Real Effects of Regional House Prices: Dynamic Panel Estimation with Heterogeneity

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Abstract

This paper uses recently developed methods for estimating dynamic heterogeneous cointegrated panel data models - which allows for heterogeneity in parameters and dynamics across agents - to study housing wealth effects in a dynamic model of the 50 US states and the District of Columbia from the 1970s to the 1990s. The results show that housing prices have a unit root and are cointegrated with consumption. Even though an aging population has some effect on consumption in some states, it cannot account for the heterogeneity in housing wealth elasticities. Finally, we find that when state heterogeneity is taken into account, housing capital gains translate into increased spending with an elasticity ranging from 0.15 to 0.23.

Keywords: E21, E31, C32, C33, G12, R31
JEL Classification Numbers: Housing Price Behaviour, Wealth Effects, Dynamic Panel Estimation

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1. Introduction

Over the past few years, the United States (US) has experienced a housing boom, with prices continuing to rise at higher rates than in the 1980s. Figure 1.1 shows how real housing prices have risen steadily since 1994.

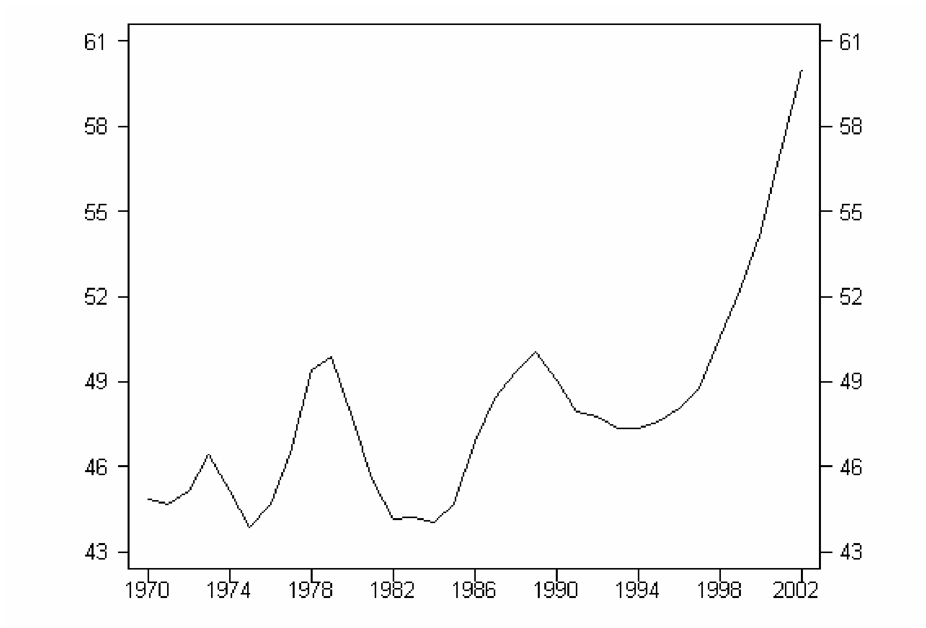

Figure 1.1: Real Housing Prices

Over the last couple of years, house prices in most parts of the US have, rather surprisingly, stayed high despite the downturn in the economy. This has coincided with the decline in the stock market. The apparently firmness of housing prices has been explained by the drop in mortgage interest rates and by the combination of a strong housing demand and the stability of housing supply[1].

The importance of housing wealth and the mortgage debt available against this wealth has increased over the last 20 years in the United States (US). In 1982 the ratio of debt to equity was 0.43 while in 2002 it reached 0.80 (See Table 1.1). Of the increase in housing stock, the greater part has been due to changes in the relative value of houses. Figure 1.2 shows that inflation-adjusted home prices explain most of the changes in real home equity. Increases in home prices have outpaced overall inflation for the last decade, so widespread home price inflation has lifted

[1] See Krainer (2002) for a discussion.

	1972	1976	1982	1986	1992	1996	2002
Home equity	3234	3380	4497	5654	5461	5435	7587
Mortgage Debt	1498	1649	1933	2703	3666	4102	6054
Mortgage Debt/Home equity	.46	.49	.43	.48	.67	.75	.80

Note: All figures are in 2002 billions of dollars

Source: Federal Reserve Flow of Funds of Accounts (Table B.100)

Table 1.1: Home Equity and Mortgage Debt

household net worth. Despite huge gains in stocks during the 1990s, housing assets still account for most of the wealth of most Americans. Home equity remains the cornerstone of household wealth, even among the majority of homeowners who also have stock holdings. In 1998 around 50 percent of homeowners held at least 50 percent of their wealth in home equity. Less than one half of all households hold stocks and the top one percent own one-third of the total value. In addition, property prices are much less volatile than share prices, so that there should be far less uncertainty surrounding gains and losses in property wealth.

