167)	(0.167)	(0.167)
loan-to-value .80 to .90	-0.307**	-0.293**	-0.309***	-0.294**
	(0.108)	(0.108)	(0.108)	(0.108)
change in real income	0.025			
	(0.045)			
age	0.012			
	(0.015)			
age squared	-0.0002**			
	(0.0001)			
sex	0.388***			
	(0.099)			
newly married	-0.105			
	(0.251)			
newly widowed	-0.515			
	(0.680)			
newly divorced	-1.33***			
	(0.196)			
nonwhite	-0.247***			
	(0.083)			
lose job	-0.091			
	(0.139)			
become employed	-0.303			
	(0.200)			
newly retired	-0.048			
	(0.313)			
change in family size	-0.375***			
	(0.078)			
real 15-year mortgage interest rat	-0.005			
	(0.005)			
Log Likelihood	-967.6	-964.93	-967.31	-964.87
N		1609		

Robust standard errors in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively

Table 1-7: Traders down

	(1) Probit	(2) Probit	(3) Probit	(4) Probit
future one year real return	--	--	-0.582	--
			(0.875)	
future two year real return	--	--	--	-0.114
				(0.441)
lagged one year real return	-1.97**	--	-1.51*	--
	(0.707)		(0.906)	
lagged two year real return	--	-1.15**	--	-1.11**
		(0.385)		(0.436)
housing price index	-0.359	-0.27	--	--
	(0.282)	(0.281)		
housing price level (log)	-0.009	-0.002	-0.035	-0.022
	(0.082)	(0.082)	(0.079)	(0.079)
loan-to-value >.95	0.017	0.005	0.024	0.009
	(0.139)	(0.140)	(0.139)	(0.140)
loan-to-value .90 to .95	0.11	0.101	0.108	0.101
	(0.157)	(0.157)	(0.157)	(0.157)
loan-to-value .80 to .90	0.003	-0.005	0.006	-0.003
	(0.107)	(0.108)	(0.107)	(0.108)
change in real income	-0.097**			
	(0.042)			
age	-0.023*			
	(0.014)			
age squared	0.0003***			
	(0.0001)			
sex	-0.336***			
	(0.091)			
newly married	0.195			
	(0.257)			
newly widowed	1.24*			
	(0.669)			
newly divorced	1.78***			
	(0.179)			
nonwhite	0.405***			
	(0.080)			
lose job	0.286**			
	(0.136)			
become employed	0.384**			
	(0.186)			
newly retired	-0.112			
	(0.322)			
change in family size	0.54***			
	(0.075)			
real 15-year mortgage interest rat	0.043**			
	(0.017)			
Log Likelihood	-955.37	-954.79	-955.96	-955.22
N		1609		

Robust standard errors in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 1-8: Traders down, homeowner to homeowner

	(1) Probit	(2) Probit	(3) Probit	(4) Probit
future one year real return	--	--	-1.14	--
			(1.34)	
future two year real return	--	--	--	-0.691
				(0.687)
lagged one year real return	-3.38**	--	-2.64*	--
	(1.153)		(1.47)	
lagged two year real return	--	-2.06***	--	-1.72**
		(0.631)		(0.717)
housing price index	0.181	-0.368	--	--
	(0.437)	(0.435)		
housing price level (log)	-0.014	-0.004	0.0007	0.015
	(0.125)	(0.125)	(0.121)	(0.121)
loan-to-value >.95	0.08	0.062	0.075	0.06
	(0.229)	(0.229)	(0.228)	(0.229)
loan-to-value .90 to .95	0.232	0.202	0.222	0.198
	(0.232)	(0.233)	(0.233)	(0.234)
loan-to-value .80 to .90	-0.429**	-0.457**	-0.431**	-0.458**
	(0.210)	(0.213)	(0.210)	(0.213)
change in real income	-0.137*			
	(0.071)			
age	0.045*			
	(0.024)			
age squared	-0.0003			
	(0.0002)			
sex	-0.172			
	(0.145)			
newly married	0.574			
	(0.357)			
newly widowed	--			
newly divorced	1.152***			
	(0.314)			
nonwhite	-0.148			
	(0.143)			
lose job	0.34			
	(0.296)			
become employed	0.301			
	(0.207)			
newly retired	0.115			
	(0.361)			
change in family size	0.429***			
	(0.116)			
real 15-year mortgage interest rat	0.063**			
	(0.026)			
Log Likelihood	-382.38	-381.22	-382.1	-381.07
N		1077		

Robust standard errors in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Chapter 2

Property Tax Abatement Programs: Does Relief Really Keep Grandma in Her Home?

2.1 Introduction

As America's elderly population has grown, economic issues affecting the elderly have become increasingly important in policy debate at all levels of government. Among the issues widely discussed over the past quarter-century is that of housing – what patterns we observe in elderly housing tenure choice, and which factors lead to those decisions. In this paper, I hope to offer greater insight into the factors influencing the elderly housing tenure decision using a duration-based methodology. In addition, I hope to shed light on the elderly response to property taxation – an issue that, until now, has gone virtually unexplored in a rigorous quantitative context.

Over the years, elderly homeowners have been particularly hard hit by increases in the reliance on the property tax; post-retirement, many find themselves with a great deal of housing wealth, yet without the income or liquid assets to cover the tax bill. As a result, many states have instituted legislation designed to relieve the elderly of all or part of what they owe. The rationale was that many elderly have strong ties to their community and deep psychological attachments to the home itself, and would face high transaction costs on a variety of levels if they were forced to move. Property tax abatement programs would benefit the elderly by lowering the costs of owning a home, and spare them the possible hardships of moving. In the end, however, state governments misjudged the effects of the legislation. As my research shows, property taxes have very little impact on the elderly's homeownership decisions, not only making the property tax a pure tax, but turning abatement programs into a pure wealth transfer to the elderly with the highest net worth in each income category.

In this paper, I present econometric evidence that puts into question the effectiveness of property tax abatement programs as a means of allowing the elderly to maintain homeownership. I compare results from three different classes of single-risk duration models and a semiparametric dual risk model in hopes of determining whether the covariates of interest are more likely to cause a response of a particular type. Wherever possible, I allow for individual heterogeneity to correct for sample bias, to capture mover-stayer effects, and to account for correlation between property taxes and omitted individual characteristics that might influence the elderly to reduce equity. This presents a significant improvement over prior literature, which has mainly employed summary statistics and static probability models as a means of analysis.

My analysis ultimately shows that a single-risk framework, in which the "failure" of equity reduction while maintaining homeownership and the failure of giving up homeownership completely are treated equally, is insufficient for capturing the overall impact of property taxes on elderly homeownership decisions. In the dual risk framework, we see strong differences in the effects of property taxes for each of the two types of failure: among elderly who move to a non-ownership situation, property taxes have no effect on the decision to move. In the alternative case, high property taxes have a pronounced positive effect on the hazard of moving.

In section 2 of the paper, I discuss the previous literature and describe the basic trends in elderly housing tenure. In section 3, I describe the data and estimation techniques, in particular the hazard models of Han and Hausman (1990) and Meyer (1990). Section 4 presents the results. In section 5, I present analysis of the results obtained from estimation of the Han and Hausman bivariate hazard specification. Section 6 concludes.

2.2 Literature Review

2.2.1 General Trends in Mobility

Prior to addressing the issue of the elderly housing tenure decision, it is important to understand the theory behind mobility and housing flows – how individuals choose their level of housing consumption and how they adjust their consumption over time. In Hanushek and Quigley (1979), the authors present a model of housing demand in which mobility decisions are based upon a disparity existing between current and desired housing consumption. The conceptual framework assumes that households derive utility from consumption of "housing services" and other goods X given socio-demographic characteristics A.

$$V = U_A(H, X)$$

The household maximizes utility subject to the standard household budget constraint

$$Y = P_H H + X$$

where Y is household income, P_H is the price of housing, and the price of other goods is normalized to one. From this maximization procedure, we get an optimal, or "desired" level of housing, H^d for the current time period,t. The current, non-optimized level of housing consumption is H_t. The authors note that, "if mobility were costless or housing capital could be modified cheaply at all residential sites, each household would continuously adjust its location or characteristics of its dwelling unit so that $H_t = H_t^d$."[1] If $H_t < H_{t+1}^d$, then individuals will prefer to increase housing consumption in the next period, and vice versa if $H_t > H_t^d$.

The strength of the incentive to alter housing consumption is measured by the difference $[H_{t+1}^d - H_t]$, which can be broken down into two components: $[H_t^d - H_t]$, the gap between initial consumption and the desired consumption level, and $[H_{t+1}^d - H_t^d]$, the change in the equilibrium level of housing consumption during the period. Assuming that households adjust housing consumption by closing the gap between actual and desired consumption at

[1] Hanushek and Quigley (1979) p. 92.

a constant rate, the relationship between consumption levels over time is:

$$H_{t+1} = \beta[H_t^d - H_t] + \gamma[H_{t+1}^d - H_t^d] + \phi H_t,$$

where β measures the speed of adjustment from the initial disequilibrium position, and γ measures the speed of adjustment to "current-period changes in equilibrium levels of housing consumption"[2] According to the authors, it is reasonable to assume that households adjust more quickly to changes in the household equilibrium position than to magnitude of the initial disequilibrium, implying that $\gamma > \beta$. The implication here is that exogenous factors affecting housing demand are likely to have the greatest effect in the period in which they occur, and less of an effect in later periods. In terms of mobility decisions, factors such as a drop in income or death of a spouse are more likely to result in a move in the period in which the shock occurs than in later periods. The analysis in this paper will test this hypothesis by including covariates representing shocks in both the current and previous survey periods.

The authors also believe there to be a "rachet effect," or asymmetry, in adjustment – that those who are currently below their desired level of housing consumption will make adjustments toward equilibrium more rapidly than those who are above their desired level of consumption. Although they do not go into the reasons as to why this may occur, subsequent research has indeed found evidence that the elderly are more likely to "trade up" than "trade down" in certain circumstances. This "rachet effect," assuming a disparity in monetary/psychological transaction costs across adjustment decisions, is one plausible explanation.

Using a continuous-time framework, Grossman and Laroque (1990) present a very similar model of mobility in the general context of illiquid durable goods. The transaction costs of moving create a band if inaction around the individual's optimal ratio of housing consumption to total wealth. The larger the transaction costs, larger the band, and the further the individual must be from the optimal level of housing consumption before he chooses to sell the current home and readjust upward or downward. Numerical simulations show that small transaction costs can lead to very infrequent changes in consumption – on the order

[2]Ibid, p.93

of 25 years or more between moves – a trend that is readily observed in mobility data.

2.2.2 Trends in Elderly Housing Tenure

Over the years, many researchers have attempted to understand the factors which affect elderly homeownership decisions at a level beyond the "adjustment" model of Hanushek and Quigley. Although a variety of approaches have been taken, they have largely come to similar conclusions. The primary theoretical work, which places the homeownership decision into a life-cycle hypothesis framework, was developed by Henderson and Ioannides (1983). The authors do not focus specifically on the elderly, however, the key concepts of the paper can be applied towards understanding the changes in their portfolio demand for housing. According to general life-cycle theory, individuals prefer to smooth consumption of the course of their lifetime, and housing consumption makes up a constant fraction of the total. When individuals hit retirement age, their income falls, and they begin to dissave from their accumulated wealth. Assuming that the elderly do not wish to experience a large drop in housing consumption during their retirement years, they will decumulate housing wealth more slowly than other forms of wealth. As a result, the elderly should be expected to move less frequently than the population as a whole.

In the realm of empirical literature, the previous work includes Merrill (1984), Feinstein and McFadden (1989), and Venti and Wise (1989, 1990), which they followed up with papers in 2000 and 2001. In each of these works, the data show strong evidence in support of the theoretical claim that the elderly should move relatively infrequently. Venti and Wise show that moving is often associated with retirement, death of a spouse, divorce, or other major demographic "shocks." However, when such shocks occur, moving is the exception and not the rule. Surprisingly, the elderly family that moves is as likely to increase housing equity as to reduce it. Given that the elderly typically have low/fixed incomes, and have little savings outside the equity in their homes, one might expect mostly downward changes in housing equity. Looking at the Table 2-1, among the elderly who rented in 1973 and moved in 1975, 17 percent became homeowners, while only 15.4 percent of homeowners in 1973 who moved in 1975 became renters. Likewise, over 22 percent of movers in non-owning, non-rent-paying situations became homeowners in 1975, while only 6.4 percent of homeowners in 1973 moved into the "other" category two years later. The reluctance to move can be attributed to a number of factors, such as attachment to the home itself, ties to the neighborhood and other community organizations, and proximity to family members. High transaction costs appear not to be a factor in the decision not to reduce housing wealth as one ages.

Table 2-1: Transition matrix for movers [3]

	Own75	Rent75	Other75
Own73	78.2%	15.4%	6.4%
Rent73	17.0%	69.9%	13.1%
Other73	22.6%	41.2%	36.2%

Relevant to the property tax issue is the fact that the elderly do not wish to reduce housing equity in order to increase consumption. The fixed costs of owning a home (namely taxes and insurance), even if fairly large and unexpected, may simply not justify the additional monetary and psychological costs of moving.

In their later work, Venti and Wise explore in greater depth the "shock" aspect of elderly housing tenure decisions. They use the successor to the RHS, the Health and Retirement Survey, to come up with much of the same findings. Families that do not experience psychological or economic shocks tend to reduce housing equity by around 0.1 percent per year for two-person households and around 1.1 percent per year for one-person households. Families who do experience shocks reduce equity by 8 percent per year on average. Additional analysis shows that income-poor and house-rich families tend to reduce equity when they move, while income-rich and house-poor tend to increase equity. One explanation put forth by the authors (which is supported by their results) is that families with high income are simply adjusting to their desired level of housing wealth, while families with low income are responding to a liquidity constraint. Another explanation for "trading up" as one ages could be related to government policy. For instance, Medicaid rules require near-exhaustion of wealth before nursing home expenses will be paid. Given that housing wealth is exempt

[3]From Venti and Wise (1990). "Other" is defined as a situation in which the individual neither owns not pays rent.

from this rule, the elderly would have a strong incentive to transfer their remaining savings into equity.

Work by Megbolugbe, Sa-Adu and Shilling (1997) examines the housing tenure decisions of the female elderly and the oldest old. These groups are found to move much less frequently in comparison to "mixed" elderly populations, and when they do, are much more likely to reduce equity. They believe the reason behind the difference in female housing tenure decisions has to do with the fact that women suffer more financially in the case of divorce and widowhood, as opposed to simple gender preferences. The additional liquidity constraint of these particular demographic shocks makes trading-down more likely.

