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Nikolay Dobrinov

University of Colorado

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Center for Economic Analysis
Department of Economics

University of Colorado at Boulder
Boulder, Colorado 80309

The Effect of Proposition 13 on Household Mobility: A Hazard Rate Approach*

(Job Market Paper)

Nikolay Dobrinov†

University of Colorado, Boulder

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Abstract

In 1978 California approved Proposition 13 which limits the annual increase in property taxes for households staying in their homes. Because this is an annual limit, the annual tax savings increase over time. On moving, a household loses this favorable tax treatment. In this paper I estimate the extent to which these tax savings reduce household mobility. The study improves upon previous studies because: (1) I use a duration model to describe the decision to stay in one's home, and (2) I correct for aggregation bias, for omitted variables bias, for measurement error bias in household income and house values, and for the co-determination of property taxes and public service provision. My analysis finds that the hazard rate of duration decreases by 3.6% for each $100 of annual taxes which are saved if the household stays in his home.

JEL: H21, H24, H31, H71, R21, R23, R28.
Keywords: property tax, assessed value, mobility, hazard.

1 Introduction

Under Proposition 13[1], enacted in California in 1978, the increase in the assessed value of a home is limited to no more than 2% per year while the homeowner remains in the home; the assessed value returns back to market value only upon sale or reconstruction (with future assessments likewise restricted to the 2% annual limit). Because the market value of most California properties has increased in many years at annual rates in excess of 10%, the differential between the owner's taxes and the taxes the same owner would pay, if he were

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†Contact: nvdobrin@sewanee.edu; Nikolay Dobrinov, 735 University Ave, Sewanee, TN 37383.

[1]Proposition 13 is a ballot initiative to amend the constitution of the state of California. The initiative was enacted by the voters of California on June 6, 1978, and is embodied in Article 13A of the California Constitution. It generated several changes in the property tax system, applicable for both residential and business property: (1) the maximum property tax rate is set at 1% of the assessed value; (2) the assessed value of each property was rolled back to its value in 1975-76 and since then increases by no more than 2% per year until the house is sold; (3) upon sale or reconstruction the property is reassessed at its full market value, and thereafter assessed value growth is limited to a maximum of 2% per year; and, (4) property transferred to a spouse, between parents and children, etc., is not reassessed.

to move to a similar house, increases the longer the homeowner stays in the house and can become quite large. The loss of property tax relief on moving increases the cost of relocation, and is thereby expected to delay relocation. In this paper I estimate the extent to which the tax relief constraints mobility, and I find that the hazard rate of duration decreases by about 3.6% for each $100 increase in property tax relief.

My finding has important policy implications as removing the property tax relief is likely to increase welfare. Economists view a household as choosing his house size and location to maximise his utility. When a household moves, his new home reflects his contemporaneous circumstances. As time moves forward and his circumstances change, the cost of moving may prevent him from moving although his pre-existing house is no longer the house he would buy if he were to freely re-choose his house. If he does not move, we can think of the household as being in short-run equilibrium but out of long-run equilibrium. By increasing the cost of relocation, the property tax relief hinders his re-optimization. It also hinders Teibout-type[2] sorting between jurisdictions, leading to an inefficient matching of households with public service expenditures[3].

Conceptually we can distinguish between two types of moves: cross-state moves and in-state moves. Cross-state moves usually occur after a job change or some other large change in personal circumstances (e.g. retirement) causes the household to get large benefit by changing his location[4]. In contrast, in-state and particularly local moves may occur after a small change in household circumstances causes a household to wish to change his housing bundle. Potential tax effects are more likely to affect the latter group and Table 1 below shows that this group constitutes between 82% and 88% of all movers[5].

[2]Tiebout predicts that residential sorting can lead to efficient provision of local public goods; if relocation is costless, and if sufficient choice of communities is available, households move to the community that provides their utility-maximizing combination of taxes and public services.

[3]Farnham and Sevak (2006) find that the presence of tax rate and (particularly severe) assessment limits constrain fiscal sorting. Mullins (2003) suggests that Proposition 13 contributes to an inefficient housing market because it provides dis-incentives for selling property. Tugend (May 2006) suggests that the problem of unavailability of housing for new buyers is exacerbated by specifics in the supply and demand of housing in California. Geographical limits and enacted environmental and growth legislation from cities and counties make new development increasingly expensive, while high migration and birth rates contribute to higher demand for housing.

[4]Cross-state moves are driven by differentials in economic opportunities, in cost of living, and in social-group-specific fiscal benefits (welfare programs, estate/inheritance/gift taxes)(Boehm et al. (1989), Cebula (1974, 1978, 2006), Davies et al. (2001), Conway and Houtenville (2003)).

[5]Quigley and Weinberg (1977) find that for the periods between the end of the second world war and 1970, on average 19% of the metropolitan households change residences within a year and 70% of these relocations are within the county. Clark and Dielman (1996) also find that most moves are made over very short distances.

Table 1. Distance of relocation for owners.

Previous location	%	Previous location	%
Same MSA, central city (to central city)	14.69	Different state, central city	3.68
Same MSA, central city (to suburb)	11.82	Different state, suburb	5.37
Same MSA, suburb (to central city)	4.52	Different state, non-metro	1.47
Same MSA, suburb (to suburb)	50.62	Outside U.S.	0.91
Same MSA, total	**81.65**	**Out of state, total**	**11.43**
Same state, different MSA, central city	2.04		
Same state, different MSA, suburb	3.70		
Same state, non-metro	1.18		
Same state, total	**88.57**		

Note: The table presents frequencies on 'Location of previous unit' for owners (information on renters is not included). The question was asked by the American Housing Survey to a subsample of 15,901 recent-movers households (households that bought their home in the last 12 months preceding the month-year of the survey), representing 36 MSAs in 25 States covered in the period 1984-1994.

Table 2 provides some indication of the frequency of moves and the size of the property tax relief provided by Proposition 13 in California. Column 3-4 show that a quarter of all homeowners change residence within three years with the median homeowner relocating every 8^{th} year. Column 7 shows that the median homeowner in California experiences a tax relief of about \$560.

Table 2. Distributions of key variables (period of observation 1984-1994)

	Duration for non-movers		Duration for movers		Effective property tax rate		Property tax relief for households in California	
	CA	NonCA	CA	NonCA	CA	NonCA	All households	Age<55 households
Mean	12.190	12.068	10.337	11.519	0.0053	0.0148	766.557	677.472
SD	11.026	11.903	10.394	11.730	0.0027	0.0251	733.411	636.047
100% Max	73	82	71	86	0.0100	0.3830	5736	4811
99%	44	49	47	53	0.0100	0.0821	3602	3014
95%	34	37	33	37	0.0096	0.0336	2210	1921
90%	29	30	25	29	0.0091	0.0263	1675	1460
75% Q3	18	18	14	15	0.0077	0.0169	1035	911
50% Median	9	8	6	8	0.0052	0.0110	563	506
25% Q1	3	3	3	4	0.0029	0.0073	248	234
10%	1	1	1	1	0.0019	0.0035	97	89
5%	1	1	1	1	0.0014	0.0011	46	45
1%	1	1	1	1	0.0003	0.0000	17	17
0% Min	1	1	1	1	0.0000	0.0000	0	0

Note: The first two columns represent distributions of duration (in years) for households who have not left their home by the last time they were surveyed. The third and fourth columns represent distributions of duration for households who were observed to move out within the period of observation. The fifth and sixth columns represent distributions of effective property tax rates, calculated as self-reported property tax payments divided by self-reported estimate of current market value of the home. The seventh column represents (based on my own calculations) the distribution of effective tax savings (in USD) experienced by all California households. The last column shows distribution of tax savings only for households with oldest spouse of age 54 or younger.

I identify three main contributions to the analysis in the previous literature. To justify estimation I first provide a theoretical model of the household's decision to relocate. In this model the household's moves are positively related to the degree to which a household's consumption of housing services deviates from an optimal bundle of such services, and negatively related to the various adjustment costs associated with changing from one dwelling to another.

Next, I estimate the model around the measurable variation in the hazard rate of duration. Survival analysis, provides a very suitable framework for estimation given the properties of the duration variable.

To correctly identify the sign and magnitude of the effect of the tax savings on mobility, I also address a number of data and methodology issues, akin to the ones hindering empirical analysis of Tiebout sorting. I correct for aggregation bias, for omitted variables bias, for measurement error bias in household income and house values, and for the co-determination of property taxes and public service provision.

In my analysis I find that the hazard rate of duration decreases with about 3.6% for each \$100 increase in the tax savings. Furthermore, I find that the hazard rate increases with time, and the rate of increase of the hazard rate is the same for households residing in and out of California. The data also reveals that the negative effect of Proposition 13, on the mobility of households targeted by Propositions 60 and 90 (See Footnote (16).), has been effectively softened. A more detailed analysis also shows that the main effect of Propositions 13, 60, and 90 on household mobility has been experienced by households that occupy more expensive dwellings; the mobility patterns of households that experience low levels of tax relief are virtually unaffected. Unlike in previous studies, the data also demonstrates a higher propensity to move for California households. This further confirms that the effect of Proposition 13 on mobility has been successfully separated from the effects of other factors.

The rest of the paper is organized as follows. Section 2 discusses in more detail the advantages of duration analysis, over more standard methods of estimation, in studying this particular problem, as well as what methodological issues arise in estimation and how these issues have been addressed in this paper. Sections 3 introduces the theoretical model and clarifies the transition to empirical estimation of this model. Section 4 discusses the estimation strategy. Section 5 discusses the data and the key variables to be used in the analysis. Sections 6 and 7 report on the empirical findings and robustness checks. Section 8 concludes the paper.

2 Data and methodology issues and their relation to the literature.

For the purposes of this study, estimation using the framework of duration (survival) analysis has numerous advantages over standard methods of estimation. First, a hazard rate empirical model preserves the framework of the theoretical model. Second, the variable 'duration' can be treated according to its information structure. Duration takes only positive values - empirical models that assume duration is normally distributed (Wasi and White (2005), Ferreira (2007)) are therefore less suitable. Furthermore, in measuring duration two decidedly different types of households are observed: households which move during the period of observation (non-censored observations), and households which do not move within the period of observation (right-censored households). Excluding households which relocate from the sample (Wasi and White (2005), Ferreira (2007)) will tend to overestimate duration, while treating right censored duration as exact (Wasi and White (2005), Ferreira (2007)) will tend to underestimate duration. The third advantage of using survival analysis is that the estimation process also reveals the duration dependence of the hazard rate. This is important for our analysis because the tax saving experienced by a household is determined both by the value of the house and by the duration. A larger house and a longer duration both contribute towards higher tax savings. Estimating the hazard rate allows for these two channels to be separated.

To correctly identify the sign and magnitude of the effect of the tax savings on mobility, I also address a number of data and methodology issues that arise in the analysis. First, I identify the motivations of potential movers by using cross-sectional data at the household level. This helps me avoid any aggregation bias[6] that may be introduced in studies analyzing the behavior of population aggregates rather than individual households (e.g. Stochs, Childs and Stevenson (2001)).

Second, there is a potential collinearity between tax levels and the level of public service provision, with education providing the largest local public expenditure category.[7] Recently, Johnson and Walsh (2008) and Farnham and Sevak (2006) seek to separate the two effects by estimating using population groups likely to be unaffected by local educational expenditures.[8]

[6]Farnham and Sevak (2006), Johnson and Walsh (2008).

[7]Oates (1969), Pollakowski (1973), Lang and Jian (2004), Farnham and Sevak (2006), and Johnson and Walsh (2008) among others.

[8]Farnham and Sevak (2006) assume that empty-nest households are indifferent to school expenditure, while Johnson and Walsh (2008) assume this holds for second-home owners.

I take a similar approach in my analysis by estimating using the subsample of households with no children of school age (in addition to estimating on the full sample).

Third, unlike in previous studies (e.g. Nagy (1997), Stochs, Childs and Stevenson (2001), Wasi and White (2006)), I use the control function approach[9] , to control for omitted variables, measurement error in housing values and measurement error in household income[10]. Omitted variables bias results from the fact that the researcher does not observe all the characteristics of the house and neighborhood that affect household's utility[11]. Since information on these characteristics is stored in the error term of the model, the house value (as an explanatory variable) is correlated with the error term in the model. Because the tax savings directly depend on the value of the home, the estimate of the effect of the tax savings on mobility is expected to be calculated with bias of unknown sign[12].