This motivates the interesting question whether house prices have influenced the real economy significantly.

Over the 25 years from 1970 to 1995 house price inflation at the national level moved relatively roughly in line with the CPI inflation. (Figure 1.3 plots house price inflation and consumer price index (CPI) inflation since 1976). Given this close comovement it was hard to identify the effect of housing wealth on consumption. In the last few years the movement of house price and CPI inflation has been different. Figure 1.3 shows how since 1995, the series have grown apart. This suggests that the relative effect of housing and CPI prices and home equity on consumption may be identified with national aggregates. However, the close correlation between national housing prices and CPI has obscured the degree of heterogeneity and diversity between states. Looking at the state level allows us to examine the high degree of diversity and helps to identify the effects of house prices on consumption.

Traditionally, empirical work on housing prices has focused on national level aggregate data, although micro-econometric studies has increased recently. We use state level data to be able to exploit cross-sectional variation and at the same time reduce the measurement error included in micro-data. The same idea has been explored by Case et al. (2001) but this paper improves the methodology used and comes to some different conclusions. In particular, this paper takes into account the long-term relationship between consumption, labour income and housing prices in order to estimate the effects of housing on consumption. As a consequence, the estimated effect of housing prices on consumption more than

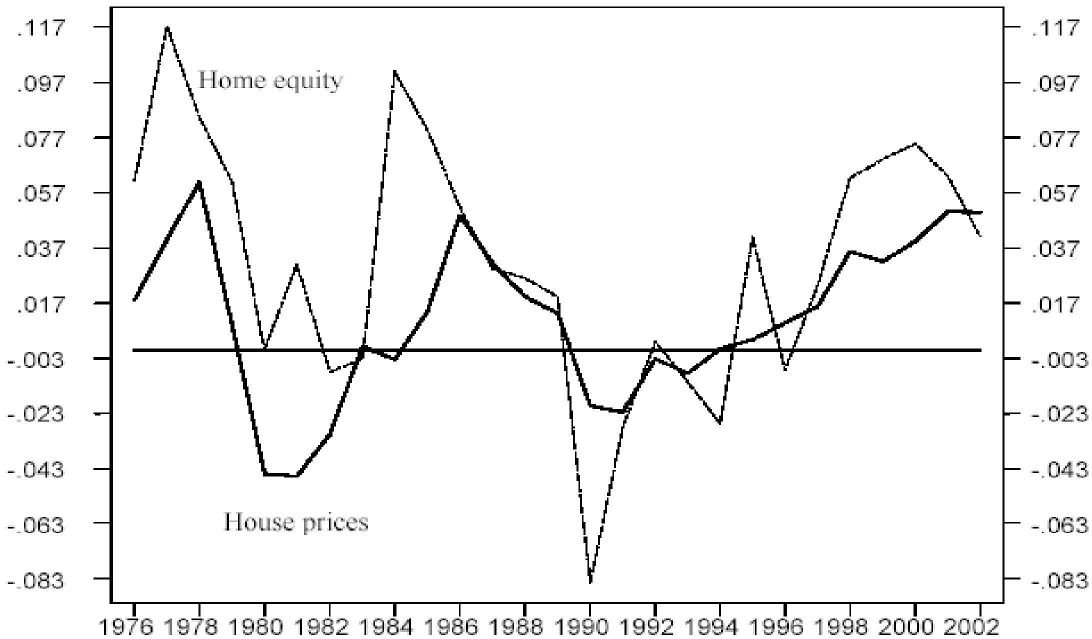

Figure 1.2: Real Home Equity and Real House Prices

doubles that of Case et al. (2001). In addition, the paper explores possible sources of heterogeneity among state estimates.

A national housing bubble has been denied by some economists, yet local inflations have appeared in New York and parts of California (The Economist March 6, 2003). Figure A.1, A.2, A.3 and A.4 show the log level of housing prices in four regions: the Northeast, Midwest, South and West. There is an obvious change in behaviour from the end of 1980s and the beginning of the 1990s. Before, they were very volatile, whilst they have been relatively smooth since. Similar patterns of boom and bust were followed by new construction before the 1990s. National data masks heterogeneity across states and regions: the plots show that only in the Northeast is there coherence amongst states. In the other regions, particularly the West, there is more diversity within region than between regions. Average annual house prices have appreciated in the West and in the Northeast during the 1976-96 period, while real prices declined in the South and Midwest. The timing of the real price changes also differs between regions. In the 1970s, real prices more than doubled in the West, while homes in the Northeast gained only 17 percent. During the late 1980s, real prices declined in all regions except