2.2.3 Movers versus Stayers

The classic "mover-stayer" issue is central to any research on elderly housing tenure decisions given that it represents individual heterogeneity that may be difficult to incorporate into econometric models. In their 1990 paper, Venti and Wise calculate a rudimentary matrix of hazard rates as a function of age in an attempt to detect such heterogeneity. Using the entire population of movers, they find a small increase in the probability of moving during the peak retirement years, ages 60-65, but insist that mover-stayer indicators "do not appear strongly in [their] tabulation." In Table 2-2, I employ the same technique used by Venti and Wise, but count only the moves in which individuals reduce equity by 10 percent or more. Following the original cohort across the ten years of the survey, I list in each column the percent of "failures" for each age in the cohort. I find a slight decline over the first four periods of the sample and a spike in equity reduction in the final year. "Stayers" in the sample would be defined by a decline in the percentage of movers as the number of years without moving increases. Given that the decline is relatively small, there may not be a strong element of unexplained heterogeneity in the data. To be sure, however, the possible presence of individual heterogeneity will be taken into account in the modeling stage.

Table 2-2: Hazard Rates for Movers

	71	73	75	77	79	All
58	4.3%					4.3%
59	5.2%					5.2%
60	5.5%	3.7%				4.6%
61	4.4%	4.1%				4.3%
62	4.5%	3.0%	4.2%			3.9%
63	4.4%	4.3%	3.7%			4.1%
64		4.1%	4.2%	3.0%		3.8%
65		6.1%	3.0%	2.9%		4.0%
66			3.3%	2.6%	4.6%	3.5%
67			1.9%	3.5%	3.2%	2.9%
68				3.2%	3.4%	3.3%
69				2.2%	3.3%	2.8%
70					3.8%	3.8%
71					6.1%	6.1%
All	4.7%	4.2%	3.4%	2.9%	4.1%	

2.2.4 Property Taxes, Relief Programs, and the Elderly

As far as property taxes are concerned, very little academic literature exists on the subject. Two notable books, a treatise on the incidence of the property tax by Aaron (1975) and an anthology entitled, "Property Tax Reform" (1973), are the main quantitatively-based publications aside from a number of reports put out in the mid-to-late 1970s by the Advisory Committee on Intergovernmental Relations (ACIR) and the Department of Housing and Urban Development (HUD). At the time of these publications, the collection of data from the Retirement History Survey was not yet complete, and no other effort had been made "to collect the data that would permit a retrospective judgment on the effect of property tax[es]... on the housing stability of the elderly."[4]

According to the HUD report, property taxes pose a significant burden on the elderly.[5]Housing costs equal, on average 35 percent of elderly income (versus 22 percent for the non-elderly population), with eight percent going towards property taxes – much higher than the thresholds required for qualification in most property tax relief programs. For the sample used my

[4]Property Tax Relief Programs for the Elderly: An Evaluation, Department of Housing and Urban Development, 1975 p.34. From now on, referred to as "the HUD report."

[5]Ibid, p.48

analysis, the mean of property taxes to income is a bit lower – between 5.9 and 7.1 percent over a period of 10 years. This small discrepancy could be due to the fact that in the earlier years of the sample, many individuals are still in the labor force. Removing the impact of outliers, we can see that in the later years of the sample, over half the sample reports property taxes equaling more than four percent of income.

Table 2-3: Summary statistics: property taxes/income

	1969	1971	1973	1975	1977
Mean	0.059	0.070	0.074	0.059	0.071
S.D.	0.126	0.133	0.129	0.105	0.089
Quartiles					
First	0.011	0.016	0.020	0.013	0.025
Second	0.296	0.037	0.042	0.040	0.046
Third	0.057	0.071	0.078	0.066	0.087
N	5147	4534	3957	3413	2606

Summary statistics: property tax dollar amounts (nominal)

	1969	1971	1973	1975	1977
Mean	315.96	388.17	465.33	386.55	537.16
S.D.	525.30	773.99	1049.80[6]	637.53	669.03
Maximum	20000	27000	37726	21200	14000
Quartiles					
First	70.00	100.00	133.00	87.00	174.00
Second	222.00	274.50	309.00	260.00	390.00
Third	426.00	500.00	600.00	500.00	700.00
% zeros	0.147	0.119	0.094	0.102	0.057
N	5147	4534	3957	3413	2606

[6]The high variance is being driven by two high outliers. Taking them out of the sample, the mean and standard deviation are 447.18 and 670.50, respectively.

Despite the burden, the HUD report concluded that the effect of property taxes on relocation decisions would be marginal at most, as the moving rate of elderly homeowners was so low to begin with. Furthermore, the programs were likely to have undesirable distributional effects, given evidence that the property tax was not regressive, as most legislators believed.

According to the "new"[7] view of property taxes, given the fact that not all goods are taxed equally, property tax increases lead holders of capital to shift their resources to less heavily taxed activities, which lowers the rate of return on all capital. If we assume capital to be concentrated in the hands of the wealthy, the property tax tends to be progressive in nature. Under the "old" view – that of the property tax as an excise tax – the burden of the tax is borne in proportion to the level of consumption of the taxed commodities. Given that consumption of housing takes up a far larger percent of the budgets of low-income families, the tax is regressive. The main problem with the claim of regressivity is that income tends to be measured only over a short period of time. If incidence is re-calculated using a measure of permanent income as a guide, the property tax turns out to be proportional or progressive over most of the income distribution (Aaron 1976). The implication here is that property tax relief based on current income ceilings/property-tax-to-income ratios will result in the highest benefits being distributed to those with the highest wealth in each income category. Along similar lines, given that property taxes have historically been correlated much more highly with housing value than "amenities" associated with the community, those with homes of greater value (a proxy for greater overall wealth) will receive higher benefits. In Figure 2-1, we see the pattern of property tax incidence across deciles of income using a sample from the Panel Study of Income Dynamics and assuming 56% shifting of property taxes to renters.[8]

Nevertheless, by 1980, 31 states had passed "circuit-breaker" legislation granting partial or complete relief from the burden of property taxes. In Appendix C, I present the major features of all circuit breaker programs in existence as of 1994. Those not offering circuit-breaker-type relief (through state rebates or reductions in the tax bill) typically offered homestead exemptions or tax deferrals instead. Only a handful of states offered little or no

[7]as of 1975.

[8]Graph from Sacher (1993) – "Housing Demand and Property Tax Incidence in a Life-Cycle Framework," *Public Finance Quarterly,* 21, p. 252.

property tax relief for the elderly. Not coincidentally, these states also tend to show a much lower reliance on property taxes for the funding of services.

The typical circuit breaker limits benefits to those families with incomes under \$15,000 (as of 1994), and grants an average benefit of around \$285, although these characteristics vary widely across states. Michigan and Vermont, for instance cover all homeowners, regardless of age, have no income or net asset limitations, and provide relief when property taxes exceed modest fractions of income (3.5 percent in Michigan and 4 to 6 percent in Vermont). Based on average effective property tax rates in those states, typical consumption patterns, and normal relationships between incomes and home values or rent, economists believe that more than half of households will qualify for some aid (insert footnote). At the other end of the spectrum, the elderly in Tennessee must have incomes of \$8,200 or less to qualify, and receive rebates for taxes paid only on the first \$15,000 of market value, for an average benefit of just under \$90. In most states, the maximum possible benefit is around \$500.

2.3 Data and Empirical Strategies

To better understand the factors that effect elderly homeownership decisions, I follow Venti and Wise (1990), employing data from the RHS. This dataset samples 11,153 households with heads between the ages of 58 and 63. The survey began in 1969, with participants being interviewed every two years until 1979. The survey includes demographic data, information on income, expenditures, social habits and relationships, and plans for retirement, among other things. To create the sample used in the estimation, I first kept only households that were non-farm homeowners in 1969 and were still in the sample in 1971. 1971 is designated as the first period in which a "failure" (move) can occur given that no data is collected on moves prior to 1969. Each observation was then truncated at the last period of complete data, in cases where periods of complete data were either followed or preceded by periods of incomplete data. Finally, post-failure data was removed from the analysis (only the first move of each household is considered). After alterations were made, the first period dataset contained 5147 observations.

Although the data cover the 1970s, I consider the dataset to be useful for a number of reasons: first of all, the data have a very straightforward structure. No individuals enter the sample after the first period, divorced individuals who move out of the household are dropped from the sample, and household heads remain the same from year to year, as long as the individuals are able to complete the survey. In addition, attrition rates are reasonably stable from year to year, and the data are reasonably complete. Perhaps most importantly, the dataset covers a time period in which there is a great deal of variation in property taxes – one which included a country-wide rise due the strain of the baby boom generation on the nation's public school system and a subsequent revolt that brought property taxes back down in some areas. On the downside, the dataset does not contain complete information on wealth, general medical expenses, or state/MSA of residence[9].

In the past, research on elderly homeownership decisions has relied largely on static probability models such as probit and logit. Despite their popularity, the models are not well suited to the dynamic nature of the question at hand. For instance, a cross-sectional probit specification leads to sample bias given the presence of unobserved individual heterogeneity. Simply put, as the years pass, more and more individuals leave the sample due to moving. Those left in the sample may have higher values of the unobserved taste for staying in their current home, and estimates based on this sample will be biased and inconsistent (Rauh 2002, Diamond and Hausman, 1984).

An alternative way to model the equity-reduction decision is through duration models, in which the dependent variable is the number of periods until failure, as opposed to a binary variable for failure that does not take into account the timing of the move. In this analysis, a "failure" is defined as a household that changes tenure from ownership to renting, from ownership to other non-owning, non-rent-paying living arrangement, or moves from

[9]Although several states have passed notable property tax-related legislation between the end of the 1970s and the present, none would appear to have a significant effect on an elderly household's propensity to reduce housing consumption. California's Proposition 13, for example, includes an amendment which allows households over age 55 to transfer the assessed valuation of their previous home when purchasing a new home of equal or lesser value for property tax assessment purposes. In other words, it prevents lock-in that might otherwise result from re-assessment at the time of purchase. For traders down that occupied their former home for a substantial amount of time, the savings from the amendment could be in the thousands of dollars per year. The only legislative lock-in effect would have come from federal law, which until 1997, allowed only the first $125,000 in capital gains to be exempt from taxes, and allowed deferral of payment only when the homeowner traded *up*. The effect of this legislation on our defined failures depends, of course, on the potential capital gains realized by each household – something which niether the RHS nor more recent data provides.

one house to another, reducing home value by at least 10 percent. This cutoff is essentially arbitrary, however, larger may be better in this case, due to data misreporting issues.[10].

I carry out estimation using four different types of models. The first two are the most widely used types of hazard models in econometric analysis: the parametric and the Cox proportional hazard. I follow up with a semi-parametric model developed by Han, Hausman, and Meyer (HHM), with and without a gamma-distributed heterogeneity component. Finally, I use the basic Han and Hausman approach to estimate a competing risks model, in which ending homeownership and trading down are treated as two separate failures, in an attempt to determine whether any of the covariates in the sample are more likely to cause either type.of failure.

Each of the four models begins with a basic proportional hazards specification,

$$h_i(t) = h_0(t)g(x_j),$$

in which $h_i(t)$ is a function of the failure time and $h_0(t)$ is the baseline hazard – in essence, the duration dependence of the "default," or non-failure situation. Among the parametric specifications, the distributions (Weibull, log-logistic, etc.) refer to the shape of the baseline hazard function. The Weibull model, which has the following baseline hazard parameterization

$$h_0(t) = pt^{p-1},$$

assumes duration dependence that is monotonically increasing or decreasing over time. Although the Weibull is a popular parametric specification, the monotonicity of the baseline hazard may be overly restrictive for the data used in this analysis.

Several specification tests on a set of preliminary parametric regressions employing the

[10]Given evidence that households tend to over-report values of assets, income, and other large-ticket items, as well as report the correct value of items recently purchased, movers in the sample have a fairly significant chance of being classified as failures when they actually did not reduce equity by more than the threshold amount. On the other hand, given the tendency to under-report housing values in times of increasing house prices, some individuals may be misclassified as non-failures. This misclassification problem can lead to both biased and inconsistent estimates in duration models, even when the mis-classification is as little as 2% (Hausman and Abrevaya 1998). Techniques to correct for this problem have been developed, however, they cannot be applied here due to the strong time-varying nature of the data.

entire range of baseline distributions pointed towards the log-logistic as the distribution that best fit the data. However, specification tests can only carry the researcher so far. Despite the variety of parametric specifications available, specification bias is a serious concern, and unless one's priors are very strong about the nature of duration dependence in the model, a parametric model may not be the ideal choice.

The Cox partial likelihood approach offers a viable alternative to the restrictiveness of the parametric models in the fact that it allows for estimation of the coefficient vector (β) without estimation of the baseline parameter. The estimation uses only information about the ordering of the durations, maximizing the following likelihood function:

$$\log L(\beta) = \sum_i \left[X_i\beta - \sum_{j \in R(i)} e^{X_i\beta} \right],$$

where $R(i)$ is the "risk set" of observation i, and contains all observations that survive at least until time t_i. Taking advantage of multiplicative separability within the proportional hazard specification, the baseline parameter has been "partialed out" of the likelihood function.

Unfortunately, the partial likelihood model has two main drawbacks that come heavily into play in the elderly homeownership context: first, the model does not handle tied failure times well – a problem, since the dataset only measures failures over a set of five periods. Correction methods exist in many statistical packages for dealing with ties, however, they are not typically suited towards data containing as large a percentage of tied failures as exist in the RHS. This inability to deal with a large number of tied failures typically results in biased and inconsistent estimates. Second, due to computational complexity, the model does not allow for the incorporation of individual heterogeneity. Given the notion that some individuals will move or stay in their homes regardless of any demographic characteristic or shock they might encounter (the classic "mover-stayer" issue), it is important to take individual heterogeneity into account in the estimation procedure. Nevertheless, it is still superior to the traditional probit approach. The Cox partial likelihood model's strength is that it takes censoring into account in a way that the probit model does not – it incorporates the fact that a move may occur after the censoring date, while the probit only recognizes that a move did not occur.

Ultimately, where the parametric and Cox models fall short, the HHM model stands out. Unlike the Cox model, in which the baseline parameters are treated as a nuisance function and partialed out of the model, the HHM model treats them as constants, estimating them simultaneously with the beta parameters in the model. This process of estimating a separate hazard for each time interval allows for a much more flexible shape, thereby minimizing the possibility of specification bias. Furthermore, this approach allows for estimation of the true beta parameter, regardless of the time interval chosen.[11]

In the HHM model, the probability of failure in period t by individual i is:

$$\int_{\delta_{t-1}-X_i\beta}^{\delta_t-X_i\beta} f(\varepsilon)d\varepsilon$$

where

$$\delta_t = \log \int_0^t \lambda_0(\tau)d\tau$$

is the log of the integrated hazard. Then the log likelihood function, assuming no censoring, is:

$$\log L = \sum_i \sum_t y_{it} \log \int_{\delta_{t-1}-X_i\beta}^{\delta_t-X_i\beta} f(\varepsilon)d\varepsilon$$

where $y_{it} = 1$ if individual i failed in period t, and 0 otherwise.