A second type of bias arises from limitations in the data sources; data on exact sale prices and exact income receipts is fairly inaccessible. As a result, most of the researchers use owner-estimated housing values and self-reported incomes to estimate their models[13]. Both variables, however, have repeatedly been shown to be measured with error in survey data[14], and can lead to bias if directly used in estimation.

Fourth, and last, I introduce enough variation at the metro area level and state level by using a data set that includes 36 metro areas from 25 states. The need for enough variation at the metro area and state levels is twofold. First, some important control variables (as market availability or price dynamics), are defined only at a more aggregated level, for instance at the MSA level. To identify the effect of such variables on mobility there must be enough variation in these variables. Second, if households of only a few states are included as controls (e.g. Stochs, Childs and Stevenson (2001), Wasi and White (2006), Ferreira (2007)) the selection of the sample may cause it to appear that households in California are, on average, less mobile than households in other states. Such a result may further be wrongly attributed to Proposition 13. It is apparent from Table 2 (columns 1-4) that, when we look across a larger selection of states, the California housing market is characterized with, on average,

[9]The approach was first developed by Hausman (1978), Heckman (1978) and Smith and Blundell (1986).

[10]Reliable instruments must be identified. I discuss my approach in Section 4.1. and in more detail in Appendix B.

[11]Ferreira (2007).

[12]In multiple regression models the sign of the bias from omitted variables is difficult to determine (See Greene (2003, pp.148-149)).

[13]Researchers usually use the following data sources: Census, the American Housing Survey, the Health and Retirement Survey , and the Panel Survey of Income Dynamics, among others.

[14]Robins and West (1977), Kish and Lansing (1954), Ihlanfeldt and Martinez-Vazquez (1985), Benítez-Silva et al. (2008), Kiel and Zebel (1999), Kain and Quigley (1972), Goodman and Ittner (1992), Kochar (2000), Shea (2000), Dahl and Lochner (2005), Luttmer (2005), Kosfeld et al. (2008) among others.

faster turnover than housing markets in other states; among the households which relocate, the median Californian household relocates every 6^{th} year, while the median non-Californian household relocates every 8^{th} year. This indicates that the effect of the tax savings on mobility can only be studied via a variable that measures the individual levels of the tax relief experienced by each household, and this is the approach I take in this paper.

For the reasons given above, my study improves on previous studies. Wasi and White (2005) use OLS to estimate a linear model of duration (coded in intervals) on the tax saving and find that duration in owned homes increases by about 0.1 years for every $100 of tax savings. Nagy (1997) estimates a hazard rate on dummies for metro-area-year, but does not find a significant effect. One of the probable reasons is that his data set includes observations from only a short period after Proposition 13 was enacted. Stochs, Childs and Stevenson (2001) regress aggregated sales rates on dummies for state, and find that California households are less mobile than households in Illinois and Masachusets. Ferreira (2007) estimates the effect on mobility of two subsequent amendments, Propositions 60 and 90[15], which allow households with oldest spouse of age 55 or older to transfer their tax saving to a house of the same or lower value. Using a probit model Ferreira (2007) finds that due to Propositions 60 and 90, a head of household of age 55 is more mobile than one of age 54.

3 Theoretical framework

The early theoretical literature on mobility is framed in terms of household dis-satisfaction and the gap that arises over time between the current level and the optimal level (given the current household characteristics) of housing and public goods consumption[16]. A central line of work is the hypothesis that dissatisfaction with the status quo results from life cycle effects[17]. If the life-cycle hypothesis were correct, changes in household composition, income and job location lead to shifts in the demand for housing, neighborhood, and fiscal characteristics. This sequence of maximization problems can be expressed with a simple model in the lines of Conway and Houtenville (2001) and Farnham and Sevak (2006). Suppose the household maximises utility over the consumption of a numéraire good, C, a vector of housing and

[15]Propositions 60 and 90 were approved in 1986 and 1988 respectively to allow households, in which at least one of the spouses is 55 years old or older, to transfer their assessed value to a new home with the same or lower market value. Proposition 60 allowed such transfers only within county, while Proposition 90 allowed transfers across counties.

[16]Rossi (1955), Tiebout (1956), Speare et al. (1974), Brown and Moore (1970), Clark and Cadwallader (1973), Brown et al. (1970), Moore (1972), Wolpert (1964, 1965, 1966), Fredland (1974), Brown (1975).

[17]Brown et al. (1970), Moore (1972), Wolpert (1964, 1965, 1966), Fredland (1974), Brown (1975)

neighbourhood characteristics including time-costs to commuting[18], HL, and state and local public services, G, subject to a budget constraint incorporating state and local income taxes and other taxes excluding property taxes T, a price per unit consumption of HL, P^{HL}, and user cost of home ownership $p = r + \tau - \pi$ (as defined by Poterba (1992)), where r is interest/mortgage rate, τ is effective property tax rate, and π is capital gain. The problem that a household solves can be expressed as

$$\max_{C,\ HL,\ G} U(C,\ HL,\ G|W)$$
$$\text{s.th.} \qquad Y - T = C + (r + \tau - \pi)P^{HL}HL + MC,$$

where W represents a vector of household characteristics, which serve as demand shifters, Y denotes household's income, and MC denotes costs of moving, implicitly assuming that a household must relocate to optimize utility. Note that for households with no children of school age, the local public expenditure G is assumed to drop out of the maximization problem. If t denotes the number of years since the household moved into the unit (the duration), the resulting utility of the status quo choice for household i in location k at time t, given the current value of W, is

$$U_{ikt}(Y_{it} - T_{ikt} - p_{ikt}P^{HL}_{kt}HL_{kt} - MC, HL_{kt}, G_{kt}|W_{it}). \tag{1}$$

If $\Omega(k^*)$ denotes the set of available housing-community alternatives, the resulting indirect utility from the optimal choice $k' \in \Omega(k^*)$ is

$$V_{ik't}(p_{ik't}P^{HL}_{k't}, HL_{k't}, G_{k't}, T_{ik't}|Y_{it}, W_{it}, MC, \Omega(k^*)) \tag{2}$$

If we assume that the psychological costs to moving, K, are positive, a *static* model would have household i relocating only if

$$V_{ik't} \geq U_{ikt} + K, \tag{3}$$

where the right hand side of inequality (3) serves as a *reservation* utility for the decision of household i to relocate after time t[19]. Changes to income and life cycle changes in W induce households to re-consider their choice of k, but do not necessarily induce the household to

[18]Commuting imposes both a monetary and an opportunity cost. The monetary cost enters the budget constraint, while the time-cost enters the utility function.

[19]A parallel to the reservation utility concept is the reservation wage rate in a model of spell of unemployment (see Lancaster (1979)).

move. In particular, the tax relief allows for a lower effective property tax rate (tax payment divided by home market value) at the status quo choice k, and thus affects the decision to move (3) through the differential in user costs $(p_{ikt} - p_{ik't})$[20].

Estimation of equation (3) can not be done directly. If we could calculate indirect utilities, if we knew the distribution of reservation utilities, $F(U_{ikt} + K)$, and if we knew the rate at which offers arrive at time t, $\varphi(t)$, we could calculate a sequence of conditional probabilities that a household leaves the dwelling within period Δt, and move to another dwelling given they have not done so by t

$$\lambda(t)\Delta t = (1 - F(V_{ik't}))\varphi(t)\Delta t, \tag{4}$$

where $\lambda(t)$ is known in the literature as a hazard or failure rate. Once again, it is worth emphasising that t measures length of time since household moved in the housing unit, and not just a calendar year.

In the data, however, we do not observe the sequence of reservation utilities for the household for each period, and we can only specify a regression model around the variation of $\lambda(t)$[21]. As Cox (1972) and Lancaster (1979) suggest, it is mathematically attractive to impose that $\lambda(t)$ factors into two functions, one that depends on variations in all factors that determine the household's decision to relocate, $\psi_1(X(t))$, and a function that determines how λ changes over time, $\psi_2(t)$.

$$\lambda(t|X(t)) = v\psi_1(X(t))\psi_2(t), \tag{6}$$

where X is a vector of regressors explaining the shifts in the probability that a household relocates, and v controls for unobserved heterogeneity, with $E(v|X(t)) = 0$. The measure of duration enters the empirical model through the so called 'baseline hazard' $\psi_2(t)$. The baseline hazard is designed to detect the effects of unobservable factors that cause the household's propensity to move to change with duration. It is also the sub-function through which we can detect the effect on mobility from larger tax savings, generated by longer duration.

To estimate the effects of different factors (including time) on the hazard rate, the maximum likelihood estimator (MLE) is employed. Details on how this is achieved are provided

[20] By rule, property tax rates in California must be no higher than 1%. Table 2 (column 5) reveals that the effective property tax rates enjoyed by the majority of households in California are far lower than 1%.

[21] The sequence of probabilities $\lambda(t)\Delta t$ can be deduced using the law of conditional probability, where

$$\lambda(t)\Delta t = g(t)\Delta t/(1 - G(t)) \tag{5}$$

with unconditional probability of moving in period Δt, $g(t)\Delta t$, and a rate of survival by time t, $(1 - G(t))$.

in the next section and in Appendices A and B.

4 Estimation strategy

To estimate the effect of the tax savings on mobility, I first calculate the individual probabilities (the likelihood elements) of the observed duration for each household, and then maximise the product of these probabilities (the likelihood function) using the maximum likelihood estimator (MLE). Each probability is a function of the hazard rate, and parameterization of the probabilities is achieved through the hazard rate. The exact structure of the individual probabilities depends on the structure of the data at hand, and in what follows I begin the discussion on estimation with a short discussion on data structure.

To examine the effect of the tax relief on household mobility I assemble a data set with observations on housing units from the American Housing Survey (AHS) (Metropolitan Areas Sample) for the years 1984-1994. A given housing unit is surveyed up to three times, approximately every fourth year, and this allows observation of a household up to three times. Through repeated observations on the housing unit, one can deduce whether a household has moved out between survey waves. The number of times a unit is surveyed for the period 1984-1994, combined with the household's choice on duration, gives eleven unique types of housing unit observations as shown on Figure 1. On Figure 1 and in what follows housing units are indexed by j, households are indexed by i, and the sequence of the surveys is indexed by m. I further denote the year of the particular survey by b^m, the year in which household i moved into unit j by a_{ji}, and the conditioning vector of explanatory variables for household i observed during survey wave m, by X_i^m. Lastly, I refer to household i as *HHi*.

To assign likelihood elements to households we need to follow households within housing units. For the first unit on Figure 1, the same household is observed in all three survey years, and during the last survey year the household is recorded to still occupy the unit. Such a household is represented in the likelihood function with only one likelihood element (one conditional probability) - an observation that is right-censored in the last (third) wave the unit was surveyed. In the second housing unit, *HH2* is observed during the year of the first survey and another household, *HH3*, is observed, during the year of the second survey, to have moved in the unit at $t = a_{23}$. There is no information on whether *HH2* has moved out exactly at $t = a_{23}$ or at an earlier date. It is also unknown whether the unit was occupied between the dates of exit of *HH2* and entry of *HH3*. What is known with certainty is that *HH2* has moved

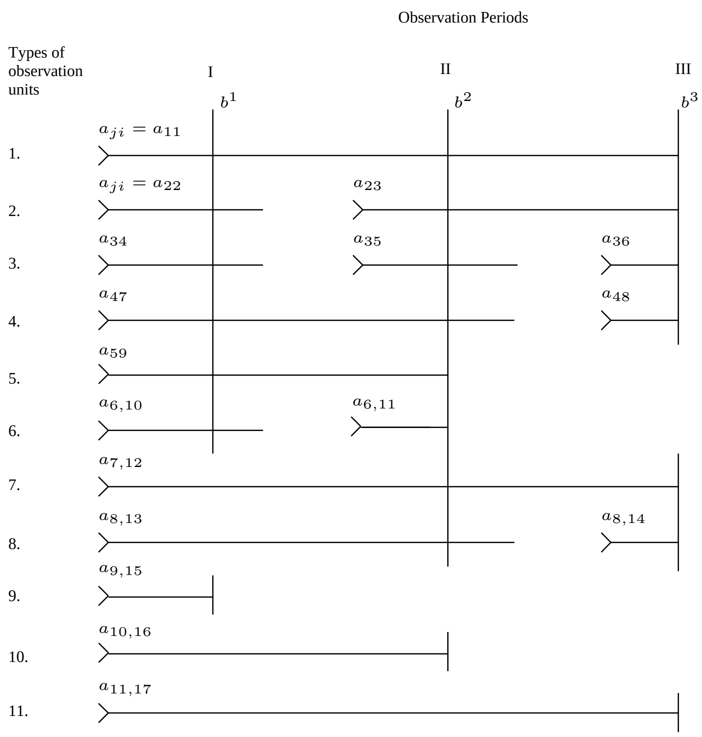

Figure 1: Observation Units.

out at $t \in (b^1, a_{23}]$, and this is all the information that can be incorporated in the likelihood element for this household. The second housing unit provides two likelihood elements: one for the first household, that moved out between the first survey wave and the time the second household moved in, and one for the second household that was right-censored at the third survey wave. Housing unit 9 has been observed only once, and HH15 is represented by one likelihood element with duration censored at the first survey wave.

Suppose the random variable T measures the length of time (the duration) a person/household resides in a given housing unit before they move out to relocate. Its cumulative distribution function and survivor function, which measures the probability of remaining in the same housing unit longer than a period t, are respectively

$$F(t|X) = P(T \leq t|X), \quad t \geq 0,$$
$$S(t|X) = 1 - F(t|X) = P(T > t|X),$$

where X represents a vector of household, housing, neighbourhood and local fiscal characteristics. The likelihood elements for right-censored and non-censored households differ. *HH1*, for instance, is right-censored and is represented in the likelihood function by the probability that the households duration is *at least* $b^3 - a_{11}$

$$P(T > b^3 - a_{11}|X_1^3) = 1 - F(b^3 - a_{11}|X_1^3).$$

If the censored duration for individual i is represented by $c_i = \check{b} - a_{ij}$, where $\check{b}$ is the date of the last survey the household has been observed, then the likelihood element for a right-censored observation is

$$P(T > c_i|\check{X}_i) = 1 - F(c_i|\check{X}_i), \tag{7}$$

where $\check{X}_i$ is the conditioning vector of explanatory variables recorded during the last survey in which the household has been observed.

Appendix A shows that the *cdf* of T can be specified as a function of the hazard rate of T, and that the hazard rate can be further specified to depend on observable and unobservable characteristics. I assume that the random variable T is distributed Weibull, with a hazard function, conditional on observed explanatory variables $\mathbf{X}_i$ and unobserved heterogeneity v_i,

$$\lambda(t; \mathbf{X}_i, v_i) = v_i \exp(\mathbf{X}_i\boldsymbol{\beta})\alpha t^{\alpha-1}, \tag{8}$$

where the parameter α takes a value $\alpha >=< 1$ when the process exhibits positive duration dependence, no duration dependence, or negative duration dependence, conditional on the observable factors and on unobservable heterogeneity.

Parameterization of the model is done at this step. I specify the following model for the hazard rate of household i associated with its current level of the tax savings $\check{TS}_i$

$$\lambda_i(t|\check{\boldsymbol{x}}_{\boldsymbol{i}}, \check{TS}_i, v_i; \boldsymbol{\beta}, \pi, \alpha) = \exp(\pi\check{TS}_i + \check{\boldsymbol{x}}_{\boldsymbol{i}}\boldsymbol{\beta})\alpha t^{\alpha-1}v, \tag{9}$$

where $\check{\boldsymbol{x}}_{\boldsymbol{i}}$ is a set of controls for household, housing, neighbourhood, local market, and local fiscal characteristics, discussed in more detail in the next section. The hypothesis of interest is H_0: $\pi < 0$.

I further assume *gamma-distributed* unobservable heterogeneity - that is, $v_i \sim Gamma(\delta, \delta)$, with $E(v_i) = 1$, $Var(v_i) = 1/\delta$. Then from equations (7) and (31, Appendix A) it follows that the final form of the likelihood element for a right-censored observation is

$$1 - F(c_i|\check{\boldsymbol{x}}_{\boldsymbol{i}}, \check{TS}_i; \boldsymbol{\beta}, \pi, \boldsymbol{\delta}) = [1 - \exp(\pi\check{TS}_i + \check{\boldsymbol{x}}_{\boldsymbol{i}}\boldsymbol{\beta})t^{\alpha}/\delta]^{-\delta}, \tag{10}$$

Now suppose a household was observed to exit the initial state at $t \in (b^1, b^2)$ or $t \in (b^2, b^3)$. For example take $HH4$, which is represented in the likelihood function by the following element

$$P(b^1 - a_{34} \leq T < a_{35} - a_{34}|X_4^1) = F(a_{35} - a_{34}|X_4^1) - F(b^1 - a_{34}|x_4^1).$$

The likelihood element for an observation that is not right-censored is

$$P(\check{b} - a_{ji} \leq T < a_{ji'} - a_{ji}|\check{X}_i) = F(a_{ji'} - a_{ji}|\check{X}_i) - F(\check{b} - a_{ji}|\check{X}_i),$$

where i' indexes the household that moves in unit j after household i has moved out.

Using equation (31, Appendix A), we can write this likelihood element as

$$\begin{aligned} &F(a_{ji'} - a_{ji}|\check{\boldsymbol{x}}_i, \check{TS}_i; \boldsymbol{\beta}, \pi, \boldsymbol{\delta}) - F(\check{b} - a_{ji}|\check{\boldsymbol{x}}_i, \check{TS}_i; \boldsymbol{\beta}, \pi, \boldsymbol{\delta}) = \\ &[1 - \exp(\pi \check{TS}_i + \check{\boldsymbol{x}}_i \boldsymbol{\beta})(\check{b} - a_{ji})^\alpha/\delta]^{-\delta} - [1 - \exp(\pi \check{TS}_i + \check{\boldsymbol{x}}_i \boldsymbol{\beta})(a_{ji'} - a_{ji})^\alpha/\delta]^{-\delta} \qquad (11) \end{aligned}$$

If $y_{ji} = 1$ when the observation is right-censored and $y_{ji} = 0$, when the observation is not censored, the likelihood and loglikelihood functions are respectively

$$L(\boldsymbol{\theta}) = \Pi_i \left\{1 - F(c_i|\check{\boldsymbol{X}}_{\boldsymbol{i}})\right\}^{y_{ji}} \left\{F(a_{ji'} - a_{ji}|\check{\boldsymbol{X}}_{\boldsymbol{i}}) - F(\check{b} - a_{ji}|\check{\boldsymbol{X}}_{\boldsymbol{i}})\right\}^{1-y_{ji}}$$

$$\begin{aligned} LL(\boldsymbol{\theta}) = \sum_i &\left[y_{ji} \lg\left\{1 - F(c_i|\check{\boldsymbol{X}}_{\boldsymbol{i}})\right\}\right. \\ &\left. + (1 - y_{ji}) \lg\left\{F(a_{ji'} - a_{ji}|\check{\boldsymbol{X}}_{\boldsymbol{i}}) - F(\check{b} - a_{ji}|\check{\boldsymbol{X}}_{\boldsymbol{i}})\right\}\right], \qquad (12) \end{aligned}$$

where $\boldsymbol{\theta} = \{\boldsymbol{\beta}, \pi, \alpha, \delta\}$ denotes the set of all paramaters to be estimated in the process of maximising the log likelihood function, with likelihood elements substituted from equations (10) and (11). The model can be further enhanced by estimating a separate α parameter for the state of California. assumed that the unobservable heterogeneity is factored out as in equation (25). Once the parameters are estimated, the hazard rate can be calculated and the estimates $\hat{\boldsymbol{\beta}}, \alpha, \pi$ are interpreted as semi-elasticities through the log of the hazard rate

$$\log \lambda = \hat{\pi} \check{TS}_i + \check{\boldsymbol{x}}_{\boldsymbol{i}} \hat{\boldsymbol{\beta}} + \hat{\alpha} \log t + \log \hat{\alpha} + \log \hat{v}. \qquad (13)$$

4.1 Controlling for omitted variables and measurement error

Suppose tax saving, TS, is correlated with the error term v due to omitted variables or measurement error; the procedure when income is measured with error is analogous. The approach is to first write a control function for the variable correlated with the error term, and then estimate the hazard rate and this control function simultaneously. The two important equations in our extended model are

$$\lambda(t|\check{\boldsymbol{x}}_{\mathbf{1}}, \check{TS}, v; \boldsymbol{\beta}_{\mathbf{1}}, \pi, \alpha) = \exp(\pi\check{TS} + \check{\boldsymbol{x}}_{\mathbf{1}}\boldsymbol{\beta}_{\mathbf{1}} + v)\alpha t^{\alpha-1} \quad (14)$$

$$\check{TS} = \check{\boldsymbol{x}}_{\mathbf{1}}\boldsymbol{\beta}_{\mathbf{21}} + \check{\boldsymbol{x}}_{\mathbf{2}}\boldsymbol{\beta}_{\mathbf{22}} + u = \check{\boldsymbol{x}}\boldsymbol{\beta}_{\mathbf{2}} + u, \quad (15)$$

where $\check{\boldsymbol{x}}_{\mathbf{1}}$ is the main vector of explanatory variables, $\check{\boldsymbol{x}}_{\mathbf{2}}$ is the vector of 'instrumental' variables, the vectors $\boldsymbol{\beta}_{\mathbf{1}}$ and $\boldsymbol{\beta}_{\mathbf{2}}$ are the vectors of parameters to be estimated for each equation, and u and v represent the unobserved heterogeneity in each equation. Because TS is measured with error it is correlated with v, and we can not assume that u and v are uncorrelated. The standard approach (Wooldridge (2002, p.472)) is to assume that u and v are jointly normally distributed, and estimate the correlation between the two error terms, ρ, in the process of simultaneous estimation of equations (14) and (15). Testing for dependence between TS and v can be easily achieved through a *t-test* on the significance of the correlation coefficient ρ. Furthermore, the credibility of the instruments is tested with an *F-test* on the joint significance of the instruments in equation (15) (Deaton (1997)). Because the procedure is fairly technical, the reader is referred to Appendix B for full details, including definition and descriptive statistics of the instruments used in the analysis.

5 Data

5.1 AHS data

The primary goal of the American Housing Survey is to measure the quality of the housing stock in the U.S.. At each survey wave, information is collected on the quality and structural characteristics of the housing unit, the quality of the neighborhood, housing unit costs (outstanding mortgage payments, property tax payments, purchase price, current market value, utility costs), household composition, household income, and the date the household moved in. The location of the housing unit is identified at the state, county, and metro area level. The household can be precisely matched to neighborhood characteristics through questions that the household representative answers on her/his opinion about such neighborhood characteristic, and through additional information the survey representative is required to collect (through personal observation) on key neighborhood features. Once a household moves out it is not followed to its new location.

The data set covers 36 metro areas (MSAs) from 25 states, of which 6 metro areas are located in California[22], for the period 1984-1994[23]. For the empirical analysis the sample is restricted to one observation per household, and only to owners who have complete data on all key variables of interest. This leaves us with 86,728 unique household observations[24].

5.2 Variables definition and descriptive statistics

The factors that determine the decision to move through inequality (3) can be divided in four subsets: (1) property tax liability, affecting the decision to move through differentials in the user-cost, r; (2) housing unit and neighborhood characteristics, affecting the decision to move through the differentials in the vector HL; (3) household characteristics, affecting the decision to move through shifts in W and Y or through differences in the psychological costs, K, experienced by different demographic groups; and, (4) housing market characteristics affecting the decision to move through the market availability, $\Omega(k^*)$, or through differentials in the user cost, r. Definitions of key variables and their descriptive statistics are presented in Table 3.

[22]The MSA's covered are (number of observations in the sample in parenthesis): Anaheim-Santa Ana, Ca (4779); Los Angeles-Long Beach, CA (3615); San Francisco-Oakland, CA (5818); Riverside-San Bernardino-Ontario, CA (4939); San Diego, CA (4588); San Jose, CA (5668); Atlanta, GA (2976); Baltimore, MD (2764); Birmingham, AL (5018); Boston, MA (4295); Buffalo, NY (4671); Chicago, IL (2691); Cincinnati, OH (2143); Cleveland, OH (4989); Dallas, TX (3804); Denver, CO (2957); Detroit, MI (6153); Hartford, CT (3049); Houston, TX (2137); Indianapolis, IN (5331); Kansas City, MO (1938); Memphis, TN (5417); Miami, FL (2441); Milwaukee, WI (4716); Minneapolis-St-Paul, MN (4842); New Orleans, LA (2394); New York-Nassau-Suffolk-Orange, NY (1772); Oklahoma City, OK (4972); Philadelphia, PA (2166); Phoenix, AZ (4581);Pittsburgh, PA (3105); Providence-Pawtucket-Warwick, RI-MA (5088); Salt Lake City, UT (5685); San Antonio, TX (2687); Tampa-St. Petersburg, FL (4466); Washington, DC (5590).