The basic HHM model resembles an ordered logit or probit, depending on the distribution of the error term. As in the Cox model, the ordering is based upon the time until failure. Gamma distributed heterogeneity is easily incorporated in closed form.[12] The modification of the likelihood function to accommodate the dual risk scenario is relatively straightforward. The derivation of both the single risk model with gamma heterogeneity and the dual risk model can be found in the Appendix.

In the final set of regressions, I include three basic types of covariates: family/individual characteristics, income and expenses, and "shocks." In the category of family or individual

[11]Smaller intervals, however, lead to more efficient estimation

[12]Although such an approach has been criticized (Heckman and Singer 1984), the nonparametric specification of the hazard function appears to reduce the sensitivity of the estimates to the parametric heterogeneity assumption.

characteristics, *race* equals 1 if nonwhite, *age62* equals 1 if the individual is between the ages of 62 and 65, and *age65* equals 1 if the individual is over 65. Preliminary results showed that linear and quadratic representations of age were not a good fit, so indicator variables were used instead. *Sex* equals 1 if the household head is female (only the case if the interviewee is widowed, divorced, or never married), and *marr* equals one if the household head is married. *Nokids* is the number of children in the family.

The variable *newwid* equals 1 if the individual is widowed since the last interview period. If there is a lag in the decision to move as a result of being widowed, the effects will be picked up in the variable *sex*. Due to high correlation between widowhood and female headship, I did not include an additional widowhood dummy. *Newret* equals 1 if the individual has exited the labor force since the last interview. In the case of retirement, I do include a dummy variable for being out of the labor force (*outlf*) to pick up any lag in the decision to reduce equity that might be based on retirement status. Finally, among the "shock" variables, I include two dummy variables, *hosp1* and *hosp2*, representing one and two or more stays in the hospital in the past calendar year, respectively. A number of other methods of measuring health shocks – reported health status, change in health over the past year, out-of-pocket/total hospital expenses, and interactions of these variables with income produced very few significant results.

Among the economic variables, I have included quartiles of income, represented by *ycat2*, *ycat3*, and *ycat4*. The variable *mort* equals one if the family has a positive mortgage on their current home, and is meant to proxy for a number of unobservables such as economic attachment to the home or potential monetary transaction costs associated with moving. Having a mortgage may also proxy for the number of years spent in the home, however such a measure of duration dependence need not be explicitly included since the individual heterogeneity component in the HHM model is already picking this up. The variable *iphr* equals 1 if the individual falls into the lowest quartile of income and the highest quartile of housing wealth – in other words, whether the family is house rich and income poor. This variable will likely be a stronger influence on the elderly's equity-reduction decision than income alone, since it gives a sense of the expenses faced by the family as well. Individuals who are pushed up against their budget constraint by the costs associated with owning an expensive home may feel greater pressure to move than those who are not.

The variable of greatest interest to this study is the ratio of property taxes to income. It is expressed in linear *(ratio)* and quartile form *(rval2-rval4)*. In cases where reported property taxes are greater than income, the value of ratio was truncated at one. In cases where the property tax value was missing in a particular year, but the family had not moved, the values from other years were used to impute the missing year One would expect that the larger the value of *ratio*, the more likely the family to reduce housing equity, assuming that families take the fixed costs of housing into consideration when making tenure decisions. To account for any potential bias from the reporting only of property taxes paid outside of a mortgage, I include an indicator variable, taxmt, equal to 1 if any part of the tax bill was included in the monthly mortgage payment from the prior year.

In each of the four econometric models, the covariates are from the current survey period, unless the variable of interest is affected by the decision to move. In the case of *ycatX, mort*, and *ratio/rvalX*, the $t-1$ value is used as a means of dealing with the potential endogeneity bias.

2.4 Results

Interpretation of results from each of the models is fairly straightforward. From the proportional hazard specification, changes in the covariates shift the baseline hazard by a constant percentage at all durations. For all specifications, a positive coefficient implies that a positive change in the covariate raises the failure rate and decreases the duration of homeownership, while a negative coefficient lowers the failure rate and increases the duration of homeownership. The exact percentage change in the likelihood of homeownership is represented by the hazard ratio, e^{β}, with the point of reference of zero change being a hazard ratio equal to 1.

Various summary statistics can be found in tables 2-4a, 2-4b, and 2-5a through c. In the first table, we see typical trends in the major demographic and economic variables. As the survey cohort ages, female headship increases as more and more women enter into widowhood. Retirement peaks as individuals reach the 62-67 age bracket, and all but 18 percent of homeowners have paid off their mortgage by 1977. We see an overall decline in health through an increase in the means of the variables representing hospital stays. Overall, these numbers present few surprises. In the second table, I present statistics on income and home value. Home value increases substantially over time – around 133% over 10 years – while income generally stays constant. Both distributions are skewed substantially to the right.

In table 2-5a, I present the rate of homeownership by year for the entire RHS sample. This measure is very important in that it may give an indication of attrition bias in the sample. If the explanation for the increase in homeownership is that movers to rental units are harder to locate, or for some reason less likely to want to continue being interviewed, the results of all estimation procedures will be biased because the number of failures observed in the sample was affected by the fact that a household *was* classified as a failure.[13] If the true explanation is that owner-occupants have a longer life-expectancy (quite likely), or that slightly more households are trading up than trading down, then the estimation results will not be affected since neither case alters the number of observed failures.[14] In table 2-5b and 2-5c, I present the number of failures and censored observations by year, broken down by failure type and sex. With the exception of 1973, the number of changes from ownership to rentership/other is significantly larger than the number of failures through equity-reduction. In each successive year, the share of female-headed failure households increases – as we might expect, given the overall increase of female-headed households in the sample. And consistent with research that found elderly women to move less frequently but experience greater decreases in equity upon moving, the increase in the ratio of female to male-headed households is far greater among renters than among traders-down.

Results for each of the three types of single-risk models (with and without heterogeneity, if applicable) are presented in tables 2-6a through c. In these tables, I present coefficient and hazard ratio estimates for two different specifications – one in which property taxes enter linearly (via *ratio*) and one in which they enter via quartile dummies (*rval2*, *rval3*, and *rval4*).

[13] All that really matters here is that individuals are leaving the sample in a non-random way.

[14] Individuals are dropped from the sample once the move to a rental unit occurs, so unless the individual dies prior to the next interview, and the death is somehow related to the move (for instance), tenure-related longevity issues should not bias the results

The directional effects of each covariate in each of the three models are very similar, and can be summed up as follows:

- Increased age has a positive effect on the duration of homeownership
- Likewise, being married has a strong positive effect on the duration of homeownership
- Being newly widowed leads to a higher probability of moving, although the effects are smaller than one might have originally expected
- Female household head-ship (or widowhood/divorce in general) has a positive effect on duration of homeownership.
- Being out of the labor force, whether in the last period or otherwise, leads to a higher likelihood of failure.
- Being nonwhite has a strong positive effect on the duration of homeownership.
- Having a larger number of children leads to a higher likelihood of failure.
- Income *on its own* has an ambiguous effect on the likelihood of failure, while being income-poor and house-rich has a strong positive effect.
- Having a mortgage (and everything it proxies for) leads to a higher likelihood of failure.
- Health "shocks" experienced by the head of household appear to have no significant effect on the duration of homeownership.
- The effect of property taxes on homeownership appears to be large, but it is questionable as to whether the two failures can be treated equally. The quartile measure, which provides a better fit than the linear measure of property taxes to income, is smaller and less significant in all of the single risk specifications.

Each of these results is consistent with prior research, with a couple of exceptions. Race, for instance, has largely been ignored in prior studies of elderly housing tenure choice, so it is difficult to say what the correct sign should be. The coefficient may be picking up income effects or some cultural unobservables. With respect to the number of children in a family, the results go against the notion that parents prefer to maintain homeownership as part of a bequest motive. Two possible explanations are that the bequest motives are outweighed by the desire to be geographically closer to one's children, or that the economic benefits of moving in with a child outweigh the benefits of remaining in one's home. Finally, regarding the ambiguity of direction and overall insignificance of income, an effect may indeed be present, but it is getting picked up instead by the lifestyle changes of retirement and widowhood, since both of them have a strong underlying income component. If we take away the income effects that are associated with shocks, there will be nothing left to the income variable to create an effect of its own.

Looking at the results from the parametric specification, we see that the largest effects coming from the over-65 age category. Such individuals see their hazard of failure cut by more than half. Likewise, females in the sample experience a 34.5 percent reduction in the hazard of moving. On the other end of the spectrum, being "income poor and house rich" leads to a 50.7 percent increase in the hazard of moving. Property taxes in the linear measure have a large effect, with a one percentage point increase in *ratio* leading to a 30.6 percent increase in the hazard of moving. *ceteris paribus*. Breaking the property tax measure into quartiles, we see a pattern in which low property taxes lead to a lower likelihood of failure and higher property taxes lead to a higher likelihood of failure. The variable *taxmt*, designed to control for any bias due to the inclusion of property taxes in mortgage payments appears to have no effect.

In the log-logistic model, inclusion of gamma heterogeneity appears to have a mixed effect in terms of its effect on the magnitude of the coefficients. Among the demographic variables, the inclusion of heterogeneity increases the coefficients by three to seven percent; among the "economic" variables, heterogeneity serves to decrease the magnitudes by three to five percent. The exception is the quartiles of the property tax – inclusion of heterogeneity results in a slight increase in the coefficients, with no effect on overall significance.

Table 2-6b and 2-6c compare the results from the Cox model, the basic HHM model, and the HHM model with gamma distributed heterogeneity. The results are very similar to one another, however, the Cox coefficients tend to be a bit smaller and less significant.

This outcome may be attributable to the large number of tied failure times in the RHS sample. The artificial construct created by the Cox estimation method to deal with tied failure times, in essence, results in a type of measurement error which biases the coefficient estimates downward.

The relative impact of the covariates in the Cox and HHM models differs substantially from the log-logistic model, most likely due to the restrictiveness of the parametric baseline specification. As can be seen in Figures 2-2 and 2-3, the shape of the unrestricted baseline from the HHM model is highly non-monotonic, and not well-represented by the baseline from the parametric model (Figure 2-4).

In the Cox and HHM models, the largest impact on the likelihood of failure comes from marital status. Being married reduces the hazard by over 60 percent, compared to only 30 percent for being over 65 years of age. Holding a mortgage and falling into the category of income poor and house rich, again, have a strong impact in the other direction, raising the likelihood of failure by as much as 88 and 114 percent, respectively for the model with gamma heterogeneity. Being out of the labor force also has a large impact, raising the likelihood of failure by nearly 90 percent. The impact of property taxes in the linear form has increased substantially in the HHM model; however, in the quartile specification, the effects are much the same as before with lower statistical significance. Overall, including gamma heterogeneity increases the magnitude of the coefficients across the board. Whether there is an increase in statistical significance is a bit less clear. The estimated variance of the gamma distribution for the linear and quartile property tax specifications are 2.841 and 1.401, respectively, although neither is statistically significant. Nevertheless, with the large impact of the inclusion of parametric heterogeneity on the estimated coefficients, we can conclude that heterogeneity is present in the model.

One potential concern over the validity of the results stems from the possibility that property taxes are correlated with various unobserved factors that may change the likelihood of one moving. Such a correlation leads property taxes to be correlated with the error term, and results in omitted variable bias. Given the nature of the data, as well as the variety of omitted factors, accounting for all of them is impossible. Incorporating individual heterogeneity into the various models helps to account for the omitted factors that make up the unobserved variance across individuals in the sample, but not the unobserved variance across time. The upside is that the omitted variable bias is likely to be small, and possibly in a direction that reinforces the claim that a high-property tax-to-income ratio does not raise the likelihood of equity reduction. If we assume, for instance, that declining property taxes over time proxy for declining neighborhood quality, we can make an argument for either positive or negative bias – declining neighborhood quality increases an elderly individual's desire to move, but at the same time prevents them from moving because home values are likely to have gone down as well. The dominating factor will determine the direction. If they exactly offset one another, the bias is zero and we are in the clear. If liquidity constraints weigh more heavily, then the coefficient on *ratio/rvalX/ptax* will be biased upward, and vice versa if preferences for higher neighborhood quality dominate. In the former case, the bias implies that property taxes have *even less* of an effect than the results show. The true beta remains unknown, but the conclusions of the research are still clear: that property tax abatement programs result in pure transfers to the wealthiest elderly. More worrisome is the case in which declining neighborhood quality dominates liquidity constraints. However, there is little evidence to believe that it would. Considering that during the time period covered by the data, many towns allocated the greatest percentage of property tax revenues to educational spending, declines in neighborhood quality should not have affected "quality".(as perceived by the elderly) by as much as it would have had the focus of revenues been on fire and police protection, for example.

2.5 The HHM Bivariate Hazard Specification

In the final stage of analysis, I look at elderly housing tenure decisions using a dual hazard framework, given evidence that certain characteristics are more likely to cause one type of failure over another. The model used in this analysis is a generalization of the single risk framework, with the unique characteristic that unrestricted correlation is permitted between the stochastic disturbances in the two equations that form the basis for the model.[15] As

[15]See Appendix.

in the single risk model, the baseline hazard (now a bivariate distribution) is estimated nonparametrically in hopes of avoiding specification bias.

Although gamma heterogeneity is not explicitly incorporated into the model, heterogeneity is built in due to the fact that the bivariate approach with normally distributed error is not derived directly from the proportional hazard specification. We can conceptualize the heterogeneity by thinking of the model as two independent proportional hazards with a bivariate mixing distribution that generates a convolution which is bivariate normal. Results can be found in tables 2-7a and b, with "Type 1" referring to complete equity reduction and "Type 2" referring to the failure of trading down.

Treating the failures of partial versus complete equity reduction as distinct from one another, we see striking differences in the factors that impact elderly homeownership decisions, and gain insight into which decisions were driving the results in the single risk model. For instance, while female headship leads to a lower likelihood of ending homeownership, it has almost no effect on the decision to trade down. Likewise, being married nearly cuts in half the likelihood of ending homeownership, but adds nearly 30 percent to the likelihood of trading down. As before, holding a mortgage has a strong positive impact on the likelihood of both types of failure. Looking at the indicator for house rich and income poor (*iphr*), we see that traders-down were driving the result in the earlier model; being income poor and house rich has almost no impact on the decision to end homeownership.

The coefficients on each of the two measures of *ratio* appear to tell the story that property taxes are somewhat important to those contemplating trading down, but not to those moving out of their homes for good. Addressing the possible concern of income effects interfering with the property tax result by looking at the log of property taxes irrespective of income, we see an effect (or lack thereof) that is even more pronounced. The log of property taxes for traders down has a statistically significant effect close to zero, while the quartile measures are both small and insignificant. Given that traders-down purchase a new home and assume all of the associated economic responsibilities, it would make sense that the economics of the current living situation (property taxes included) factor more strongly into the decision making process than for those transitioning to non-ownership.