[23]All units were re-sampled (all units in the sample discarded and new units drawn) in 1984 and 1995, and I choose to use a sample for the years 1984 through 1994 for two reasons. First, for the surveys before 1984 information on the housing unit value has been measured in intervals, and information on housing unit living area (in sq.ft.) has not been reported at all. Second, the metro areas in the sample for 1995 and after are not surveyed in regular intervals. A large portion of the metro areas are surveyed only once or surveyed in intervals of 6-8 years.

[24]From a total of 172,537 household observations collected by AHS for the period 1984-1994, the households which have complete data on key variables for each year they have been observed are 140,226. Since some of the households are surveyed more then once, this leaves us with 86,728 unique household observations.

Table 3. Key variable definitions and descriptive statistics.

Property tax liability		Mean	SD
TAXRLF55	tax relief/savings, as defined in equation (16) (AHS);	\$678	\$636
TAXRLF	tax relief/savings, as defined in equation (17) (AHS);	\$766	\$733
TAXRLF*AGE55	AGE55=1 if in CA and AGE$\geq$ 55; AGE=0 else (AHS);	\$678	\$636
AMTX	effective yearly property tax payments (in 1000s) (AHS, BLS);	0.944	0.812
Housing unit and neighbourhood characteristics			
DTCH1	=1 if one housing unit in building and also detached (AHS);	0.842	0.364
OLDH	how many years since the housing unit was built (AHS);	27.488	19.772
ROOMPER	number of rooms in housing unit per household member (AHS);	6.449	1.718
HOWNH	=1 if neighbourhood quality, self rated 8 and higher on a scale from 1 to 10 (AHS);	0.748	0.434
Household characteristics			
AGE	age of HH head (AHS);	49.471	16.131
GENDER	=1 if household head is male (AHS);	0.723	0.448
WHITE	=1 if white or white-hispanic, ref. group: non-WHITE (AHS);	0.895	0.306
MARR	=1 if household head is married, ref. group: 'not married' (AHS);	0.678	0.467
CHILD3	A FIRST CHILD of AGE $\in [1,3]$ in HH (AHS);	0.052	0.221
CHILD6	A FIRST CHILD of AGE $\in [4,6]$ in HH (AHS);	0.055	0.227
CPLWORK	=1 if household head and spouse both have jobs (AHS);	0.341	0.474
ZINC	total yearly income of all household members (in 1,000s) (AHS, BLS);	\$37.489	\$26.439
CARS	number of cars and trucks owned by HH (AHS);	2.001	1.013
Housing market characteristics			
MG30YR	current (YEAR of survey) 30-Year mortgage fixed-rate (Freddie Mac);	0.097	0.018
NGAINL2	Net nominal rate of capital gain from housing value appreciation for the last two years before the date of the survey (OFHEO);	0.070	0.122
SALEPERC	(available housing units for sale)/(number of housing units owned) in MSA-YEAR (AHS);	0.028	0.014
METRO	=1 if central city (AHS)	0.235	0.424
STATECA	=1 if the HH lives in California (AHS)	0.176	0.381
Measures of duration			
DUR1	duration of right-censored observations (in years) (AHS);	12.090	11.754
DUR2	duration of households who moved out (in years) (AHS);	11.301	11.504
			Analysis sample n=86,728

Note: All income and price variables are deflated using CPI (provided by the Bureau of Labor Statistics) except for the variable NGAINL2. HH stands for 'household'. AHS stands for American Housing Survey. BLS stands for Bureau of Labor Statistics. OFHEO stand for Office of Federal Housing Enterprise Oversight.

5.2.1 Property tax liability

The main variable of interest, TAXRLF55, is calculated as the dollar value of the tax savings experienced by a California-based household[25]

[25]According to Mullins and Cox (1995), in the period I study, 1984-1994, the sample includes metro areas of only one other state that imposed an assessment growth limitation - Phoenix, Arizona. Assessment increases

$$\text{TAXRLF55} = \begin{cases} 0 & \text{if STATE} \neq \text{California} \\ 0 & \text{if STATE=California} \\ & \text{and YEAR}\geq\text{1986 and AGE}\geq\text{55} \\ \text{MarketValue*1\% - AmountTaxPaid} & \text{else,} \end{cases} \tag{16}$$

$$\text{TAXRLF} = \begin{cases} 0 & \text{if STATE} \neq \text{California} \\ \text{MarketValue*1\% - AmountTaxPaid} & \text{else,} \end{cases} \tag{17}$$

where property tax rate is assumed to be equal to 1% (as noted in Footnote 1, page 1) due to the provisions of Proposition 13. The condition AGE≥ 55 subsets households in which the head of the household or the spouse of the head is of age 55 or older. Such subsetting reflects the provisions of Propositions 60 and 90, enacted in 1986 and 1988 respectively, which allow households with oldest spouse of age 55 or older to transfer their tax savings to a house of the same or lower value in the same county; households with oldest spouse of age 55 and older are assumed to experience no constraint in mobility from the tax savings they enjoy in their present home[26].

I further define the variable TAXRLF (eq.(17)), which assumes that households with oldest spouse of age 55 or older do not benefit from Propositions 60 and 90. Using this variable in the model, instead of the variable TAXRLF55, and additionally including an interaction term (TAXRLF*AGE55) of this variable with a dummy for household in California with oldest spouse of age 55 and older (past year 1986), allows for simultaneously testing the effects of Proposition 13, 60, and 90. In particular if the coefficient to the variable TAXRLF*AGE55 is positive (while the estimate to TAXRLF is negative) this indicates that Proposition 60 and 90 alleviated the (supposedly) negative effect of Proposition 13 on mobility among households of age 55 and older.

As noted in Section 4, since one of the components of the variable TAXRLF55 is the self-

in Arizona are limited to the greater of 10% of value or 25% of difference between current year full cash value and prior year limited value. However, based on the Housing Price Index, the nominal growth rate of housing prices in Phoenix for the period 1984-1994 ranged from -1% to 8% per year. Based on this information I assume that the assessment increase constraint in Arizona is not binding.

[26]Proposition 90 was not mandatory and there is clear evidence that very few counties adopted it. Upon approval only a few, albeit relatively large, counties in California adopted Proposition 90 immediately, namely: Alameda, Contra Costa, Inyo, Kern, Los Angeles, Marin, Modoc, Monterrey, Orange, Riverside, San Diego, San Mateo, Santa Clara, and Ventura (Ferreira (2007)). Today (as of June 2008) only seven counties accept Proposition 90: Alameda, Los Angeles, Orange, San Diego, San Mateo, Santa Clara, and Ventura (WEISS & WEISSMAN, INC). However, Ferreira (2007) shows that Proposition 60 and 90 have a clear effect on the mobility of 55 years old and older. For this reason in the formulation of this variable it is assumed that Propositions 60 and 90 offset the effect of Proposition 13 on mobility for this group of households.

reported market value of the house, and since self-reported market value is measured with error, I test whether TAXRLF55 is also measured with error.

The variable AMTX represents effective property tax payments (self-reported, actual yearly tax payment made), and reflects the findings of Farnham and Sevak (2006) that, as a result of Tiebout type sorting, cross-state, empty-nest movers experience large gains in the form of reduced exposure to local school expenditure and property taxes, while local empty-nest movers experience no fiscal adjustment. The variable affects the decision to move (3) through the user cost r_{ikt}. Since 82% of the moves in the sample are local, we would expect the effect of AMTX on mobility to be insignificant.

5.2.2 Housing unit and neighborhood characteristics

The set of variables on housing and neighborhood characteristics, DTCH1, HOWNH, OLDH and ROOMPER reflect the findings that such characteristics have a significant effect on the choice of a house and location[27]. One would, for instance, expect households to prefer detached, one family houses, over all other types of construction. A household occupying a detached, one family house, would be less likely to relocate.

5.2.3 Household characteristics

The set of variables on household characteristics and life cycle effects - AGE, CARS, CHILD3, CHILD6, CPLWORK, GENDER, MARR, WHITE, and ZINC - reflect the strong agreement among researchers on what factors, among many, are important. The prevailing results are that[28]: (1) a recent change in marital status increases mobility; (2) the birth of the first child, the move of the first child from pre-school to elementary school, and the moment child rearing ceases are related to significant changes in housing consumption; (3) increases and decreases in family size increase mobility significantly; (4) there is an inverse relationship between the age of the household head and mobility, with the effect possibly being non-linear; (5) white individuals have higher mobility rates than African-Americans and Hispanics; (6) education and income levels have no clear effect on mobility; (7) a job change often acts as a trigger for a residential move even for a change of workplace within the metro area; and, (8) dual earner

[27] Boyce (1969), Droettboom et al. (1971), Greeberg and Boswell (1972), Moore (1972), Varady (1974), Molin (1999).

[28] The reader is referred to Quigley and Weinberg (1977) for a very detailed review of early studies that mainly relate the household's decision to relocate to factors leading to a gap between current housing consumption and preferred housing consumption, and Dielman (2001) for more recent studies that focused attention on more refined choice making processes within the household, and on market conditions that strongly constrain the ability of a household to move when they need to adjust their housing consumption.

households relocate less often than one earner households.

Since changes in household composition are not observed in our data set, the variables I create attempt to, as closely as possible, incorporate the findings in the previous literature: The variables CHILD3 and CHILD6 are calculated to reflect the previous findings that the birth of the first child, and the transition of the first child from pre-school to elementary school, are important predictors of change in the level of housing consumption. The variable CARS is intended to proxy for the importance of commuting time. The more cars the family has, the more flexible are household members in commuting. The variable CPLWORK is introduced due to previous findings that double earner households relocate less often. The variable MARR acts as a proxy for a household with more than one choice maker (more then one set of preferences). The variable AGE proxies for various life-cycle effects as well as psychological costs of relocation. Furthermore, the variable AGE is important because older households would tend to remain in their homes longer, and accumulate larger than average tax savings. Omitting the variable AGE from the main equation, may tend to overestimate the effect of TAXRLF55 on mobility. The variable GENDER can affect the decision to relocate through the cost parameter K (costs of relocation perceived differently by male and female household heads) or through the vector W if the frequency of job change is different for male versus female workers. The variable WHITE is included based on consistent findings in previous studies that mobility depends on race.

Finally the variable ZINC serves as a demand shifter through income, Y. Since ZINC is measured with error (as noted in Section 3), I control for the measurement error bias in estimation.

5.2.4 Housing market characteristics

The variables MG30YR, NGAINL2, SALEPERC, METRO, and STATECA reflect the recent, in the empirical literature, findings that local and non-local market characteristics, and local market constraints, affect the incentive and ability of households to obtain their optimal bundle of housing/location characteristics. Four major results have emerged from this discussion: (1) costs of moving (as measured by mortgage rates or other financial or psychological costs) are inversely related to household mobility[29]; (2) availability of alternative dwellings is positively related to mobility[30]; (3) investment incentives are high in the list of

[29] Weinberg (1975), Amundsen (1985), Quigley (1987).

[30] Strassmann (2000), Dieleman et al. (2000), and Grling and Friman (2001).

priorities for buyers, and capital gains differ substantially across time and metro areas[31]; and (4) the propensity to move and the resulting market 'turnover' vary considerably from place to place [32].

The variable MG30YR is derived from the '15-Year and 30-Year Fixed-rate Historic Tables' provided by Freddie Mac. It represents the 30-Year fixed mortgage rate and is expected to affect the household's decision to move (3) through the user cost $r_{ik't}$. However, since the data does not include a variable that measures the business cycle, MG30YR may take the role of a proxy for employment rate (for example). Mortgage rates are usually high in 'good' times, when people have high expectations about the future. For that reason the variable MG30YR may affect the decision to move through the expected future disposable income, which can not be measured in our data.

The variable NGAINL2 is designed to measure the household's expectations about future local housing market capital gains, and affects the decision to move (3) through the user cost, r. It is calculated as the average nominal capital gain from holding a house as an asset in a given MSA for the last two years

$$\text{NGAINL2}_{\text{MSA},t} = \frac{\text{HPI}_{\text{MSA},t} - \text{HPI}_{\text{MSA},t-2}}{\text{HPI}_{\text{MSA},t-2}},$$

where HPI represents the housing price index for each metro area, provided by the Office of Federal Housing Enterprise Oversight.

To control for market supply of housing units for sale in a given MSA-YEAR (MSA-YEAR $\equiv$ particular metro area in a particular year), the variable SALEPERC is calculated as the total number of vacant housing units for sale in the given MSA-YEAR over the total number of owner occupied housing units for the same MSA-YEAR[33]. A second variable, METRO (=1 if housing unit is in central city), is formulated to control for the supply of land, which Brasington (2002) finds is an important determinant for the magnitude of capitalisation of taxes and public services in housing values. The variables SALEPERC and METRO affect the decision to move (3) through the distribution of market availability $\Omega(k')$.

Finally, the variable STATECA controls for the observed in the data, higher propensity to move in California.

[31] Case and Shiller (1988), Poterba (1992), Dieleman et al. (2000).

[32] Lu (1998), Pawson and Bramley (2000).

[33] To obtain correct values of the variable, each observation of a housing unit for sale and each observation of owner-occupied housing unit is inflated by its corresponding 'pure weight', PWT (provided by AHS), where PWT measures the inverse of the probability that the housing unit is sampled. All weighting in the sample, when necessary, is achieved using the variable PWT.

6 Results

The model is estimated on two separate samples: all households, and households with no children of school age (66% of all households). The objective is to control for the possible collinearity between property tax levels and local public expenditure.

For each sample the model is estimated three times: a baseline model with no corrections, based on specification (9); a model with corrections for omitted variables and measurement error in TAXRLF55, based on specification (14)-(15); and, a model with corrections for measurement error in household income, ZINC, based on specification (14)-(15)(but this time controlling for income and not tax savings). Controlling for omitted variables and measurement error is achieved via a two-step procedure described in detail in Appendix B[34]. In the second step of the procedure, simulation of an error term is used to approximate an integral. Each model is estimated based on 600 draws (per observation) of the *iid*, normally distributed error term[35]. Furthermore, the standard errors of all estimates in the second step are corrected for the additional variation introduced by the two-step process using the covariance matrix suggested by Greene (2003, p.510). The important parameters that result from this procedure are the F statistic, measuring the joint significance of the instruments in the first step, and the correlation coefficient ρ, which measures the correlation between the error term v in the main equation (14) and the error term u in the control function (15). The standard error of the correlation coefficient is calculated using the Delta method (Greene (2003, p.913)), and a *t-test* of the hypothesis H_0:$\rho = 0$ reveals whether the problem of omitted variables or measurement error is present in the data.

A caveat in the data is a possible influence of outliers in self-reported dollar-valued variables (e.g. income, tax payments, home value, etc.). All dollar-valued variables are top-coded[36] by the AHS at the 97^{th} percentile. I further winsorize[37] the lower tail of the distributions of these variables at the 1^{st} percentile. All models are estimated on the top-coded-winsorized samples.

In all models that I present in this and next section estimation revealed that TAXRLF55

[34] An alternative approach is to estimate the full information maximum likelihood (FIML), which is more efficient than any two-step estimator, but at the same time far more computationally-intensive. Estimation of FIML was attempted, but due to the large number of estimates, the large number of observations, and the complexity of the model, the estimation procedure would either not converge or the Hessian would not be correctly calculated.

[35] To determine the appropriate number of draws for consistent estimation, I estimated one of the models repeatedly increasing the number of draws with a 100 at each step. I found that estimates and standard errors settle down in models estimated with more than 600 draws.

[36] Any value in the top 3% tail of the distribution takes the value of the 97th percentile. This is done by the AHS to maintain confidentiality.

[37] Any value in the lower 1% tail of the distribution takes the value of the 1^{st} percentile.

is not related to the error term in equation (14) due to omitted variables or measurement error. For brevity I present results only for the baseline models and models with correction for measurement error in household income.

The main results are presented in Table 4. Results for a modification of the models in Table 4, where the metro-state area dummy variables are replaced by an indicator variable for residence in California, are presented in Table 5[38].

Tax savings, TAXRLF55, is consistently negatively related to mobility across models. The magnitude of this effect, however, is not stable because each of these models incorporates a different set of assumptions. We focus on the models in Table 4, as those are more precise than the models in Table 5 (judging by the magnitudes of the log-likelihoods for each model).

Specifications (2) and (4) rely on the assumption of correlation between household income (ZINC) and the error term in equation (14). This correlation however is not confirmed for the specification that includes metro-state indicator variables as controls: the correlation coefficient ρ is insignificantly different from zero in both models, given the confirmed by the F statistic validity of the instruments. For that reason specifications (2) and (4) are invalid, and we focus on specifications (1) and (3).

The most important difference between models (1) and (3) should be revealed through differences in the estimated effect of the tax payment, AMTX, on the hazard rate. However, it appears that the effect of the tax payments on mobility is insignificant in both models.

To a large extent this may result from the predominantly local moves in the sample; this result complies with the findings of Farnham and Sevak (2006) that, among empty-nest households, only households that migrate across states are able to reduce their exposure to local expenditure and property taxes. Further evidence that the two models are very similar are the consistent estimates of all parameters and their standard errors. It appears there is no ground for rejecting model (3) on the basis of collinearity between tax levels and school expenditure levels. However, since model (1) is theoretically more correct than model (3)[39], I choose model (1) to discuss the effect of the selected factors on the hazard rate of duration. All estimated effects are interpreted as semi-elasticities of the hazard rate with respect to the factors that determine mobility (see equation (13)).

[38]More controls could be included in the models, however, estimation with maximum likelihood requires a careful balance between specifying a meaningful model and being able to estimate it. The models in Table 4 and 5 represent a measured selection of controls, which comply with the theoretical framework and the empirical literature on mobility.

[39]Data on local school expenditures can be used to purge the effect of local spending from the variable AMTX. Using the residuals from such a regression to estimate model (3), would make models (1) and (3) more comparable. The assembling of a data set on local school expenditure is in progress.

Table 4. Hazard rate determinants: MSA controls; controlling for measurement error in ZINC

	HHs with no child of school age		Full sample	
	(1) Baseline model	(2) Control function	(3) Baseline model	(4) Control function
TAXRLF55	-0.000362***	-0.000526***	-0.000365***	-0.000330***
	(0.000060)	(0.000112)	(0.000048)	(0.000099)
AMTX	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
DTCH1	-0.445***	-0.495***	-0.479***	-0.431***
	(0.035)	(0.059)	(0.030)	(0.065)
OLDH	-0.031***	-0.035***	-0.028***	-0.029***
	(0.001)	(0.002)	(0.001)	(0.002)
ROOMPER	0.039***	0.039**	0.069***	0.066***
	(0.010)	(0.017)	(0.008)	(0.017)
HOWNH	0.145***	0.198***	0.134***	0.220***
	(0.029)	(0.050)	(0.023)	(0.050)
AGE	-0.073***	-0.073***	-0.074***	-0.075***
	(0.001)	(0.003)	(0.001)	(0.003)
GENDER	0.055*	0.066	0.053**	0.187***
	(0.032)	(0.056)	(0.027)	(0.059)
WHITE	0.328***	0.386***	0.241***	0.212**
	(0.054)	(0.096)	(0.040)	(0.085)
MARR	0.014	0.075	0.038	0.031
	(0.038)	(0.067)	(0.032)	(0.071)
CHILD3	0.451***	0.662***	0.511***	0.320***
	(0.047)	(0.081)	(0.043)	(0.096)
CHILD6	0.319***	0.255**	0.400***	0.364***
	(0.072)	(0.127)	(0.042)	(0.090)
CPLWORK	0.173***	-0.031	0.146***	-0.017
	(0.034)	(0.083)	(0.025)	(0.067)
ZINC	0.005***	0.007*	0.005***	0.007**
	(0.001)	(0.004)	(0.000)	(0.004)
CARS	-0.255***	-0.265***	-0.212***	-0.232***
	(0.016)	(0.038)	(0.012)	(0.033)
MG30YR	53.178***	52.956***	53.112***	52.924***
	(0.908)	(1.922)	(0.757)	(1.900)
NGAINL2	3.730***	2.637***	3.629***	2.531***
	(0.133)	(0.216)	(0.110)	(0.220)
SALEPERC	15.731***	15.533***	15.740***	15.543***
	(2.446)	(4.270)	(1.952)	(4.143)
METRO	0.074**	0.221***	0.052**	0.079
	(0.031)	(0.054)	(0.026)	(0.057)
MSA dummies	Yes	Yes	Yes	Yes
α	1.976***	1.959***	1.991***	1.983***
	(0.023)	(0.049)	(0.019)	(0.046)
α(CA)	1.947***	2.062***	1.988***	2.087***
	(0.034)	(0.068)	(0.030)	(0.071)
Const	-8.543***	-8.547***	-8.684***	-8.768***
	(0.184)	(0.367)	(0.147)	(0.338)
ρ		-0.848		-0.835
		(0.587)		(0.567)
$F_{(6,n)}$ first step		1583.237***		2223.398***
LL (log lik)	-69722.477	-70181.648	-105990.239	-107109.236
n (# of obs.)	57,758	57,758	86,728	86,728

Note: See the note to Table 5 below.

Table 5. Hazard rate determinants: no MSA controls; controlling for measurement error in ZINC

	HHs with no child of school age		Full sample	
	(5) Baseline model	(6) Control function	(7) Baseline model	(8) Control function
TAXRLF55	-0.000696***	-0.000629***	-0.000649***	-0.000786***
	(0.000060)	(0.000100)	(0.000051)	(0.000081)
AMTX	-0.000***	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
DTCH1	-0.412***	-0.378***	-0.385***	-0.378***
	(0.031)	(0.052)	(0.029)	(0.044)
OLDH	-0.033***	-0.034***	-0.031***	-0.029***
	(0.001)	(0.001)	(0.000)	(0.001)
ROOMPER	0.054***	0.049***	0.076***	0.049***
	(0.009)	(0.017)	(0.008)	(0.014)
HOWNH	0.096***	-0.000	0.096***	0.000
	(0.026)	(0.034)	(0.023)	(0.027)
AGE	-0.069***	-0.070***	-0.075***	-0.073***
	(0.001)	(0.002)	(0.001)	(0.002)
GENDER	0.075***	0.129***	0.065**	0.129**
	(0.030)	(0.040)	(0.027)	(0.034)
WHITE	0.408***	0.674***	0.365***	0.674***
	(0.049)	(0.081)	(0.039)	(0.061)
MARR	-0.010	-0.100**	-0.046	-0.100**
	(0.035)	(0.049)	(0.032)	(0.041)
CHILD3	0.468***	0.727***	0.624***	0.727***
	(0.043)	(0.074)	(0.043)	(0.063)
CHILD6	0.420***	0.000	0.489***	0.000
	(0.063)	(0.097)	(0.041)	(0.056)
CPLWORK	0.201***	0.295***	0.175***	0.295***
	(0.031)	(0.055)	(0.025)	(0.039)
ZINC	0.004***	0.006*	0.005***	0.006***
	(0.001)	(0.003)	(0.000)	(0.002)
CARS	-0.228***	-0.241***	-0.214***	-0.241***
	(0.015)	(0.034)	(0.012)	(0.023)
MG30YR	50.252***	52.706***	53.065***	52.706***
	(0.522)	(1.400)	(0.675)	(1.091)
NGAINL2	1.992***	2.224***	2.461***	2.224***
	(0.089)	(0.203)	(0.082)	(0.170)
SALEPERC	8.022***	13.435***	15.554***	13.435***
	(0.804)	(1.431)	(0.713)	(1.173)
METRO	0.087***	0.154***	0.101***	0.154***
	(0.027)	(0.035)	(0.024)	(0.029)
STATECA	1.099***	0.780***	0.903***	0.780***
	(0.083)	(0.154)	(0.075)	(0.128)
α	1.890***	1.920***	2.001***	1.919***
	(0.016)	(0.052)	(0.019)	(0.039)
α(CA)	1.629***	1.835***	1.809***	1.836***
	(0.026)	(0.067)	(0.027)	(0.055)
Const	-7.914***	-8.837***	-8.593***	-8.837***
	(0.117)	(0.346)	(0.108)	(0.249)
ρ		-0.858**		-0.858***
		(0.346)		(0.238)
$F_{(6,n)}$ first step		1604.000***		3543.300***
LL (log lik)	-70810.776	-70941.684	-107602.699	-107794.920
n (# of obs.)	57,758	57,758	86,728	86,728

Note: The variable TAXRLF55 is measured in dollars. α is the parameter of the Weibull distribution measuring duration dependence of the hazard rate. A separate parameter, α(CA), is estimated for California households. Models (2,4,6,8) control for measurement error in ZINC, using a two-step procedure. The second step of models (2,4,6,8) requires simulation of the error term, and the models are estimated with 600 draws of the error term per observation. The standard errors for models (5) and (6) are corrected for the two-step procedure using the approach suggested by Greene (2003, p.510). ρ is the correlation between the error terms of the main equation (14) and the control function (15) in the two-step procedure. A *t-test* on H_0: $\rho = 0$ reveals whether ZINC is measured with error. F denotes the *F-stat* measuring the joint effect of the instruments on ZINC in the first step of the two-step procedure. ***, **, and * indicate significance at the 1, 5, and 10% levels.