Consistent with the striking differences in the estimated coefficients, Figure 2-5 shows a strong contrast in the baseline hazards for each of the two failure types with the quartile measure of *ratio* as the variable of interest. Across the entire duration of the sample, individuals have a higher likelihood of ending homeownerhsip than of trading down. Again, the baselines for both hazards are non-monotonic, making the unrestrictiveness of the Han and Hausman bivariate specification an important feature of the model.

In light of both the coefficient and baseline estimates, we can conclude that estimation methods which treat all moves equally present a misleading picture of the factors that affect elderly mobility, and that the impact of property taxes on homeownership decisions is marginal at best. The semiparametric bivariate hazard specification, which has never before been used in such a context, disentangles the effects of the covariates through the assumption that the durations leading to each failure may be drawn from different distributions. With such a strong negative correlation between the constituent proportional hazards, we see that lumping all forms of equity reduction together is clearly the wrong way to go.

As far as policy implications are concerned, although property taxes raise the hazard of moving for traders-down by nearly one-third, the hazard of trading down is so small that relief is likely to end up in the pockets of those who never would have moved anyway. Mobility arguments aside, property tax abatement programs may indeed ease the burden of homeownership for some individuals with depressed incomes relative to housing wealth, but given the fact that relief is typically based only on income and not on wealth measures, such transfers will lead to undesirable redistributional outcomes. Adding in the low rate of elderly mobility will only exacerbate such results.

2.6 Conclusion

Thirty years ago, in response to what was believed to be a growing "excess burden" of property taxes on the elderly, legislators in a number of states made an attempt to provide relief to those most affected. The popularity of the so-called "circuit breakers" grew over the next two decades to the point that nearly every state had an abatement program in some form or another. In this paper, I provide evidence that property taxes have little impact on elderly mobility, and that abatement programs, therefore, have the effect of providing a pure transfer to the wealthiest elderly in each income bracket. Through a semiparametric bivariate specification, we can see that high property taxes do not increase the likelihood of ending homeownership. Individuals do appear to take property taxes into account in the decision to trade down, but it is far from the most important factor affecting the likelihood of failure. Looking at property taxes outside of their relationship to family income, the effect is even lower for both types of failure. Given this evidence, legislators might want to rethink abatement policy. Is the real goal of the legislation to keep the elderly in their current home, to maintain the elderly's homeownership status in any home, or something else entirely?

Ideally, I would like to compare my results with the successor to the RHS, the Health and Retirement Survey (HRS), to determine whether the factors affecting elderly homeownership decisions have changed across decades. As of the time of this writing, however, the HRS data are not of the quality needed to carry out a new round of regressions. Nevertheless, the current set of results provide a good starting point for further elderly housing policy analysis.

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[20] Venti, Steven F. and David A. Wise (1990) – "But They Don't Want to Reduce Housing Equity," *Issues in the Economics of Aging*, David Wise, ed. Chicago: University of Chicago Press, pp. 13-29.

[21] Venti, Steven F. and David A. Wise (2000) – "Aging and Housing Equity," NBER Working Paper Series, no. 7882.

Table 2-4a: Summary Statistics

	1971	1973	1975	1977	1979
age	62.41	64.13	66.03	67.87	69.80
	(1.71)	(2.34)	(2.52)	(2.78)	(2.80)
sex	0.201	0.257	0.281	0.308	0.346
	(0.401)	(0.437)	(0.450)	(0.462)	(0.476)
race	0.078	0.081	0.082	0.084	0.083
	(0.268)	(0.272)	(0.275)	(0.278)	(0.276)
newwid	0.038	0.046	0.052	0.055	0.056
	(0.191)	(0.210)	(0.221)	(0.228)	(0.229)
newret	0.175	0.253	0.180	0.146	0.094
	(0.379)	(0.435)	(0.384)	(0.353)	(0.292)
outlf	0.335	0.550	0.680	0.776	0.814
	(0.472)	(0.497)	(0.467)	(0.417)	(0.389)
nokids	2.42	2.37	2.45	2.46	2.48
	(2.14)	(2.13)	(2.14)	(2.13)	(2.12)
mort	0.389	0.336	0.272	0.211	0.175
	(0.487)	(0.472)	(0.445)	(0.408)	(0.380)
iphr	0.024	0.028	0.024	0.023	0.023
	(0.155)	(0.164)	(0.152)	(0.151)	(0.150)
hosp1	0.107	0.109	0.113	0.122	0.127
	(0.308)	(0.309)	(0.318)	(0.328)	(0.333)
hosp2	0.026	0.034	0.046	0.047	0.046
	(0.160)	(0.183)	(0.210)	(0.212)	(0.211)
ratio	0.059	0.070	0.074	0.059	0.071
	(0.126)	(0.133)	(0.128)	(0.105)	(0.089)
N	5147	4534	3957	3413	2606

Table 2-4b: Summary statistics for income and housing value

	1969	1971	1973	1975	1977	1979
mean income	$9,200	$9,158	$9,349	$9,327	$9,488	—
med. income	$7,684	$7,621	$7,500	$7,460	$7,644	—
mean house value	$17,668	$19,441	$22,577	$26,222	$31,385	$40,358
med. house value	$15,000	$16,500	$20,000	$22,000	$26,900	$35,000
N	5147	4534	3957	3413	2606	3423

Table 2-5a: Homeownership by year, full sample

	1969	1971	1973	1975	1977	1979
Own = 1	0.670	0.683	0.699	0.712	0.716	0.712
s.d	(0.470)	(0.465)	(0.459)	(0.453)	(0.451)	(0.453)
N	9904	10169	9423	8716	7993	7352

N in 1969 is less than N in 1971 because the question, "Do you rent or own this residence?" was only asked of the non-farm population in 1969. In 1971 and beyond, it was asked of the entire population. The total number of observations in the 1969 sample is 11,153.

Table 2-5b: Failures and censored observations, by year

	1971	1973	1975	1977	1979	
Failure	240	203	144	119	109	815
Rent	148	101	71	67	66	453
Trade-down	92	102	73	52	43	362
Censored	373	374	400	688	2497	4332
Total	634	577	544	793	2560	5147

Table 2-5c: Failures and censored observations, by year and sex of householder

	1971		1973		1975		1977		1979		
	M	F	M	F	M	F	M	F	M	F	
Failure	185	55	139	64	95	47	65	50	64	44	815
Rent	111	37	62	39	45	26	34	33	35	31	453
Trade-down	74	18	77	25	52	21	34	18	30	13	362
Censored	291	82	238	136	259	141	483	205	1640	857	4332
Total	476	137	377	200	356	188	551	256	1705	901	5147

Table 2-6a: Log Logistic parametric distribution

	no heterogeneity				gamma heterogen.			
	(1)		(2)		(1)		(2)	
age62	-0.354***	0.702	-0.357***	0.699	-0.374***	0.687	-0.381***	0.683
	(0.066)		(0.066)		(0.064)		(0.063)	
age65	-0.787***	0.455	-0.794***	0.452	-0.812***	0.443	-0.823***	0.439
	(0.069)		(0.069)		(0.067)		(0.065)	
sex	-0.422***	0.655	-0.427***	0.652	-0.423***	0.655	-0.430***	0.651
	(0.068)		(0.168)		(0.065)		(0.065)	
race	-0.364***	0.695	-0.354***	0.702	-0.371***	0.690	-0.362***	0.696
	(0.088)		(0.088)		(0.087)		(0.087)	
married	-0.510***	0.600	-0.503***	0.604	-0.519***	0.595	-0.515***	0.598
	(0.069)		(0.070)		(0.067)		(0.066)	
newwid	0.072	1.074	0.080	1.083	0.037	1.038	0.036	1.037
	(0.076)		(0.076)		(0.079)		(0.078)	
ycat2	-0.023	0.977	-0.022	0.978	-0.022**	0.978	-0.019	0.981
	(0.061)		(0.059)		(0.059)		(0.058)	
ycat3	-0.069	0.933	-0.053	0.948	-0.070***	0.932	-0.052	0.949
	(0.065)		(0.064)		(0.063)		(0.062)	
ycat4	-0.026	0.974	-0.001	0.999	-0.034	0.966	-0.008	0.992
	(0.067)		(0.068)		(0.066)		(0.065)	
newret	0.307***	1.359	0.308***	1.361	0.290***	1.336	0.286***	1.331
	(0.050)		(0.050)		(0.051)		(0.050)	
outlf	0.152***	1.164	0.152	1.164	0.140	1.150	0.136**	1.145
	(0.052)		(0.052)		(0.053)		(0.053)	
nokids	0.017*	1.017	0.018	1.018	0.020	1.020	0.022**	1.022
	(0.009)		(0.009)		(0.009)		(0.009)	
mort	0.366***	1.442	0.364***	1.439	0.353***	1.423	0.346***	1.413
	(0.051)		(0.051)		(0.053)		(0.053)	
iphr	0.410***	1.507	0.408***	1.503	0.401	1.492	0.392***	1.480
	(0.097)		(0.096)		(0.103)		(0.101)	
hosp1	0.015	1.015	0.014	1.014	0.018	1.018	0.017	1.017
	(0.059)		(0.059)		(0.058)		(0.057)	
hosp2	-0.064	0.938	-0.066	0.936	-0.060	0.941	-0.061	0.941
	(0.096)		(0.096)		(0.097)		(0.096)	
ratio	0.267**	1.306			0.250*	1.284		
	(0.137)				(0.146)			
rval2			-0.073	0.929			-0.076	0.927
			(0.057)				(0.059)	
rval3			0.002	1.002			-0.004	0.996
			(0.058)				(0.058)	
rval4			0.117***	1.124			0.118***	1.125
			(0.059)				(0.059)	
taxmt	0.044	1.045	0.039	1.040	0.057	1.059	0.057	1.058
	(0.060)		(0.064)		(0.063)		(0.068)	
scaling param.	-0.493***		-0.491	0.612	-0.464***		-0.455***	
	(0.015)		(0.014)		(0.027)		(0.026)	
theta					0.740		0.946	
LR: theta = 0					1.74*		2.80**	
N subjects	5147				5147			
N failures	815				815			
Log Likelihood	-2494.59		-2490.85		-2493.71		-2489.45	

Table 2-6b: Cox (1) vs. single-risk HHM (2) vs. HHM gamma (3)

	(1)	(2)	(3)	(1)	(2)	(3)
age62	-0.263**	-0.272**	-0.274**	-0.275**	-0.284***	-0.289***
	(0.115)	(0.117)	(0.119)	(0.115)	(0.138)	(0.121)
age65	-0.326**	-0.341**	-0.347***	-0.348***	-0.362**	-0.375**
	(0.128)	(0.128)	(0.132)	(0.128)	(0.153)	(0.135)
sex	-0.469***	-0.499***	-0.524***	-0.476***	-0.505***	-0.558***
	(0.119)	(0.104)	(0.111)	(0.119)	(0.142)	(0.115)
race	-0.601***	-0.621***	-0.640***	-0.597***	-0.618***	-0.658***
	(0.164)	(0.166)	(0.176)	(0.164)	(0.161)	(0.181)
married	-0.920***	-0.958***	-1.007***	-0.912***	-0.950***	-1.047***
	(0.124)	(0.103)	(0.121)	(0.125)	(0.142)	(0.125)
newwid	0.228*	0.240	0.215	0.235*	0.246*	0.195
	(0.132)	(0.128)	(0.133)	(0.132)	(0.175)	(0.135)
ycat2	0.097	0.097	0.101	0.091	0.091	0.100
	(0.110)	(0.108)	(0.110)	(0.108)	(0.119)	(0.112)
ycat3	0.093	0.096	0.101	0.107	0.111	0.124
	(0.117)	(0.115)	(0.118)	(0.118)	(0.128)	(0.121)
ycat4	0.245**	0.248**	0.251**	0.272*	0.276**	0.285**
	(0.123)	(0.117)	(0.120)	(0.125)	(0.135)	(0.124)
newret	0.300***	0.312***	0.304***	0.300***	0.313***	0.297***
	(0.091)	(0.093)	(0.096)	(0.091)	(0.109)	(0.097)
outlf	0.583***	0.600***	0.615***	0.585***	0.603***	0.632***
	(0.098)	(0.098)	(0.105)	(0.098)	(0.104)	(0.107)
nokids	0.042***	0.043***	0.046***	0.042***	0.043***	0.051***
	(0.015)	(0.016)	(0.017)	(0.016)	(0.018)	(0.018)
mort	0.604***	0.624***	0.632***	0.603***	0.622***	0.637***
	(0.089)	(0.094)	(0.101)	(0.090)	(0.109)	(0.104)
iphr	0.705***	0.726***	0.763***	0.725***	0.748***	0.816***
	(0.163)	(0.170)	(0.181)	(0.162)	(0.166)	(0.181)
hosp1	0.028	-0.079	-0.078	0.025	-0.079	-0.078
	(0.106)	(0.107)	(0.109)	(0.106)	(0.120)	(0.122)
hosp2	-0.043	-0.038	-0.038	-0.048	-0.037	-0.037
	(0.172)	(0.093)	(0.095)	(0.172)	(0.093)	(0.097)
ratio	0.517**	0.526**	0.527**			
	(0.226)	(0.261)	(0.266)			
rval2				-0.184*	-0.191*	-0.204*
				(0.106)	(0.120)	(0.121)
rval3				-0.051	-0.052	-0.064
				(0.107)	(0.120)	(0.116)
rval4				0.119	0.117	0.125
				(0.108)	(0.122)	(0.116)
taxmt	0.056	0.057	0.070	0.013	0.028	0.036
	(0.104)	(0.132)	(0.131)	(0.112)	(0.143)	(0.131)
$1/\theta$			2.841			1.401
			(5.720)			(1.483)
N subjects		5147			5147	
N failures		815			815	

Table 2-6c: Cox (1).vs. single-risk HHM (2), vs. HHM gamma, hazard ratios

	(1)	(2)	(3)	(1)	(2)	(3)
age62	0.769**	0.763**	0.760**	0.759**	0.752***	0.750***
age65	0.721**	0.711**	0.706**	0.706***	0.696**	0.687**
sex	0.625***	0.609***	0.592***	0.621***	0.604***	0.572***
race	0.548***	0.537***	0.527***	0.550***	0.539***	0.518***
married	0.398***	0.383***	0.365***	0.402***	0.387***	0.351***
newwid	1.257*	1.271	1.239	1.264*	1.279	1.216
ycat2	1.101	1.102	1.106	1.096	1.095	1.105
ycat3	1.098	1.102	1.106	1.113	1.117	1.132
ycat4	1.278**	1.281**	1.285**	1.313*	1.317**	1.329**
newret	1.350***	1.366***	1.355***	1.353***	1.366***	1.346***
outlf	1.791***	1.822***	1.849***	1.795***	1.827***	1.882***
nokids	1.042***	1.044***	1.049***	1.043***	1.044***	1.052***
mort	1.831***	1.866***	1.881***	1.828***	1.863***	1.879***
iphr	2.023***	2.067***	2.144***	2.065***	2.112***	2.262***
hosp1	1.028	0.923	0.925	1.026	0.923	0.925
hosp2	0.957	0.962	0.963	0.953	0.963	0.963
ratio	1.678**	1.692**	1.692**			
rval2				0.832*	0.825*	0.815*
rval3				0.950	0.949	0.938
rval4				1.126	1.125	1.113
taxmt	1.058	1.058	1.073	1.013	1.012	1.037
N subjects		5147			5147	
N failures		815			815	