The tax savings has the predicted negative effect on mobility. Since the tax savings is measured in dollars, the hazard rate decreases by about 3.6% for every \$100 increase in the tax savings. This results in about 20% decrease in the hazard rate for the median California household.

More information is revealed by the estimates on the duration dependence of the hazard rate. The effect of time on the hazard rate is measured by the estimate of the Weibull distribution parameter α, and is common for all households. When duration is Weibull distributed, the hazard rate increases with time if $\alpha > 1$, and the data consistently shows that the hazard rate of duration increases over time ($\hat{\alpha} = 1.976$)[40]; the longer a household occupies a house, the higher the probability the household will relocate. It comes in support of the hypothesis that, over time, as circumstances change, a household grows more dis-satisfied with their current choice of house and location.

The more important for us result, however, is revealed through estimation of two separate duration dependence parameters: one for households in California, $\hat{\alpha}$(CA)= 1.947, and one for households outside of California, $\hat{\alpha} = 1.976$. The hazard rate for California-based households increases at the same rate[41] as the hazard rate of households outside of California. It appears that the effect of tax savings on the hazard rate is not propagated through duration: if you compare two households with the same duration but different levels of tax savings, the influence of duration on their probability to relocate at that particular moment is exactly the same for both households. In other words, we can reject the hypothesis that because savings increase with duration, the duration dimension of the tax saving will have any influence on the probability to move. The only thing that appears to be important is the level of the tax relief: the effect of tax savings on mobility is stronger for higher levels of tax savings no matter how much time it took for these tax savings to accumulate.

The justification for such an interpretation of this results comes from the fact that the value of the tax savings depends both on the value of the house, and on the length of time a household remains in their home. The two effects are separated by the inclusion of both variables on the right hand side of the equation estimating the hazard rate. Then, the effect of the variable TAXRLF55 would more precisely be interpreted as the shift in the hazard rate from an increase in tax savings for a given duration. This is the effect of higher tax savings on mobility due to higher value of the house. The effect of the duration component of the tax

[40] $\hat{\alpha}$ is significantly different from 1 because it is more than three standard deviations from 1.
[41] Note that $\hat{\alpha}$(CA)= 1.947 is only about 1.2 standard deviations away from $\hat{\alpha} = 1.973$.

savings on mobility is incorporated in the parameter α.[42]

From the last two results it may appear that households in California are less mobile than households outside of California. However, the estimate of the effect of the dummy variable STATECA (Table 5, models 6 and 8) on mobility reveals exactly the opposite effect. California-based households are statistically significantly more mobile than households outside of California. This last result in no way contradicts the previous two results; the propensity to move and the tax savings do not change the hazard rate over time, instead, for any value of duration, they only act as shifters of the hazard rate.

The estimates of the coefficients to the control variables have the predicted signs and meaningful magnitudes. A few results deserve attention. First, the effect of the current mortgage rate on mobility is very strong, but consistently positive and significant. It appears that mortgage rates indeed serve as a proxy for business cycle effects. The negative effect of high mortgage rates on the propensity to buy a house is trumped by the prospects for low unemployment rate and stable future incomes. Third, the variable NGAINL2 has a positive and significant effect on mobility. This shows that investment considerations are of high importance for home owners, and that markets that offer higher capital gains will exhibit higher rates of turnover.

7 Robustness checks

The first robustness check I perform is to split the sample in three by year of observation. The resulting three subsamples include observations for the periods 1984-1987, 1988-1991, and 1992-1994 respectively. The models are estimated only on the first two subsamples because the third subsample includes only censored observations. The results are presented in Table 6, Panels A and B. The estimated magnitude of the estimated effect of tax relief on mobility tends to vary over the years. This may be a result of unobserved local market factors or unobserved business cycle factors.

A potential concern with our measure of tax relief is the large number of households (non-Californian) for which tax relief takes a value of zero. I re-estimate the models from Table 5 using only observations for Californian households. The results are presented in Table 6, Panel C. The estimated magnitude of the estimated effect of the tax relief on the hazard rate slightly decreases when we exclude households from controlling MSAs, which should be

[42] Because we explicitly control for unobserved heterogeneity in the model, the parameter α incorporates only the effects of factors working towards a change in the propensity to move over time.

expected.

Table 6. Robustness of the results to subsamples based on year of observation, and based on location (controlling for measurement error in ZINC)

	HHs with no child of school age		Full sample	
	Baseline model	Control function	Baseline model	Control function
	Panel A: Subsample with observations for 1984-1987			
TAXRLF55	-0.001763***	-0.001733***	-0.001434***	-0.001786***
	(0.000434)	(0.000197)	(0.000090)	(0.000167)
LL (log lik)	-42,997	-42,868	-66,412	-65,377
n (# of obs.)	14,036	14,036	21,333	21,333
	Panel B: Subsample with observations for 1988-1991			
TAXRLF55	-0.000323***	-0.000310***	-0.000349***	-0.000320***
	(0.000083)	(0.000130)	(0.000060)	(0.000098)
LL	-26,894	-26,642	-40,202	-40,336
n	19,904	19,904	29,860	29,860
	Panel C: Subsample with observations for Californian households only			
TAXRLF55	-0.000534***	-0.000561***	-0.000505***	-0.000548***
	(0.000077)	(0.000090)	(0.000062)	(0.000086)
LL	-14,459	-14,485	-21,057	-21,102
n	10,477	10,477	15,236	15,236
	All models			
MAIN CONTROLS	Yes	Yes	Yes	Yes
MSA dummies	No	No	No	No

Note: This table represents the sensitivity of the hazard rate to variation in the tax relief for subsamples of the data. In Panel A only observations for the period 1984-1987 are included. On Panel C only observations for California based households are included. The variable TAXRLF55 is measured in dollars. The control function models control for measurement error in ZINC, using a two-step procedure. The second step of the control function models requires simulation of the error term, and the models are estimated with 600 draws of the error term per observation. The standard errors for these models are corrected for the two-step procedure using the approach suggested by Greene (2003, p.510). ***, **, and * indicate significance at the 1, 5, and 10% levels.

The last subsampling allows for a better understanding on the types of households who's mobility is affected by Proposition 13. Table 7 presents results on subsamples of households based on the value of the dwelling the household occupies. The whole sample is divided into four subsamples, each including 25% of the households, with dwellings of lowest value in the first subsample, and dwellings with highest value in the last subsample. Comparing Panels A, B, C, and D it is clear that the mobility of households that occupy dwellings of lower than median value has not been affected by the tax relief. Richer households tend to benefit to a larger extent from the tax savings induced by Proposition 13, by accumulating larger tax savings.

Table 7. Robustness of the results to subsamples based on housing value (controlling for measurement error in ZINC)

	HHs with no child of school age		Full sample	
	Baseline model	Control function	Baseline model	Control function
	Panel A: Subsample with housing values below 1^{st} quartile			
TAXRLF55	-0.000548	-0.000254	0.000105	-0.001264
	(0.000879)	(0.001293)	(0.000832)	(0.001162)
LL (log lik)	-14,775	-14,812	-20,951	-21,025
n (# of obs.)	15,096	15,096	21,493	21,493
	Panel B: Subsample with housing values between 1^{st} and 2^{nd} quartiles			
TAXRLF55	-0.000516	0.000195	-0.000317	0.000670
	(0.000595)	(0.000880)	(0.000520)	(0.000797)
LL	-17,550	-17,637	-26,629	-26,779
n	14,569	14,569	21,659	21,659
	Panel C: Subsample with housing values between 2^{nd} and 3^{rd} quartiles			
TAXRLF55	-0.000880***	-0.000943***	-0.000999***	-0.001114***
	(0.000221)	(0.000350)	(0.000186)	(0.000292)
LL	-19,067	-19,186	-29,506	-29,649
n	14,065	14,065	21,670	21,670
	Panel D: Subsample with housing values between 3^{rd} and 4^{th} quartiles			
TAXRLF55	-0.000299***	-0.000354***	-0.000299***	-0.000343***
	(0.000069)	(0.000106)	(0.000056)	(0.000089)
LL	-17,604	-17,717	-27,909	-28,114
n	13,723	13,723	21,519	21,519
	All models			
MAIN CONTROLS	Yes	Yes	Yes	Yes
MSA DUMMIES	Yes	Yes	Yes	Yes

Note: This table represents the sensitivity of the hazard rate to variation in the tax relief for subsamples based on house value. The observations in the main sample are sorted in ascending order by house value and separated in four subsamples. The variable TAXRLF55 is measured in dollars. The control function models control for measurement error in ZINC, using a two-step procedure. The second step of the control function models requires simulation of the error term, and the models are estimated with 600 draws of the error term per observation. The standard errors for these models are corrected for the two-step procedure using the approach suggested by Greene (2003, p.510). ***, **, and * indicate significance at the 1, 5, and 10% levels.

7.1 Assessing the effects of Propositions 60 and 90

In this subsection I present results from models where the main variable of interest, TAXRLF55, was replaced by the variables TAXRLF and TAXRLF*AGE55. I have two goals in doing this: (1) redefine the main variable of interest and check for robustness of the results in the previous section; (2) investigate whether Propositions 60 and 90 indeed, as found in Ferreira (2007), alleviate the negative effect of Proposition 13 on households in California with at least one spouse of age 55 or older. I re-estimate the models of this and previous section and the results are presented in Tables 8-10.

Table 8. Hazard rate determinants: MSA controls; controlling for measurement error in ZINC

	HHs with no child of school age		Full sample	
	Baseline model	Control function	Baseline model	Control function
TAXRLF	-0.000547***	-0.000475***	-0.000464***	-0.000418***
	(0.000123)	(0.000131)	(0.000097)	(0.000101)
TAXRLF*AGE55	0.000184***	0.000249***	0.000174**	0.000245***
	(0.000086)	(0.000089)	(0.000074)	(0.000072)
AMTX	-0.000	-0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
DTCH1	-0.485***	-0.454***	-0.452***	-0.463***
	(0.070)	(0.070)	(0.061)	(0.059)
OLDH	-0.031***	-0.029***	-0.028***	-0.026***
	(0.002)	(0.002)	(0.001)	(0.002)
ROOMPER	0.045***	0.014	0.061***	-0.005
	(0.013)	(0.013)	(0.010)	(0.011)
HOWNH	0.114***	-0.000	0.108***	-0.000
	(0.031)	(0.031)	(0.025)	(0.025)
AGE	-0.072***	-0.068***	-0.074***	-0.069***
	(0.003)	(0.003)	(0.002)	(0.002)
GENDER	0.121***	0.118***	0.117***	0.110***
	(0.038)	(0.039)	(0.033)	(0.033)
WHITE	0.291***	0.586***	0.247***	0.547***
	(0.091)	(0.101)	(0.069)	(0.075)
MARR	-0.009	-0.237***	-0.048	-0.237***
	(0.050)	(0.052)	(0.042)	(0.043)
CHILD3	0.422***	0.446***	0.546***	0.453***
	(0.094)	(0.096)	(0.086)	(0.085)
CHILD6	0.331***	0.154	0.397***	0.162**
	(0.114)	(0.119)	(0.067)	(0.068)
CPLWORK	0.184***	0.278***	0.173***	0.243***
	(0.057)	(0.074)	(0.043)	(0.053)
ZINC	0.004***	0.007**	0.005***	0.008***
	(0.001)	(0.003)	(0.001)	(0.002)
CARS	-0.243***	-0.268***	-0.230***	-0.277***
	(0.033)	(0.041)	(0.025)	(0.031)
MG30YR	53.155***	52.962***	53.068***	52.960***
	(1.891)	(2.020)	(1.573)	(1.708)
NGAINL2	3.889***	2.741***	3.433***	2.744***
	(0.277)	(0.258)	(0.221)	(0.213)
SALEPERC	15.750***	15.551***	15.656***	15.551***
	(4.937)	(5.075)	(3.888)	(4.027)
METRO	0.086*	-0.071	0.072*	-0.054
	(0.050)	(0.052)	(0.042)	(0.042)
MSA dummies	Yes	Yes	Yes	Yes
α	1.967***	1.829***	1.979***	1.854***
	(0.048)	(0.047)	(0.038)	(0.038)
α(CA)	2.004***	1.932***	2.071***	1.952***
	(0.073)	(0.074)	(0.064)	(0.063)
Const	-8.544***	-8.547458***	-8.609***	-8.479***
	(0.375)	(0.409)	(0.297)	(0.313)
ρ		-0.867***		-0.878***
		(0.282)		(0.225)
$F_{(6,n)}$ first step		2406.700***		3379.400***
LL (log lik)	-69361.691	-69618.135	-105542.312	-105897.660
n (# of obs.)	57,758	57,758	86,728	86,728

Note: See the Note to Table 9 on next page.

Table 9. Hazard rate determinants: no MSA controls; controlling for measurement error in ZINC

	HHs with no child of school age		Full sample	
	Baseline model	Control function	Baseline model	Control function
TAXRLF	-0.000888***	-0.000967***	-0.000768***	-0.000857***
	(0.000133)	(0.000163)	(0.000102)	(0.000130)
TAXRLF*AGE55	0.000575***	0.000613***	0.000525***	0.000563***
	(0.000086)	(0.000094)	(0.000072)	(0.000078)
AMTX	-0.000	-0.413	0.000	-0.000
	(0.000)	(0.067)	(0.000)	(0.000)
DTCH1	-0.432***	-0.413***	-0.379***	-0.388***
	(0.069)	(0.067)	(0.058)	(0.058)
OLDH	-0.034***	-0.033***	-0.031***	-0.031***
	(0.002)	(0.002)	(0.001)	(0.002)
ROOMPER	0.061***	0.054***	0.080***	0.062***
	(0.013)	(0.012)	(0.010)	(0.010)
HOWNH	0.124***	0.124***	0.106***	0.102***
	(0.032)	(0.031)	(0.025)	(0.025)
AGE	-0.074***	-0.072***	-0.074***	-0.074***
	(0.003)	(0.003)	(0.002)	(0.003)
GENDER	0.085**	0.107***	0.074**	0.088***
	(0.039)	(0.038)	(0.033)	(0.032)
WHITE	0.406***	0.630***	0.392***	0.674***
	(0.089)	(0.097)	(0.067)	(0.061)
MARR	0.042	-0.089*	-0.033	-0.110**
	(0.050)	(0.052)	(0.042)	(0.045)
CHILD3	0.488***	0.618***	0.626***	0.642***
	(0.095)	(0.097)	(0.085)	(0.086)
CHILD6	0.420***	0.082	0.494***	0.159**
	(0.114)	(0.123)	(0.066)	(0.071)
CPLWORK	0.209***	0.211***	0.181***	0.122**
	(0.057)	(0.078)	(0.043)	(0.058)
ZINC	0.004***	0.007*	0.004***	0.008**
	(0.001)	(0.004)	(0.001)	(0.003)
CARS	-0.274***	-0.258***	-0.220***	-0.230***
	(0.033)	(0.047)	(0.024)	(0.038)
MG30YR	53.084***	52.712***	53.050***	52.706***
	(1.629)	(2.560)	(1.390)	(2.250)
NGAINL2	2.698***	2.260***	2.561***	2.247***
	(0.205)	(0.211)	(0.168)	(0.180)
SALEPERC	15.538***	13.433***	15.547***	13.434***
	(1.784)	(1.753)	(1.433)	(1.405)
METRO	0.100**	0.105**	0.108***	0.102***
	(0.047)	(0.046)	(0.039)	(0.038)
STATECA	0.986***	0.826***	0.863***	0.808***
	(0.182)	(0.189)	(0.151)	(0.157)
α	1.996***	1.985***	1.995***	2.001***
	(0.046)	(0.072)	(0.038)	(0.063)
α(CA)	1.845***	1.917***	1.861***	1.916***
	(0.067)	(0.188)	(0.058)	(0.076)
Const	-8.353***	-8.814***	-8.663***	-8.850***
	(0.274)	(0.433)	(0.221)	(0.359)
ρ		-0.889***		-0.886***
		(0.334)		(0.292)
$F_{(6,n)}$ first step		2454.700***		3585.600***
LL (log lik)	-70424.886	-70455.700	-107123.944	-107177.487
n (# of obs.)	57,758	57,758	86,728	86,728

Note: The variable TAXRLF is measured in dollars. α is the parameter of the Weibull distribution measuring duration dependence of the hazard rate. A separate parameter, α(CA), is estimated for California households. The models for which the control function approach is used are estimated in the usual way as the models in Tables 4 and 5 (See the note to Table 5). ***, **, and * indicate significance at the 1, 5, and 10% levels.

Tables 8 (including MSA dummies) and 9 (not including MSA dummies) reveal that the negative effect of Proposition 13, on the mobility of households targeted by Propositions 60 and 90, has been effectively softened.

In addition to the main results presented in Tables 8 and 9, table 10 also reveals that the main effect of Propositions 60 and 90 is observed among households occupying the most expensive houses in California. This is in line with the fact that older households occupy their houses longer than average and thus would tend to live in more expensive houses given the incentives presented by Proposition 13.

Table 10. Robustness of the results to subsamples based on housing value (controlling for measurement error in ZINC)

	HHs with no child of school age		Full sample	
	Baseline model	Control function	Baseline model	Control function
	Panel A: Subsample with housing values below 1^{st} quartile			
TAXRLF	-0.000111	-0.000870	0.000522	-0.000221
	(0.001478)	(0.001409)	(0.001380)	(0.001322)
TAXRLF*AGE55	0.001150	0.001234	0.001145	0.001218
	(0.001360)	(0.001291)	(0.001268)	(0.001187)
LL (log lik)	-14,773	-14,830	-20,896	-21,008
n (# of obs.)	15,096	15,096	21,493	21,493
	Panel B: Subsample with housing values between 1^{st} and 2^{nd} quartiles			
TAXRLF	-0.000221	0.001070	0.000239	0.001394
	(0.001112)	(0.001095)	(0.000916)	(0.000956)
TAXRLF*AGE55	0.000705	0.001166	0.000696	0.000908
	(0.001360)	(0.001291)	(0.000831)	(0.000818)
LL	-17,550	-17,628	-26,623	-26,751
n	14,569	14,569	21,659	21,659
	Panel C: Subsample with housing values between 2^{nd} and 3^{rd} quartiles			
TAXRLF	-0.001804***	-0.001133***	-0.001860***	-0.001231***
	(0.000453)	(0.000462)	(0.000360)	(0.000369)
TAXRLF*AGE55	0.000220	0.000483	0.000334	0.000343
	(0.000383)	(0.000390)	(0.000340)	(0.000343)
LL	-19,054	-19,189	-29,468	-29,644
n	14,065	14,065	21,670	21,670
	Panel D: Subsample with housing values between 3^{rd} and 4^{th} quartiles			
TAXRLF	-0.000493***	-0.000556***	-0.001802***	-0.000474***
	(0.000137)	(0.000144)	(0.000120)	(0.000113)
TAXRLF*AGE55	0.000165*	0.000258***	-0.004829***	0.000252***
	(0.000096)	(0.000098)	(0.001063)	(0.000082)
LL	-17,598	-17,712	-28,180	-28,088
n	13,723	13,723	21,519	21,519
	All models			
MAIN CONTROLS	Yes	Yes	Yes	Yes
MSA DUMMIES	Yes	Yes	Yes	Yes

Note: This table represents the sensitivity of the hazard rate to variation in the tax relief for subsamples based on house value. The observations in the main sample are sorted in ascending order by house value and separated in four subsamples. The variable TAXRLF is measured in dollars. The control function models control for measurement error in ZINC, using a two-step procedure. The second step of the control function models requires simulation of the error term, and the models are estimated with 600 draws of the error term per observation. The standard errors for these models are corrected for the two-step procedure using the approach suggested by Greene (2003, p.510). ***, **, and * indicate significance at the 1, 5, and 10% levels.

8 Conclusion

In this paper I estimate the effect of the property tax savings, induced by Proposition 13, on the hazard rate of duration. To correctly quantify this effect I overcome a number of identification issues typical of empirical models in Tiebout sorting. I find that the hazard rate of duration decreases with about 3.6% for each $100 increase in the tax savings. Furthermore, I find that the hazard rate increases with duration and that the rate at which the hazard rate increases with duration for households located in California is not statistically significantly different from the rate at which the hazard rate increases with duration for households located outside of California (see Footnote 41 on p.25). It appears that the effect of tax savings on the hazard rate is not propagated through duration, but only through the level of the tax saving (which depends on the value of the house for a given duration). The data also reveals that the negative effect of Proposition 13, on the mobility of households targeted by Propositions 60 and 90, has been effectively softened. A more detailed analysis also shows that the main effect of Propositions 13, 60, and 90 on household mobility has been experienced by households that occupy more expensive dwellings; the mobility patterns of households that experience low levels of tax relief are virtually unaffected. Unlike in previous studies, the data also demonstrates a higher propensity to move for California households. This further confirms that the effect of Proposition 13 on mobility has been successfully separated from the effects of other factors. My analysis gives one more confirmation that households decisions to relocate are affected by local tax policy. It compliments the results in Farnham and Sevak (2006) and Johnson and Walsh (2008) that households respond to local tax incentives in their across-state relocation decisions, by showing that intra-metro area moves are also affected by local tax policy.

Our understanding of the effect of the limit in increase of assessed value on mobility can further be augmented by answering two additional questions: first, how much of the disincentive to relocate was capitalised in housing values; and, second, to what extent is the negative effect of the tax savings on mobility exacerbated by a network effect, where households willing to sell cannot do so, because they cannot find an adequate house to move to. Answering these questions is a subject of ongoing and future research.

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Appendices:

A The Hazard function with observable explanatory variables and unobserved heterogeneity

The exposition in Appendix A closely follows Wooldridge (2007).

The random variable T measures the length of time a person/household resides in a given housing unit before they move out to relocate. One can easily show (see Wooldridge (2007)) that the cumulative probability, the survival function and the density can be expressed as functions of the hazard rate:

$$F(t) = 1 - \exp\left[-\int_0^t \lambda(s)ds\right], \quad t \geq 0. \tag{18}$$

$$S(t) = \exp\left[-\int_0^t \lambda(s)ds\right] \tag{19}$$

$$f(t) = \lambda(t)\exp\left[-\int_0^t \lambda(s)ds\right] \tag{20}$$

The shape of the hazard function is of primary interest. The simplest case is a constant hazard function, $\lambda(t) = \lambda$, with T following an exponential distribution, with *cdf* $F(t) = 1-\exp(-\lambda t)$. In this case the process is memoryless, but the hazard rate can also be duration dependent. An often used distribution which allows for duration dependence is the *Weibull* distribution with

$$F(t) = 1 - \exp(-\gamma t^\alpha), \quad \gamma, \alpha \geq 0; \tag{21}$$

$$f(t) = \gamma\alpha t^{\alpha-1}\exp(-\gamma t^\alpha); \tag{22}$$

$$\lambda(t) = \gamma\alpha t^{\alpha-1}. \tag{23}$$

When $\alpha >=< 1$ the hazard is respectively monotonically increasing, constant, and monotonically decreasing for all t.

For modeling purposes, the hazard function can be specified to depend on observable characteristics and unobservable heterogeneity. The most widely used class of models, first suggested by Cox (1972), is the *proportional hazard model*

$$\lambda(t, \mathbf{x}(t), v) = v\, k(\mathbf{x}(t))\lambda_0(t), \tag{24}$$

where $v > 0$ represents the influence of unobservable heterogeneity (independent from the observable factors) on the hazard, $k(\mathbf{x}(t)) > 0$ is a function of the explanatory variables, which can be time varying or time-invariant, and $\lambda_0(t)$ is called the *baseline hazard*. The model is called proportional because $\lambda_0(t)$ measures the duration dependence, which is common for all households, while $k(\mathbf{x}(t))$ serves to shift the hazard function through the influence of the regressors.

Typically $k(\cdot)$ is parametrised as $k(\mathbf{x}(t)) = \exp(\mathbf{x}(t)\boldsymbol{\beta})$ (which is always positive), where $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and the error term v is assumed to be supported on $v \in [0; \infty]$.