Table 2-7a: Han and Hausman bivariate risk specification

	Failure type				Failure type			
	(1)		(2)		(1)		(2)	
age62	-0.156*	0.855	-0.239**	0.787	-0.155*	0.856	-0.248**	0.780
	(0.082)		(0.089)		(0.082)		(0.091)	
age65	-0.627***	0.534	-0.912***	0.402	-0.626***	0.534	-0.924***	0.396
	(0.084)		(0.095)		(0.083)		(0.098)	
sex	-0.486***	0.615	0.086	1.089	-0.485***	0.615	0.081	1.084
	(0.094)		(0.103)		(0.094)		(0.103)	
race	-0.292***	0.746	-0.433***	0.648	-0.293***	0.746	-0.419***	0.658
	(0.108)		(0.133)		(0.108)		(0.134)	
married	-0.708***	0.492	0.249**	1.282	-0.708***	0.492	0.264***	1.302
	(0.908)		(0.106)		(0.091)		(0.107)	
newwid	0.121	1.130	0.204	1.226	0.121	1.128	0.228	1.256
	(0.123)		(0.168)		(0.123)		(0.170)	
ycat2	-0.174**	0.840	0.042	1.043	-0.172**	0.841	-0.041	0.959
	(0.088)		(0.406)		(0.088)		(0.103)	
ycat3	-0.272***	0.761	0.079	1.082	-0.271***	0.726	-0.095	0.909
	(0.094)		(0.104)		(0.094)		(0.104)	
ycat4	-0.121	0.756	0.089	1.093	-0.123	0.884	0.124	1.132
	(0.090)		(0.105)		(0.091)		(0.105)	
newret	0.322***	1.380	0.506***	1.658	0.322***	1.380	0.502***	1.652
	(0.091)		(0.100)		(0.091)		(0.101)	
outlf	-0.047	0.954	0.046	1.047	-0.458	0.632	0.048	1.049
	(0.075)		(0.083)		(0.075)		(0.048)	
nokids	0.017	1.017	0.017	1.017	0.017	1.017	0.021	1.021
	(0.015)		(0.012)		(0.013)		(0.013)	
mort	0.404***	1.497	0.331***	1.392	0.404***	1.498	0.332***	1.393
	(0.072)		(0.082)		(0.073)		(0.082)	
iphr	0.015	1.015	0.557***	1.745	0.0009	1.001	0.551***	1.734
	(0.176)		(0.194)		(0.174)		(0.185)	
hosp1	0.014	1.014	0.033	1.036	-0.016	0.984	0.048	1.049
	(0.088)		(0.107)		(0.089)		(0.108)	
hosp2	-0.009	0.991	0.033	1.034	0.008	1.008	0.041	1.042
	(0.079)		(0.093)		(0.080)		(0.094)	
ratio	-0.064	0.938	0.477*	1.611				
	(0.225)		(0.270)					
rval2					0.036	1.037	-0.010	0.990
					(0.093)		(0.111)	
rval3					-0.019	0.981	0.101	1.106
					(0.093)		(0.102)	
rval4					0.0004	1.000	0.282***	1.325
					(0.090)		(0.103)	
taxmt	-0.028	0.972	-0.010	0.990	-0.002	0.998	0.004	1.004
	(0.085)		(0.097)		(0.095)		(0.114)	
rho		-0.860				-0.908		
		(2.356)				(3.430)		
N subjects		5147				5147		
N failures		815				815		
Log Likelihood		-3662.72				-3658.29		

Table 2-7b: Han and Hausman bivariate risk specification

	Failure type (1)		(2)		Failure type (1)		(2)	
lnptax	-0.016	0.984	0.033*	1.034				
	(0.016)		(0.016)					
ptval2					-0.037	0.936	-0.116*	0.890
					(0.093)		(0.084)	
ptval3					-0.093	0.911	0.113	1.119
					(0.093)		(0.113)	
ptval4					0.007	1.007	0.026	1.026
					(0.090)		(0.100)	
taxmt	-0.076	0.926	-0.079	0.924	-0.030	0.970	-0.054	0.947
	(0.099)		(0.112)		(0.095)		(0.096)	
rho	-0.816				-0.803			
	(1.544)				(1.381)			
N subjects	5147				5147			
N failures	815				815			
Log Likelihood	-3662.50				-3660.62			

All demographic, and other economic variables are the same as in Table 2-7a

2.7 Appendix

2.7.1 Derivation of the Han and Hausman Single Risk Duration Model with Gamma Heterogeneity

To incorporate gamma distributed heterogeneity with mean 1 and variance $1/\theta$, we continue from the text in the following way:[16]

Let $I_i(t)$ represent the survivor function in the absence of heterogeneity. We assume that $I_i(t)$ has an exponential distribution.and is monotonically increasing in t. Letting $s_i = w_i + \epsilon_i$, we define

$$I_i(t) \equiv q_i(t)$$

where

$$\begin{aligned} q_i(t) &= \exp(s_i) \\ &= \exp(w_i + \epsilon_i) \\ &= \exp(-X_i\beta)\exp(\delta_t) \end{aligned}$$

The survivor function with heterogeneity (represented by $g(\bullet)$) is therefore the integral of q_i from $I_i(t)$ to infinity. This gives us equation (8) in Han and Hausman (1990).

$$\int_{I_i(t)}^{\infty} g(q)dq = [1 + (1/\theta)I_i(t)]^{-\theta}$$

Labeling this integral $S(t)$, the probability of failure at time t given survival up to period $t-1$ is

[16] from Han and Hausman (1990).

$$
\begin{aligned}
P(\text{failure at time t}) &= S(t-1) - S(t) \\
&= \int_{I_i(t-1)}^{\infty} g(q)dq - \int_{I_i(t)}^{\infty} g(q)dq \\
&= [1 + (1/\theta)I_i(t-1)]^{-\theta} - [1 + (1/\theta)I_i(t)]^{-\theta}.
\end{aligned}
$$

Using the same indicator variable as before, the log-likelihood function is therefore

$$
\log L = \sum_i \sum_t y_{it} \log \left\{ [1 + (1/\theta)I_i(t-1)]^{-\theta} - [1 + (1/\theta)I_i(t)]^{-\theta} \right\}.
$$

2.7.2 Basic Explanation of the Dual Risk Model

The specification begins in the same way as with the single risk, however, we have two equations representing each of the two failure types.

$$
\begin{aligned}
\delta^1_{t_1} &= -\log \int_0^{t_1} \lambda^1_0(s)ds = X\beta_1 + \epsilon_1 \\
\delta^2_{t_2} &= -\log \int_0^{t_2} \lambda^2_0(s)ds = X\beta_2 + \epsilon_2
\end{aligned}
$$

If we suppose that the failure is of type 1 so that $t_1 = \min(t_1, t_2)$, the probability of this outcome, given the underlying grouping of the data, is

$$
\int_{\delta^1_{t-1} - X\beta_1}^{\delta^1_t - X\beta_1} \int_{m(\epsilon_1)}^{\infty} f(\epsilon_1, \epsilon_2) d\epsilon_1 d\epsilon_2
$$

where $m(\epsilon_1)$ is such that the implied type 2 failure time is greater than the implied type 1 failure time. Given a realization of ϵ_1^* and assuming linearity, we solve for the implied failure time:

$$X\beta_1 + \epsilon_1^* = -\log \int_0^{t^*} \lambda_0^1(s)ds$$

where $t^* \in (t-1, t)$. After a bit of algebraic manipulation, we obtain the likelihood function

$$\log L \sum_{i=1}^{N} \sum_{t=1}^{T} y_{it} \left[\begin{array}{c} (1-d_i) \log \int_{\delta_{t-1}^1 - X_{1i}\beta_1}^{\delta_t^1 - X_{1i}\beta_1} \int_{[\delta_t^2 - X_{2i}\beta_2]+h_1}^{\infty} f(\epsilon_1,\epsilon_2) d\epsilon_1 d\epsilon_2 \\ +d_i \log \int_{\delta_{t-1}^2 - X_{2i}\beta_2}^{\delta_t^2 - X_{2i}\beta_2} \int_{[\delta_t^1 - X_{1i}\beta_1]+h_2}^{\infty} f(\epsilon_1,\epsilon_2) d\epsilon_1 d\epsilon_2 \end{array} \right]$$

where

$$\begin{aligned}
-\infty &< \delta_1^1 < \delta_2^1 < ... < \delta_T^1 < \infty, \\
-\infty &< \delta_1^2 < \delta_2^2 < ... < \delta_T^2 < \infty, \\
h_1 &= [(\epsilon_1 - (\delta_t^1 - X_{1i}\beta_1))\lambda_t] \\
h_1 &= [(\epsilon_2 - (\delta_t^2 - X_{2i}\beta_2))/\lambda_t], \quad \text{and} \\
\lambda_t &= \frac{\delta_t^2 - \delta_{t-1}^2}{\delta_t^1 - \delta_{t-1}^1} \quad \text{for } t = 2, ...T-1 \ \text{ with } \ \lambda_1 = \lambda_T = 1
\end{aligned}$$

2.7.3 History of Property Tax Abatement (Circuit-Breaker) Programs for the Elderly

	Form of relief	Earliest legislation	Eligibility floor / ceiling: Age	Eligibility floor / ceiling: Income (1976)	Eligibility floor / ceiling: Wealth (1976)	Estimated Number of beneficiaries: 1976	Estimated Number of beneficiaries: 1985	Estimated Number of beneficiaries: 1994	Average benefit per person: 1976	Average benefit per person: 1985	Average benefit per person: 1994
Northeast region											
CT	2	1974	65, widows 50	$7,500		***	24,137	36,238	$243.70	$289.83	$449.52
ME	3	1971	62, widows 55	$4,500/$5,000	$20,000	16,000	20,137	17,562	$209.10	$278.00	$321.00
NJ	2	1990	none	***		***	***	1,447,191	***	***	$214.00
NY	2	1978	65	$3,000*		***	296,878	449,718	***	$73.20	$96.00
PA	3	1971	65, all widows	$7,500		413,974	441,637	417,115	$142.32	$222.66	$262.88
RI	3	1977	65	$7,500		***	2,039	3,836	***	$176.80	$170.28
VT	3, (1 optional)	1969	none	none[a]		36,516	21,622	47,046	$210.05	$259.48	$514.95
Midwest region											
IL	3	1972	65, all disabled	$10,000		290,000	315,000	384,000	$250.00	$250.00	$272.00
IN	1	1985	65	***		***	***	***	***	***	***
IA	3	1973	65, widows 55	$8,000		83,800	53,000	42,896	$114.56	$200.50	$245.31
KS	3	1970	60, all disabled	$8,190		62,955	52,994	50,397	$140.17	$157.51	$196.00
MI	1	1973	none	none		1,234,800	1,523,100	1,655,200	$223.18	$396.77	$535.29
MN	3, (1 optional)	1967	none	none		857,277	***	463,000	$156.54	***	$290.00
MO	1	1973	65	$7,500		56,260	44,565	68,600	$124.57	$138.17	$263.69
ND	3	1969	65, all disabled	$5,000		9,969	8,206	6,576	$120.20	$215.61	$332.23
OH	2	1971	65, all disabled	$10,000		329,462	353,842	263,973	$135.42	$134.44	$201.74
SD	2	1976	65	$2,400/$4,000		15,095	5,877	7,580	$98.51	$110.75	$175.28
WI	1	1964	none	$7,000		234,201	284,000	238,838	$205.55	$370.00	$458.00
West region											
AZ	1	1973	65	$3,500/$5,000		38,619	***	24,566	$200.19	***	$274.08
CA	3	1967	62	$20,000		***	85,000	24,625	***	$92.00	$85.32
CO	1	1971	65, widows 58	$5,400/$6,300	$20,000	58,875	55,468	39,262	$187.00	$270.80	$344.00
ID	2	1974	65, all widows	$5,500		17,323	17,417	22,324	$231.00	$181.00	$336.04
MT	2	1981	62	***		***	15,428	19,070	***	$194.45	$265.62
NV	3	1973	62	$10,000		10,560	10,639	12,550	$127.84	$168.00	$210.00
NM	1	1977	none	$6,000		***	22,100	25,663	***	$100.44	$157.05
OR	1	1971	none	$15,000		502,575	343,052	***	$147.62	$232.00	***
UT	2	1977	65	$4,000/$4,500		10,000	14,523	***	$95.00	$113.22	***
WY	2	1975	65	$4,000/$6,000		***	***	9,181	***	***	$521.00
South region											
AR	1	1973	65, widows 62	$8,000		8,916	36,439	30,747	$75.76	$91.20	$118.34
DC	1	1974	none	$20,000		12,632	16,239	11,859	$285.00	$352.85	$377.00
MD	2	1975	60	none	$150,000	8,863	8,977	16,003	$248.12	$413.22	$662.02
OK	1	1974	65	$6,000		4,159	1,979	3,387	$85.93	$89.41	$117.45
TN	3	1973	65	$4,800		***	70,000	78,432	***	$87.11	$89.68
WV	3	1972	65	$5,000		***	106	***	***	$17.72	***

Codes for form of relief:
1 = state income tax credit or rebate
2 = reduction in tax bill
3 = state rebate

*** = information not available
[a] - "none" indicates benefits based upon property taxes being above a certain pergentage of income