If $F(t|\mathbf{x}(t), v; \boldsymbol{\beta})$ is the *cdf* of T conditional on $(\mathbf{x}(t), v)$, the distribution of T conditional only on $\mathbf{x}(t)$ can be obtained by integrating out the unobservable effect, v. Because v and $\mathbf{x}$ are independent, the *cdf* of T given $\mathbf{x}(t)$ is

$$F(t|\mathbf{x}(t); \boldsymbol{\beta}, \boldsymbol{\rho}) = \int_0^\infty F(t|\mathbf{x}(t), v; \boldsymbol{\beta})h(v; \boldsymbol{\rho})dv \tag{25}$$

where the density of v, $h(v; \boldsymbol{\rho})$, is assumed to be continuous and depends on the unknown parameters $\boldsymbol{\rho}$.

For a random draw i from the population, a Weibull hazard function, conditional on observed effects $\mathbf{x}_i(t)$ and unobserved heterogeneity v_i is

$$\lambda(t; \mathbf{x}_i(t), v_i) = v_i\ \exp(\mathbf{x}_i(t)\boldsymbol{\beta})\alpha t^{\alpha-1} \tag{26}$$

Then, from equation (18)

$$F(t|\mathbf{x}_i(t), v_i; \boldsymbol{\beta}) = 1 - \exp\left[-v_i \int_0^t \exp(\mathbf{x}_i(s)\boldsymbol{\beta})\alpha s^{\alpha-1}ds\right]. \tag{27}$$

I assume *gamma-distributed* unobservable heterogeneity - that is, $v_i \sim Gamma(\delta, \delta)$ - then $E(v_i) = 1$, $Var(v_i) = 1/\delta$ and

$$h(v; \boldsymbol{\delta}) = \delta^{\delta} v^{\delta-1} \exp(-\delta v)/\Gamma(\delta). \tag{28}$$

Denoting $\xi(t, \mathbf{x}_i(t), \boldsymbol{\beta}) = \int_0^t \exp(\mathbf{x}_i(s)\boldsymbol{\beta})\alpha s^{\alpha-1} ds$, and using equations (25) and (28), we can integrate out the unobservable heterogeneity to find the distribution of T conditional only on the observable explanatory variables, $\mathbf{x}_i(t)$

$$F(t|\mathbf{x}_i(t); \boldsymbol{\beta}, \boldsymbol{\delta}) = 1 - [1 - \xi(t, \mathbf{x}_i(t), \boldsymbol{\beta})/\delta]^{-\delta}. \tag{29}$$

Further, assuming $\mathbf{x}_i(t) = \mathbf{x}_i$ we can write

$$\xi(t, \mathbf{x}_i, \boldsymbol{\beta}) = \exp(\mathbf{x}_i\boldsymbol{\beta}) \int_0^t \alpha s^{\alpha-1} ds = \exp(\mathbf{x}_i\boldsymbol{\beta}) t^{\alpha}. \tag{30}$$

and the *cdf* of T_i conditional on the observable explanatory variables $\mathbf{x}_i$ is

$$F(t|\mathbf{x}_i; \boldsymbol{\beta}, \boldsymbol{\delta}) = 1 - [1 - \exp(\mathbf{x}_i\boldsymbol{\beta}) s^{\alpha}/\delta]^{-\delta}. \tag{31}$$

Finally, another way to incorporate the unobservable heterogeneity is by parameterising $k(\mathbf{x}(t)) = \exp(\mathbf{x}_i(t)\boldsymbol{\beta} + v_i)$. This allows to relax the assumption that v is independent of $\mathbf{x}$.

B Controlling for omitted variables and measurement error in prices and income

In this section I describe the procedure I use to estimate the hazard rate when one of the explanatory variables is correlated with the error term in the model. For the exposition in this section I assume this variable is the tax savings, *TS*, but the derivations when income is measured with error are analogous.

In nonlinear estimation controlling for measurement error is a somewhat more complicated procedure than the instrumental variables approach. We need to simultaneously estimate the hazard rate and a control function for the variable correlated with the error term in the hazard rate. The two important equations in our extended model are

$$\lambda(t|\mathbf{x}_1, TS, v; \boldsymbol{\beta_1}, \pi) = \exp(\pi TS + \mathbf{x}_1\boldsymbol{\beta_1} + v)\alpha t^{\alpha-1} \tag{32}$$

$$TS = \mathbf{x}_1\boldsymbol{\beta_{21}} + \mathbf{x}_2\boldsymbol{\beta_{22}} + u = \mathbf{x}\boldsymbol{\beta_2} + u, \tag{33}$$

where $\mathbf{x_1}$ is the main vector of explanatory variables, $\mathbf{x_2}$ is the vector of 'instrumental' variables, the vectors $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ are the vectors of parameters to be estimated for each equation, and u and v represent the unobserved heterogeneity in each equation. The parameters of the two equations are identified when $\boldsymbol{\beta_{22}} \neq 0$. Because TS is correlated with v we can not assume that u and v are uncorrelated. The standard approach (Wooldridge (2002, p.472)) is to assume that u and v are jointly normally distributed

$$(u, v) \sim N(0, \Xi), \qquad \Xi = \begin{bmatrix} \sigma_u^2 & \rho\sigma_u\sigma_v \\ \rho\sigma_u\sigma_v & \sigma_v^2 \end{bmatrix}, \tag{34}$$

where (u, v) is independent from $\mathbf{x}$. Since $u \sim N(0, \sigma_u^2)$ then $TS|\mathbf{x} \sim$*Normal*. The model is applicable when $E(v|TS) \neq 0$. Under joint normality of u and v we can write (Wooldridge (2007, p.473), Greene (2003, p.868))

$$v = \frac{Cov(u, v)}{\sigma_u^2}u + \varepsilon = \frac{\sigma_v}{\sigma_u}\rho u + \varepsilon = \theta u + \varepsilon, \tag{35}$$

where $E(\varepsilon|u, \mathbf{x}) = 0$ and thus $E(\varepsilon|TS) = 0$. Since u and v are jointly normal then ε is also normal[43]

$$\varepsilon \sim N(0, \sigma_v^2(1 - \rho^2)) \tag{37}$$

Then we can write the hazard rate as

$$\begin{aligned} \lambda &= \exp(\mathbf{x}_1\boldsymbol{\beta_1} + \pi TS + \theta u + \varepsilon)\alpha t^{\alpha-1} \\ &= \exp(\mathbf{x}_1\boldsymbol{\beta_1} + \pi TS + \theta(TS - \mathbf{x}\boldsymbol{\beta_2}) + \varepsilon)\alpha t^{\alpha-1} \\ &= \exp(\varepsilon)\exp(\mathbf{z}\boldsymbol{\psi})\alpha t^{\alpha-1} \end{aligned} \tag{38}$$

The model can be estimated in two steps, where in the first step we estimate equation

[43]

$$Var(\varepsilon) = Var(v) - \left(\frac{Cov(u, v)}{\sigma_u^2}\right)^2 Var(u) = \sigma_v^2(1 - \rho^2) \tag{36}$$

(33) by OLS or ML, save the residuals, $\hat{u}$, and their standard error, $\hat{\sigma}_u$, and in the second step we estimate equation (32) by ML, using the estimated in the first step residuals and their standard error. To estimate standard errors for the two-step procedure a correction to the standard errors in the second step is needed because in equation (32) we do not use the true value of $\boldsymbol{\beta_2}$ but its estimate from the first step, $\hat{\boldsymbol{\beta}}_{\mathbf{2}}$, and in such cases the variance of $\hat{\boldsymbol{\beta}}_{\mathbf{1}}$ depends on the variance of $\hat{\boldsymbol{\beta}}_{\mathbf{2}}$. The procedure for calculating the corrected standard errors of $\hat{\boldsymbol{\beta}}_{\mathbf{1}}$ is described in Greene (2003, p.510).

Once we estimate $\hat{u}$ and $\hat{\sigma_u}$ in the first step, we can use equation (21) to write the likelihood elements for the censored and uncensored observations

$$f(T > c_i|\mathbf{z}, \hat{u}, \hat{\sigma}_u) = \int_{-\infty}^{+\infty} \left[1 - \exp(-e^{\mathbf{z}\ \boldsymbol{\psi}+\varepsilon} c_i^{\alpha})\right] f(\varepsilon) d\varepsilon, \tag{39}$$

$$f(b - a_{ij} \leq T < a_{i'j} - a_{ij}|\mathbf{z}, \hat{u}, \hat{\sigma}_u) =$$
$$\int_{-\infty}^{+\infty} \left[\exp(-e^{\mathbf{z}\boldsymbol{\psi}+\varepsilon}(b - a_{ij})^{\alpha}) - \exp(-e^{\mathbf{z}\ \boldsymbol{\psi}+\varepsilon}(a_{i'j} - a_{ij})^{\alpha})\right] f(\varepsilon) d\varepsilon, \tag{40}$$

where from equation (37) we have $f(\varepsilon) = \frac{1}{\sqrt{2\pi\sigma_v^2(1-\rho^2)}} \exp\left\{-\frac{\varepsilon^2}{\sigma_v^2(1-\rho^2)}\right\}$.

The conditional probabilities (39) and (40) are usually averaged out for ε through simulation (Train (2003))[44] or quadrature method (Waldman (1985)). Summing up the logs of the likelihood elements (39) and (40) over all households and maximising gives the MLE of $\boldsymbol{\beta_1}, \pi, \sigma_\varepsilon, \theta, \alpha$. Once θ and σ_ε are estimated, one can easily derive $\hat{\rho}$ and $\hat{\sigma}_v$. Testing for the credibility of the instruments is done with an *F-test* on the joint significance of the instruments in the first regression (Deaton (1997)). Testing for dependence between TS and v can be easily achieved through a *t-test* on the significance of the correlation coefficient ρ. For the purposes of the *t-test* the variance of the correlation coefficient is derived from the covariance matrix of θ and σ_ε using the Delta method (Greene (2003, p.913)).

Credible instruments must be used to control for the omitted variables and measurement error in prices and income. It is fairly difficult, however, to find instruments that are correlated with the house value but uncorrelated with any of the unobservable determinants of utility a household experiences from living in their current house. To instrument for housing values I use some of the instruments suggested by Capozza and Hesley (1990), Capozza and Sick (1994), and Capozza and Seguin (1995).

[44]Consistency and efficiency of simulation assisted estimators are discussed in Train (2003 pp.241-242,246-247).

Appendix Table 1. Key instrumental-variables definitions and descriptive statistics.

		Mean	SD
INC	average household income in MSA-YEAR (in 1,000s) (AHS, BLS);	$24.758	$4.602
INCGR	yearly average-income growth rate for MSA-YEAR (AHS, BLS);	-0.006	0.030
POP	total population of MSA-YEAR (in 1,000,000s) (AHS);	2.165	1.676
POPGR	yearly population growth rate for MSA-YEAR (AHS);	0.004	0.030
QALIM	=1 if income from alimony (AHS);	0.039	0.192
QBUS	=1 if income from business (AHS);	0.144	0.351
QINT	=1 if income from interest (AHS);	0.396	0.489
QRENT	=1 if income from rent (AHS);	0.124	0.329
QSS	=1 if income from social security (AHS);	0.301	0.459
QWELF	=1 if income from welfare programs (AHS);	0.020	0.140

Note: All income variables deflated using CPI (provided by the Bureau of Labor Statistics). AHS stands for the American Housing Survey. BLS stands for the Bureau of Labor Statistics.

Since about 82% of the households relocate within the metro area, aggregate measures of characteristics of the metro area should determine prices but not the decision to move. Four variables are calculated as measures of metro area characteristics. The population variable POP is calculated by inflating the number of persons per household, using PWT, and then the numbers are summed within each MSA-YEAR to calculate the population of the MSA for the given survey year. The variable INC is calculated by averaging out the household income, using PWT to weight the income of each household. The growth rates, POPGR and INCGR, represent average yearly growth rates between the year of the current survey and the year of the previous survey[45]. To control for measurement error in income I use dummy variables that identify whether a household has income from business, interest, rent, welfare programs, social security, and child alimony[46]. These variables are based on questions asked separately from the questions calculating the total self-reported income, and are hypothesized to be unrelated to the unobservable determinants of household utility. All instrumental variables with their descriptive statistics are listed in Appendix Table 1.

[45]In most occasions consecutive surveys for a given metro area are taken each four years, but sometimes the gaps are longer or shorter. To maintain consistency of the growth rates calculated for each MSA-YEAR, an average yearly growth rate is calculated.

[46]Authors have used a variety of instruments for income depending on the nature of the problem they study. Some of the widely used instruments are lagged income, educational level, and industry/occupation codes.