Figure 2-1: Property Tax Incidence

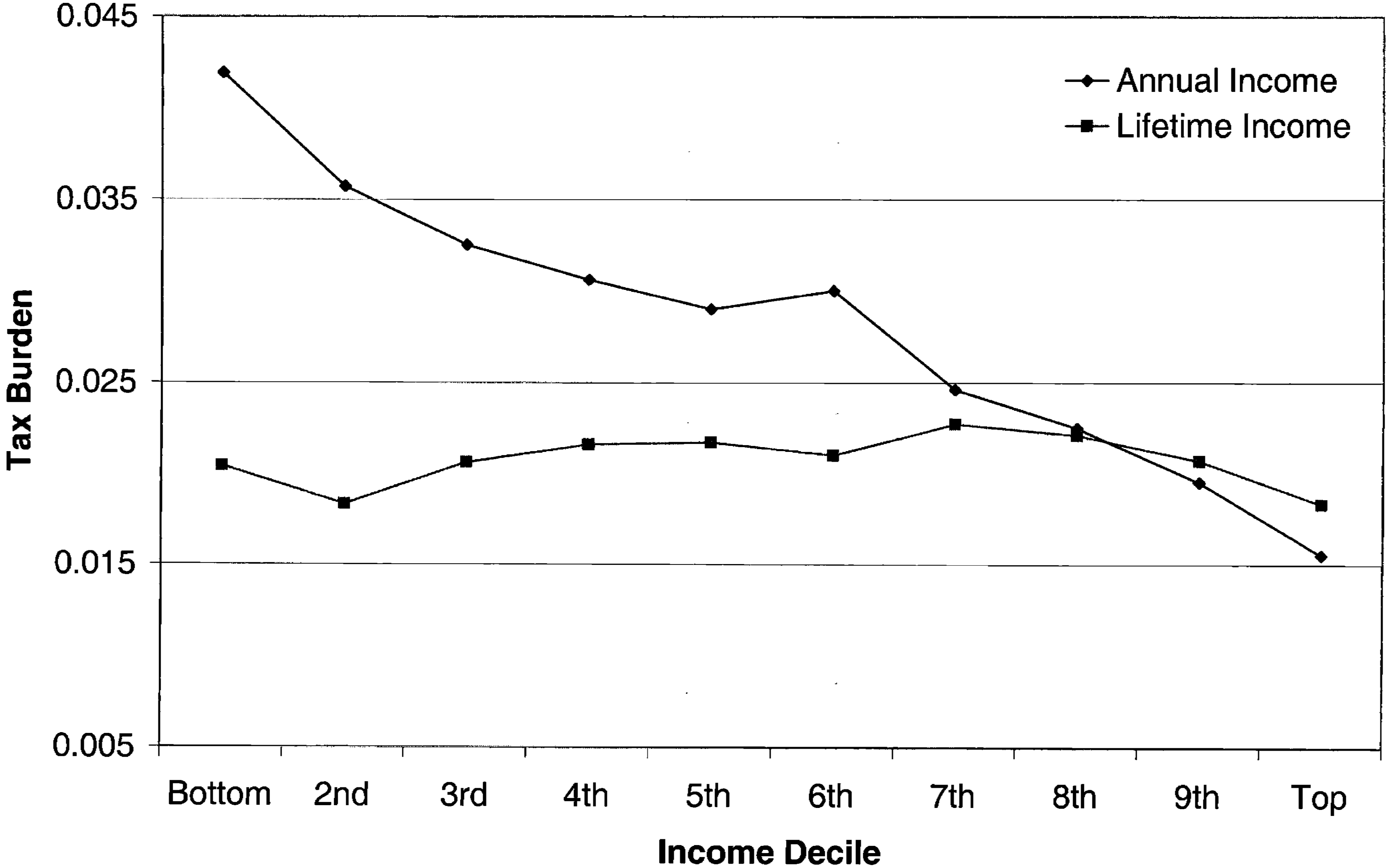


Figure 2-2: Hazard function, HHM with Linear Ratio Measure

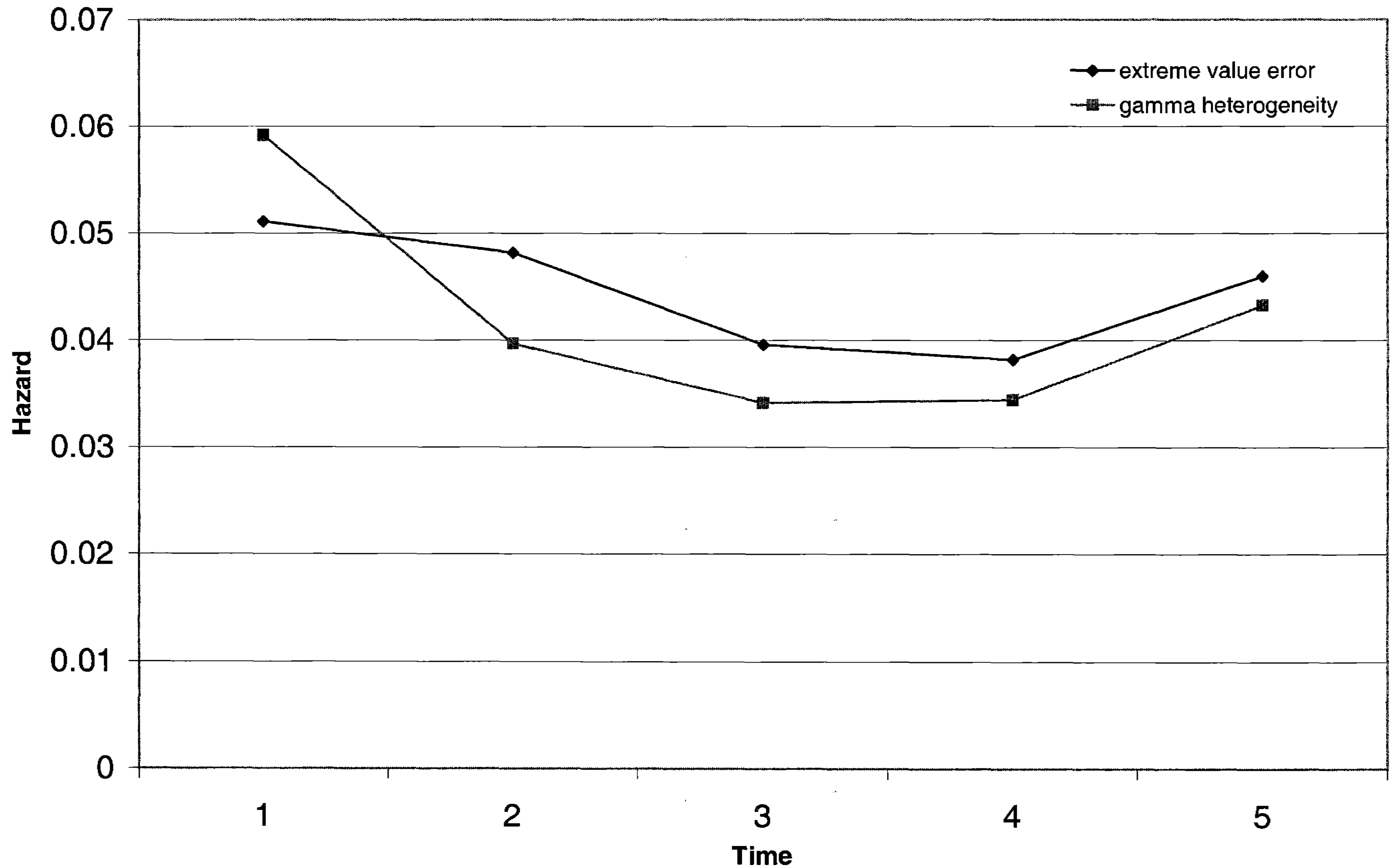


Figure 2-3: Hazard function, HHM with Quartile Ratio Measure

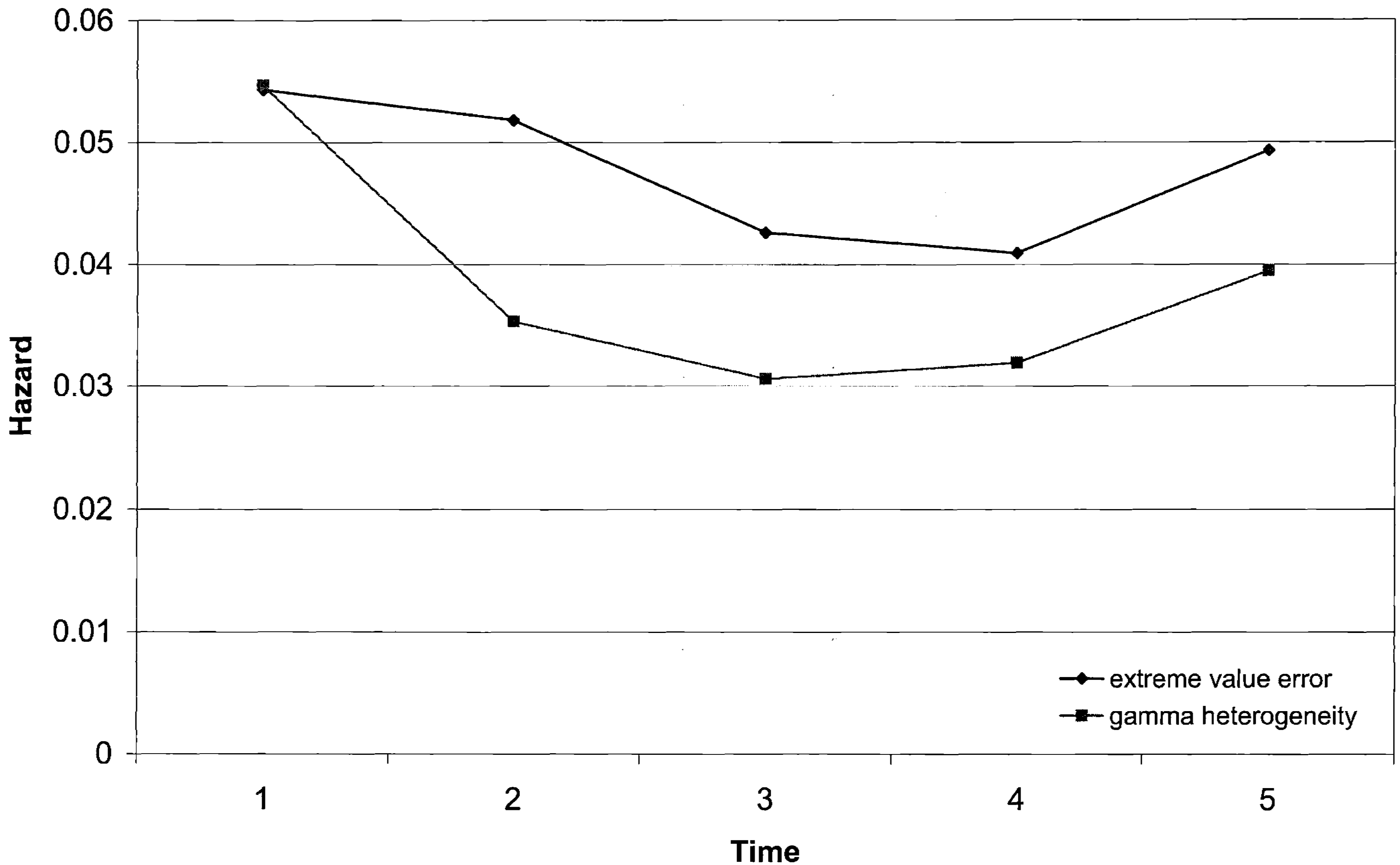


Figure 2-4: Hazard function, log-logistic model

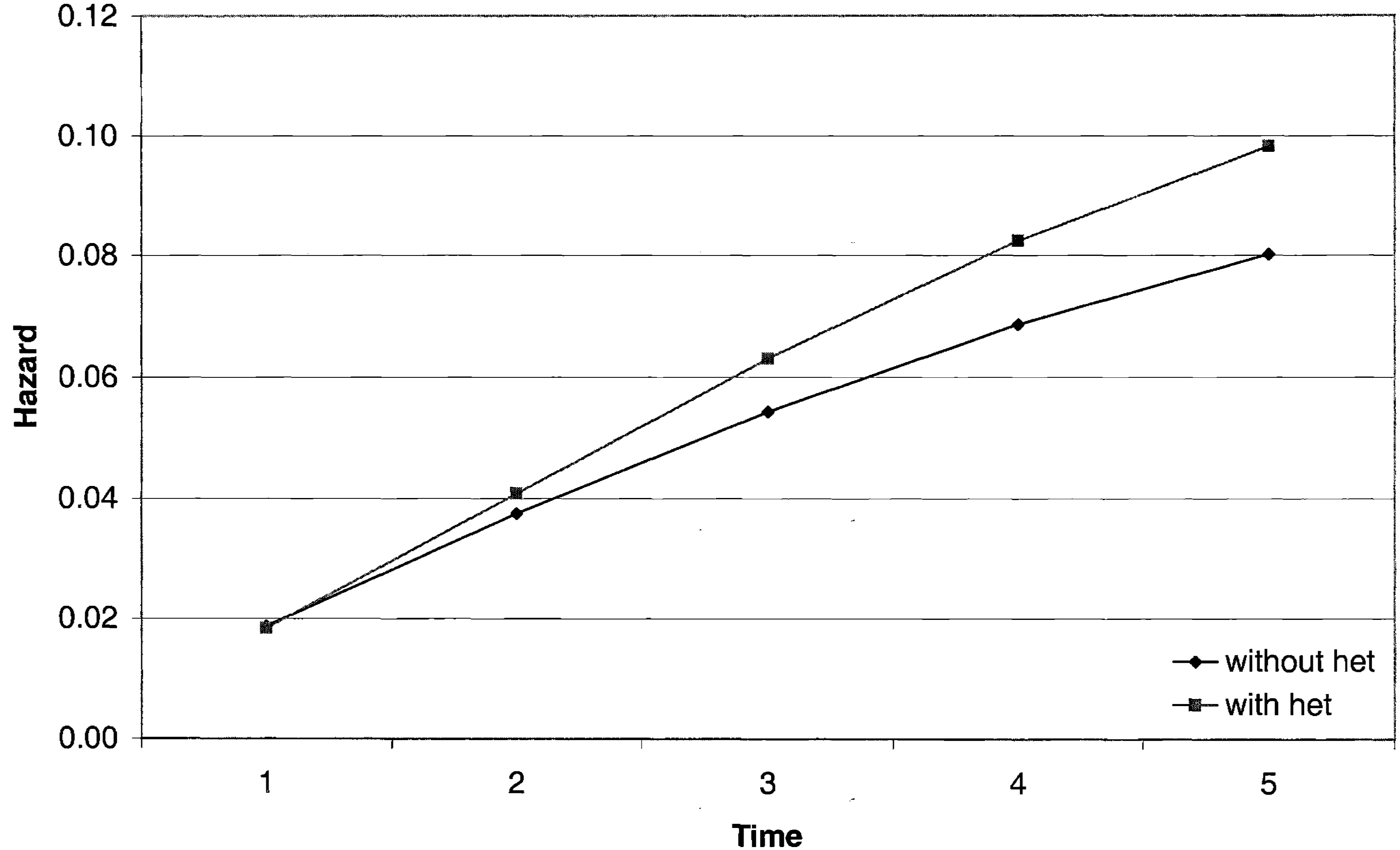
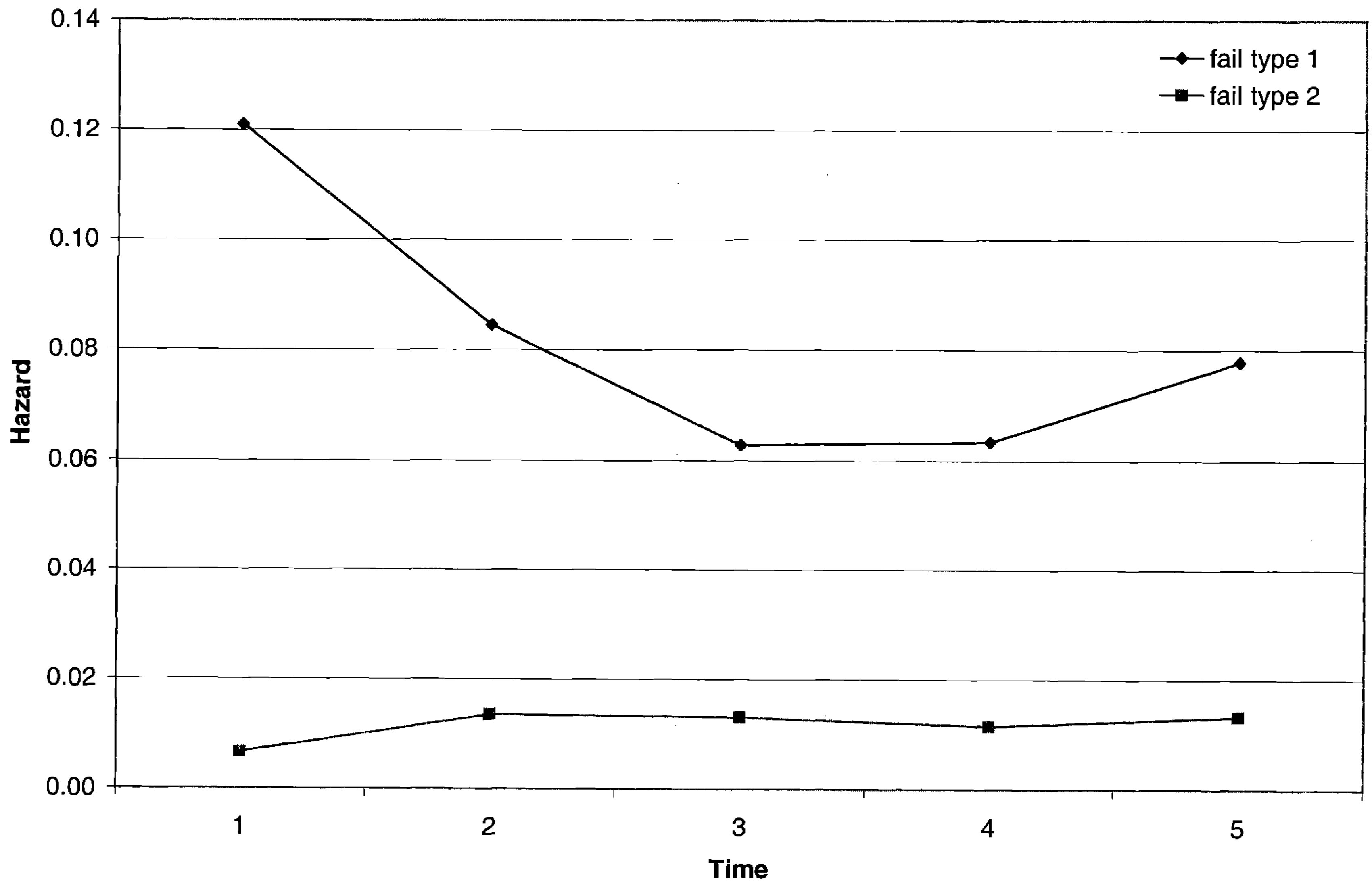


Figure 2-5: Hazard function, bivariate HHM model



Chapter 3

Neighborhood Wealth Distributions

3.1 Introduction

Research in economics and sociology has drawn attention neighborhood sorting of individuals according to income and other characteristics. Following Tiebout (1956), individuals are seen to sort themselves into communities according to their preferences for local public services. While the literature in the Tiebout tradition has been able to explain income stratification across communities, it has also in a sense predicted too much stratification. This has been remedied by recent contributions, especially by the work of Epple and Platt (1998), Epple, Romer and Sieg (1999) and Epple and Sieg (1999). Epple and Platt show that if individuals differ with respect to income and an additional characteristic, then the resulting sorting at equilibrium is partial but incomplete. Individuals with identical incomes may be found in different communities at equilibrium, which accords with the facts. Since the additional characteristic could be a preference parameter, or a socioeconomic characteristic other than income, such an outcome would be consistent with a variety of motives. The determinants of residential sorting are important to policy makers as well. For example, local communities, state governments and even the U.S. government have staked out positions on the desirability of income (and ethnic) mixing in residential patterns and adopted policies to promote them.

This paper aims at a better understanding of the distribution of income and wealth within urban neighborhoods and contrasts them with the national income and wealth distribution. It uses the American Housing Survey neighborhood clusters data for metropolitan areas in the United States. Ioannides (1999), Hardman and Ioannides (1998) and Ioannides (2001) also use the same data for studying neighborhood income distributions. Using US government definitions of income categories, Hardman and Ioannides describe the extent of income mixing in US residential neighborhoods, defined as comprised of a randomly selected household and ten nearest neighbors of the basic random sample. They find that low income households are widely represented in small neighborhoods: very low and extremely low income households are present, for example, in almost nine- tenths of all US neighborhoods. In three out of five neighborhoods sampled, the poorest two or three households (out of ten) come from the poorest 30 % of the population. High income households (the richest 30 %) are widely distributed. They are present in almost three fourths of all neighborhoods, and are represented by at least two or three households out of ten in about two in about two fifths of all neighborhoods. Most previous work on neighborhood sorting has used contextual information associated with the census tract where a unit of observation belongs. The importance of analysis at the micro neighborhood level is emphasized by the work of Thomas Schelling [Schelling (1978))].

If individuals differ with respect to many characteristics, observed imperfect sorting would be consistent with different behavioral patterns. Sorting according to income is particularly interesting. But, economic theory provides little or no guidance regarding sorting in terms of other characteristics on their own. Here we examine neighborhood sorting in terms of wealth. Differences among individuals in terms of income may not necessarily imply differences in terms of wealth. That is, neighborhoods may be mixed in terms of people of different ages, whose incomes differ because they happen to be on different points in the life cycles and but whose wealths might differ by less. Although it is known that wealth is more unequally distributed than income in the entire economy,

The paper aims at mitigating a basic difficulty one encounters in studying neighborhood wealth distributions, which is due to unavailability of direct data. Micro data on housing wealth and debt are the only components of wealth that are available within the AHS. The paper exploits a fortuitous occurrence, that is, availability of data from on wealth, income and other socioeconomic characteristics from the Panel Study of Income Dynamics and its wealth supplement for 1989, which may be used to predict household wealth based on data on neighbors' characteristics in AHS. It then compares the distribution of income and wealth across neighborhoods, metropolitan areas, regions as well as the entire US.

Our comparisons rest on a decomposable inequality index due to Bourguignon [Bourguignon (1979); see also Shorrocks (1999)]. This index allows us to compare the contribution to total inequality of dispersion in income and wealth at different levels of geographic disaggregation.

The remainder of this paper is organized as follows. Section 3.2 outlines an intuitive model of neighborhood sorting. Section 3.3 discusses the data, where we explain how we combine data from both the American Housing Survey and the Panel Study of Income Dynamics. Section 3.4 presents the results and 3.5 concludes.

3.2 Neighborhood Sorting

We fix ideas and set notation as follows. Let $\mathcal{I}$ denote a set comprising of all individual members of the economy at each of the time periods when the data are collected, possibly very large, and let I denote the total population of the economy at the corresponding time, $I = |\mathcal{I}|$. Let $F(y)$ denote the distribution function of household income y in the entire economy. Suppose the population is distributed into N different geographical areas, neighborhoods, $\mathcal{I}_\nu$, $\nu = 1, \ldots, N$, each with population $I_\nu = |\mathcal{I}_\nu|$, and neighborhood distribution function F_ν, $\nu = 1, \ldots, N$. The decomposition of the population into neighborhoods is assumed to be exhaustive: $\mathcal{I} = \bigcup_{\nu=1}^{N} \mathcal{I}_\nu$. We will make this assumption for simplicity. In that case, the *the national income distribution,* is given by:

$$F(y) = \sum_{\nu=1}^{N} \frac{I_\nu}{I} F_\nu(y). \tag{3.1}$$

We shall say that the national income distribution exhibits *perfect mixing,* if all neighborhood income distributions are identical to the national one: $F_\nu(y) \equiv F(y),\ \forall \nu$. It exhibits *perfect sorting,* if the supports of the neighborhood income distributions do not overlap. E.g., in the simplest case where the $F_\nu(y)$'s are degenerate, then: $F_\nu(y) = 1, \text{if } \ y = y_\nu;\ F_\nu(y) = 0, \text{if } y \neq y_\nu, \forall \nu$, and where all the y_ν's are all different. The objective of decomposable inequality indices is to express an inequality measure for $F(\cdot)$ in terms of those for the $F_\nu(\cdot)$'s.

Why should income distributions differ across neighborhoods? To answer this question requires that we consider how individuals sort themselves into neighborhoods. Let individuals differ in terms of income y, and of a preference characteristic. In terms of the above notation, how do individuals allocate themselves) into N neighborhoods so as $F(y)$ decompose into the $F_\nu(y)$'s, as in Equ. (3.1)?

In the Epple and Sieg (1999) sorting model, individuals sort themselves into neighborhoods according to their evaluation of a neighborhood characteristic and of the price of housing in each neighborhood. If individuals do not differ in terms of their evaluation of the neighborhood characteristic, then the neighborhood income distributions are simply doubly truncated segments of the national distribution. The double truncation occurs because individuals have to choose from a discrete set of alternatives, indexed by housing prices. For any two neighborhoods characterized by different prices, there exists a value of income which makes an individual indifferent between the respective two alternatives. If, on the other hand, individuals' evaluations differ, the neighborhood income distribution extends over the entire support of the national income distribution, even if income and the individual preference characteristic are uncorrelated. That is, for each individual there exists a threshold value of income, which determines location between any two alternatives. Since the threshold depends on the individual's preference characteristic, even if it is uncorrelated with income, preference heterogeneity causes the truncation points to differ across individuals, thus producing a greater income dispersion within each neighborhood. As Hardman and Ioannides (1998) and Ioannides (2001) argue, neighborhood selection may cause bimodal neighborhood income distributions to emerge at equilibrium sorting. This is more likely to happen, the closer the neighborhood mean income is to mean national income.

This basic model of sorting can be extended to the case of individuals' differing with respect to other observable characteristics. Since several observable characteristics are good predictors of household wealth, our strategy is to use predictions of household wealth, obtained from micro data to infer properties of neighborhood wealth distributions.

3.2.1 Decomposable Measures of Inequality

In order to assess the importance of the neighborhood component of income and wealth distributions, it would be helpful to be able to measure inequality at every level of aggregation. The population-weighted decomposable inequality index proposed by Bourguignon (1979) allows exactly that. It is defined as the logarithm of the arithmetic mean minus the geometric mean of income, that is, the mean of the logarithms of income, within each grouping of the population. Proposition 4 in Bourguignon (1979) proves that this measure is the only differentiable, symmetric and zero-homogeneous in incomes *population-weighted* decomposable measure.[1] That is, the inequality measure for a group of size I_ν with incomes $(y_1, \ldots, y_j, \ldots, y_{I_\nu})$ is:

$$L_\nu(y_1, \ldots, y_j, \ldots, y_{I_\nu}) = \ell n \left(\frac{1}{I_\nu} \sum_{j=1}^{I_\nu} y_j \right) - \frac{1}{I_\nu} \sum_{j=1}^{I_\nu} \ell n y_j. \tag{3.2}$$

Concavity of the logarithm function ensures that the Bourguignon measure is positively valued; it is equal to zero for the case of equality. The higher its magnitude, the greater the inequality in the underlying distribution. The inequality index for a population consisting of groups of sizes $\{I_1, \ldots, I_\nu, \ldots, I_N\}$ is given by:

$$L = \sum_{\nu=1}^{N} \frac{I_\nu}{I} L_\nu + L_N(\bar{y}_{I_1}, \ldots, \bar{y}_{I_1}, \ldots, \bar{y}_{I_\nu}, \ldots, \bar{y}_{I_\nu}, \ldots, \bar{y}_{I_N}, \ldots, \bar{y}_{I_N}), \tag{3.3}$$

where $\bar{y}_{I_\nu}$ denotes mean income in group ν, and $\sum_{\nu=1}^{N} I_\nu = I$. That is, the index for a population which consists of the N neighborhoods of sizes $\{I_1, \ldots, I_\nu, \ldots, I_N\}$ is defined as the average value of the index among all groups, the first term in the RHS of (3.3) plus the index defined for the entire population, with each individual being assigned the mean income for the group to which she belongs. The second term in the RHS of (3.3) may be written out as:

$$L_N = \ell n \left(\frac{1}{I} \sum_{\nu=1}^{N} I_\nu \bar{y}_{I_\nu} \right) - \frac{1}{I} \left(\sum_{\nu=1}^{N} I_\nu \ell n \bar{y}_{I_\nu} \right). \tag{3.4}$$

[1]Proposition 5 in *ibid.* proves that Theil's coefficient, also known as Theil's entropy measure, is the only decomposable *income-weighted* measure.

For small deviations, the measure may be approximated by the average relative deviations around the geometric mean, $\bar{y}^g = \frac{1}{I}\sum_{j=1}^{I} \ell n y_j$. That is: $\frac{1}{I}\sum_{j=1}^{I} y_j = \bar{y}^g \frac{1}{I}\sum_{j=1}^{I} \frac{y_j - \bar{y}^g}{\bar{y}^g}$. By taking logarithms, we have: $L \approx \frac{1}{I}\sum_{j=1}^{I} \frac{y_j - \bar{y}^g}{\bar{y}^g}$.

Here is why the decomposability of the Bourguignon measure is particularly useful in describing the contribution to inequality from hierarchical levels of aggregation.In our data, observations are classified into: Census regions, $r = 1, \ldots, R$; each region r contains $s = 1, \ldots, S_r$; MSAs, each MSA s contains $\nu = 1, \ldots, N_s$ neighborhood clusters; and, each cluster ν contains I_ν observations. That is, we may consider that (3.3) measures inequality within an SMSA s, in terms of the inequality within each neighborhood cluster $\nu = 1, \ldots, N_s$, where we apply (3.2), Therefore, inequality within a region r is made up of the sum of the mean inequality across all SMSAs in the region, $s = 1, \ldots, S_r$, plus the index defined for the entire set of SMSAs, with each SMSA being assigned the mean wealth for the group to which it belongs. Equ. (3.2) is used first, for each neighborhood cluster in the data, and then it is applied at the level of each SMSA according to (3.3) and (3.4). Then these computations are aggregated at the level of the region and then again for the entire country. Descriptive statistics for the Bourguignon measure across SMSAs and for aggregate measure for each of four regions are reported in Table 3-4. Decomposability, even after it has been generalized [Shorrocks (1980; 1999)] comes, unfortunately, at the price of exclusion of zero or of negatively valued variables.

3.3 Data

The empirical investigation reported here is based on data from the 1989 wave of the American Housing Survey (AHS) and on data from the 1989 wave of the Panel Study of Income Dynamics (PSID). We discuss first the AHS data and then the PSID data.

The AHS is a panel of housing units and involves more than 50,000 dwelling units that are interviewed each two years. This paper explores an additional dimension of the urban subsample of the data, namely data on neighborhood clusters, which are available for years 1985, 1989, and 1993. In those years only, a random sample of originally 680 (and subsequently more)urban units were selected and for each one of them a number of neighbor units, usually ten, were interviewed. Each such cluster includes the randomly chosen member of the national file (which is an urban AHS unit), the so-called *kernel,* and the ten homes closest to it [Hadden and Leger (1990), p. 1-51]. The cluster may contain fewer than 10 units if some could not be interviewed. The total number of observations for 1989 was 8433, however, only 7705 were usable for estimation purposes due to missing data. A basic set of descriptive statistics are given in Table 3-1. Among household heads, 84.1% are white, with an average age of 48.4 years, and 60.9% owner occupants. For additional details on the data, see Hardman and Ioannides, *op. cit.,* and Ioannides, *op. cit.*.

The AHS does not contain information on wealth. While we could pursue an analysis of dispersion of household characteristics within neighborhoods, we think that predicting the dispersion of wealth within and across neighborhoods provides a meaningful way to summarize dispersion in terms of a multitude of characteristics. We proceed by using data from another micro data, the PSID, which provides comparable detail in terms of socioeconomic characteristics. Both data sets' 1989 surveys provide 1988 data.

The PSID, begun in 1967, is a annual longitudinal survey of a representative sample of U.S. individuals and the households in which they live. The main (family) survey includes a variety of economic and demographic data, with emphasis on income sources and amounts, employment, and changes in family composition [Hill (1992)]. In 1989, but also in 1984 and in 1994, the PSID includes a supplement on household wealth. In this paper, we employ the 1989 main PSID data set and wealth supplement as a means of predicting wealth in the 1989 wave of AHS data including the neighborhood cluster survey. The 1989 main survey includes data from 7114 heads of household and their wives (if applicable). Referring again to Table 3-1, we see that 84.5% of respondents are white, 60.9% of respondents are home-owners, and their average age is 47.2 years. With regard to housing tenure, 54.1% own their home. Average real net wealth is $108,043, with a standard deviation of $8494. Unlike the AHS, the PSID main survey includes very limited contextual (geographical) data. Households are identified by state and county only. Hence, by using these data sets together, we are able to predict household wealth within much smaller geographic areas than we would be able to by using the PSID alone.

The computations of the Bourguignon measure of inequality for income and house value are straightforward, that for wealth generates a practical difficulty. Of 7114 observations nearly 10%, that 687 observations, are negatively valued and additional 675 observations have zero values for wealth. In the entire sample, the mean is equal to \$ 85,416, while the mean among the negative values is \$ -7,661. For these observations, the Bourguignon measure cannot be computed. The standard deviation of real wealth is equal to \$ 1,035,739, and is obviously influenced by the minimum value of \$ -659,249 and the maximum value of \$ 84,500,000. In order to compute the Bourguignon measure without having to delete all observations with negative and zero values, we computed the measure by adding, alternatively, the values of \$ 5000, \$7500, \$ 10000 and \$ 12500. We report results with all those samples, which allows us to assess the sensitivity of this obviously arbitrary procedure.

3.4 Results

Real wealth is defined as assets minus liabilities. Assets include both financial assets and real assets like housing, etc. Letting Ω_i, Y_i, and X_i, denote, respectively, real wealth, income and a vector of socioeconomic characteristics for individual i. The basic regression we use to predict real wealth is:

$$\Omega_i = a_0 + a_1 Y_i + AX_i, \tag{3.5}$$

where a_0, a_1, are scalar parameters and A a vector of parameters. The vector of individual characteristics was limited to variables available in both data sets, to insure the most accurate predictions of wealth later on. In order to constrain our predictions of wealth to positive values, we carried out weighted OLS regressions in logs, and one Tobit regression, in which the dependent variable was truncated at a value of one and then logged. Regression results are reported in Table 3-2.

The OLS regressions produced reasonably good fits, with the fit worsening as the adjustment of the wealth measure increased. The Tobit regression, unfortunately, did not perform as well as we had hoped, both in terms of fit (R^2 of 0.13 versus 0.60) and signs of coefficients as expected. Home ownership, as might be expected, had the largest and most statistically significant effect on total net wealth in all regressions. Among other personal characteristics, age, sex, race, highest grade completed, and number of children had more modest, but significant, effects.[2]

Using the predicted values of wealth for individuals within neighborhoods, we calculated Bourguignon statistics aggregated at the SMSA, regional, and national level. The results can be found in Table 3-3, along with the Bourguignon statistics for income and housing value. As one would expect, in all categories, the degree of mixing in all categories grew as the level of aggregation increased. Housing value showed the smallest amount of mixing at all levels, followed by income, and then total net wealth. No particular region showed greater mixing across categories than any other region. In our sensitivity analyses, the Bourguignon statistic for wealth decreased as the amount of the adjustment increased, implying that the closer the prediction of wealth gets to the "unbiased" prediction, the greater the dispersion of wealth at both the SMSA and regional levels. Only with a $15,000 adjustment did the dispersion of predicted wealth at either level of aggregation dip below the dispersion level of income.

3.5 Conclusion

Given that ours is the first study using decomposable indices to compare income and wealth mixing at various levels of aggregation, we are hard pressed to comment on the closeness of our results to the true measures of mixing. Hence we set these numbers out as a benchmark for future studies in the area of spatial economics as it relates to inequality. The results, however, do support the findings of Epple and Platt (1998) in that individual sorting by both income and wealth results in partial but incomplete sorting in both characteristics. Given that mixing is greater in wealth than in income, our findings thus do not support the hypothesis that the substantial income mixing [as found in Hardman and Ioannides (1998)] masks sorting on a secondary level, that of wealth. Work with more general measures, as proposed by Shorrocks (1999), appears to be promising.

[2]Ideally, we would have liked to regress nonhousing wealth on housing wealth, income, and our vector of demographic characteristics, predict nonhousing wealth, and add that to the data on housing wealth that already exists in the AHS. Unfortunately, the AHS data on residual mortgages (or housing "debt") proved to be extremely unreliable in terms of the number of missing values/nonresponses.

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Table 3-1: Descriptive Statistics

PSID descriptive statistics, weighted values

Number of observations (*) = 7114

Mean	Estimate	Standard Error
assets89	124891.3	8552.468
rwlth89	108042.8	8494.309
rhouse89	47583.55	1146.364
equity89	33055.77	992.7519
nhasst89	77307.76	8191.085
nhwlth89	74987.02	8191.492
hdebt89	14527.77	452.7575
odebt89	2320.747	153.8509
rinc89	30682.47	665.5357
age89	47.16219	0.2874708
sex89	0.6804662	0.0074208
white89	0.8454902	0.0052153
marry89	0.5256161	0.0076463
widow89	0.1247432	0.0055283
divor89	0.1835509	0.006235
own89	0.6086501	0.007408
grade89	12.57423	0.0456688
retd89	0.1979552	0.0065327
child89	0.6687234	0.0144879
moved88	0.2146381	0.0061473
ne	0.2149494	0.0065462
so	0.3294724	0.0069362
west	0.179298	0.0058561

(*) Some variables contain missing values

key to variables:

assets89	gross worth
rwlth89	net worth
rhouse89	gross housing wealth
equity89	net housing wealth
nhasst89	gross nonhousing wealth
nhwlth89	net nonhousing wealth
hdebt89	mortgage debt
odebt89	other debt
rinc89	family money income
linc89	log of family income
own89	homeowner
grade89	highest grade completed
retd89	retired
child89	number of children
moved88	whether moved in past year
ne	northeast region
so	southern region
west	western region

AHS descriptive statistics

Number of observations = 7705

Variable	Mean	Std. Dev.
linc89	10.02168	0.9187738
rinc89	31741.52	25967.76
age89	48.39883	17.16288
sex89	0.6716418	0.4696464
white89	0.8407528	0.3659302
marry89	0.5645685	0.4958456
widow89	0.1117456	0.3150737
divor89	0.1671642	0.3731466
retd89	0.219987	0.4142644
own89	0.6093446	0.487929
grade89	12.71019	3.249648
child89	0.7358858	1.165193
moved88	0.2495782	0.432797
ne	0.2628164	0.4401921
so	0.2725503	0.4453003
west	0.2743673	0.4462239

Descriptive statistics for predicted wealth

Number of observations = 5168

Variable	Mean	Std. Dev.
5K adjustment	66186.00	62746.11
7.5K adjustment	68705.69	60261.22
10K adjustment	71666.92	58986.56
12.5K adjusment	74446.12	57924.33
15K adjustment	77929.20	57848.11

Table 3-2: Regression Results

	5K adjustment	7.5K adjustment	10K adjustment	12.5K adjustment	15K adjustment
linc89	0.2527	0.2322	0.2165	0.2091	0.2009
	(0.0476)**	(0.0445)**	(0.0421)**	(0.0401)**	(0.0386)**
age89	0.0464	0.0433	0.0432	0.0397	0.0379
	(0.0059)**	(0.0054)**	(0.0051)**	(0.0048)**	(0.0046)**
age2	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(0.001)**	(0.0001)**	(0.0001)**	(0.00004)**	(0.00004)**
sex89	0.1996	0.1707	0.1465	0.1284	0.1058
	(0.0495)**	(0.0467)**	(0.0421)**	(0.0401)**	(0.0368)**
white89	0.2706	0.2255	0.2224	0.1763	0.1604
	(0.0407)**	(0.0389)**	(0.0385)**	(0.0347)**	(0.0329)**
marry89	0.0350	0.0876	0.0753	0.0630	0.0690
	(0.0643)	(0.0607)	(0.0556)	(0.0523)	(0.0511)
widow89	-0.1425	-0.0906	-0.1194	-0.1275	-0.1309
	(0.0727)*	(0.0679)	(0.0639)	(0.0606)*	(0.0573)*
divor89	-0.2428	-0.1749	-0.1713	-0.1841	-0.1737
	(0.0549)**	(0.0515)**	(0.0457)**	(0.0445)**	(0.0411)**
retd89	0.0351	0.0168	0.0090	0.0115	0.0086
	(0.0581)	(0.0525)	(0.0498)	(0.0478)	(0.0460)
own89	1.3266	1.1729	1.0652	0.9953	0.9163
	(0.0447)**	(0.0401)**	(0.0374)**	(0.0360)**	(0.0330)**
grade89	0.1034	0.0981	0.0904	0.0871	0.0784
	(0.0221)**	(0.0202)**	(0.0187)**	(0.0182)**	(0.0169)**
grade2	-0.0003	-0.0004	-0.0004	0.0005	-0.0002
	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
child89	-0.0702	-0.0624	-0.0529	-0.0537	-0.0498
	(0.0148)**	(0.0137)**	(0.0128)**	(0.0126)**	(0.0118)**
moved88	-0.0392	-0.0448	-0.0201	0.0079	-0.0016
	(0.0421)	(0.0380)	(0.0345)	(0.0327)	(0.0309)
ne	0.2418	0.2291	0.2244408	0.2109	0.1955
	(0.0448)**	(0.0413)**	(0.0391)**	(0.0381)**	(0.0363)**
so	0.0036	-0.0078	-0.0128023	-0.0115	-0.0174
	(0.0369)	(0.0346)	(0.0330)	(0.0309)	(0.0291)
west	0.2126	0.1827	0.1762174	0.1591	0.1540
	(0.0442)**	(0.0409)**	(0.0383)	(0.0368)**	(0.0344)**
constant	3.8505	4.4993	4.962486	5.3906	5.7664
	(0.4051)**	(0.3767)**	(0.3586)**	(0.3389)**	(0.3243)**
R^2	0.6020	0.5921	0.5855	0.5691	0.5667
N	6865	6917	6962	6983	6990

* significant at the 5% level
**significant at the 1% level
Dependent variable is log of wealth, with adjustments as indicated

Table 3-3: Bourguignon Statistics

	Income	Housing Value (rhouse>0)	Total Predicted Wealth 5K adj	Total Predicted Wealth 7.5K adj	Total Predicted Wealth 10K adj	Total Predicted Wealth 12.5K adj	Total Predicted Wealth 15K adj.
Northeast	0.43726	0.4158886	0.7381022	0.6210442	0.5365573	0.4745321	0.4239671
	(1546)	(724)	(1546)	(1546)	(1546)	(1546)	(1546)
South	0.5158966	0.3585368	0.7770654	0.655346	0.5699251	0.5018961	0.4515758
	(1236)	(591)	(1236)	(1236)	(1236)	(1236)	(1236)
West	0.4227946	0.401548	0.9555831	0.8032646	0.6909792	0.6111535	0.5463476
	(1519)	(660)	(1519)	(1519)	(1519)	(1519)	(1519)
Midwest	0.4388515	0.4024127	0.7303269	0.6158032	0.5326092	0.4674194	0.4183921
	(867)	(415)	(867)	(867)	(867)	(867)	(867)
Mean across Regions	0.4537007	0.3945965	0.8002694	0.6738645	0.5825177	0.5137503	0.4600706
Variance across Regions	0.0420884	0.0249204	0.1055422	0.0880311	0.0742197	0.0666146	0.0593196
	(4)	(4)	(4)	(4)	(4)	(4)	(4)
Entire Sample	0.6113116	0.3012571	1.141562	0.9626265	0.8332546	0.7358152	0.6594054
	(5168)	(2390)	(5168)	(5168)	(5168)	(5168)	(5168)
Mean across SMSAs	0.2680944	0.1865654	0.4296821	0.360368	0.3102671	0.2730156	0.2438591
Variance Across SMSAs	0.1508328	0.144781	0.2424982	0.2029802	0.1735408	0.1520774	0.1357082
	(98)	(96)	(98)	(98)	(98)	(98)	(98)
	PSID income	PSID Housing>0	PSID wealth	AHS income	AHS Housing>0	AHS Wealth 5K	
Entire Sample	0.4322367	0.4017668	1.261708	0.3436985	0.3009472	0.5259857	
(Not accounting for grouping)	(7114)	(3847)	(6942)	(7705)	(2965)	(7705)	
				0.3485403		0.5587399	
				(5168)		(5168)	