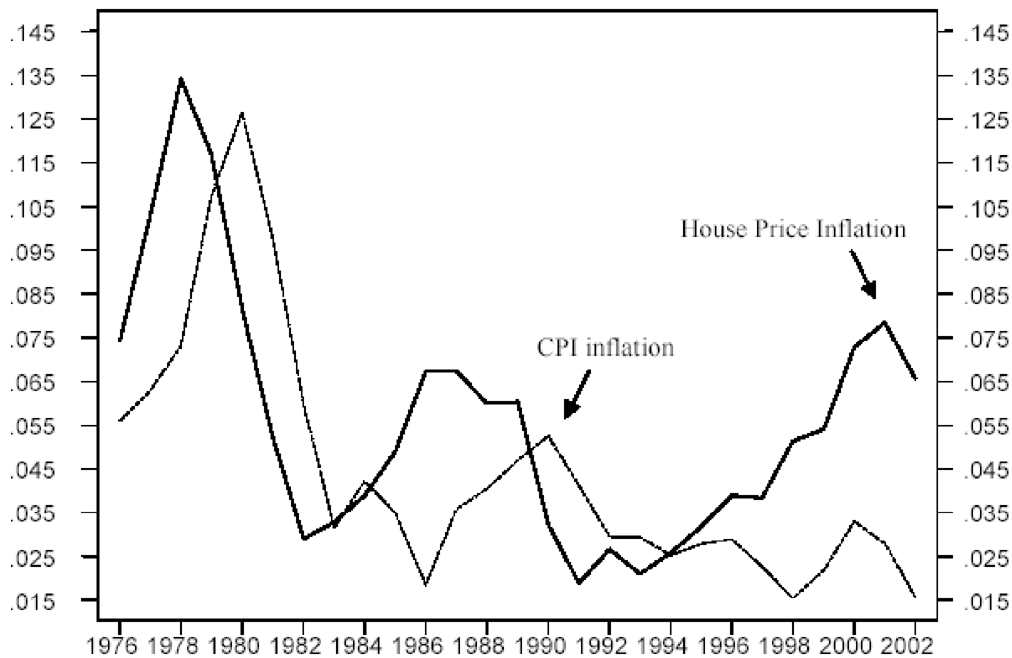

Figure 1.3: CPI Inflation and House Price Inflation

the Northeast. Despite reductions at the end of the decade, real prices in the Northeast climbed 39 percent between 1980 and 1990. Homes in the West declined in value by nearly 10 percent, and those in the South and Midwest lost more than 20 percent of their real value.

The contribution of the paper is twofold: it describes the time series properties of state housing prices in the US and it shows how house prices are related to consumption taking into account state heterogeneity, demography and homeownership rates.

Since there is a great diversity of state housing market activity in the US, it will be necessary to study state disaggregated consumer spending and house prices in order to allow inter-state and regional differences and, then, achieve a tighter estimation. The model will seek to overcome the drawbacks of national level aggregate data in imposing equal slope parameters across states. In addition, since individuals in states can borrow from each other, each state in the panel is considered as an open economy where shocks can be transmitted through the housing and credit markets. To this end, we will use state cross-sectional and quarterly time-series data for the period 1975:1 to 1996:4. The choice of state data for this exercise is explained by the fact that wealth effects coming from housing prices are locally driven - while wealth effects coming from the stock market and capital inflows are nationally driven. The study will estimate dynamic heterogeneous panel models and will allow for spillover effects between states.

The paper is organized as follows. Section 2 assesses the links between housing wealth and consumption and reviews the empirical literature. Section 3 describes the behaviour of state housing prices in the United States. Section 4 shows efficient ways of modelling state variables such as consumption and house prices. Section 5 compares and contrast my results with Case et al. (2001) and section 6 concludes.

2. Theoretical Assessment of the Links between Housing Wealth and Consumption: An Empirical Literature Review

The fact that consumer spending has amounted to about 90 percent of income has led some earlier analysts to suppose that income alone could explain consumption. Yet different studies have shown that wealth can explain up to one fifth of total consumption. Income and wealth do not move tightly together over time, and their relationship is generally not stable. As a consequence, the behaviour of wealth represents an additional instrument in understanding consumption.

Housing prices can have an effect on consumption through both the easing of liquidity constraints and wealth effects. The easing of liquidity constraints is very intuitive. If households are liquidity constrained, access to credit against the value of the house would alleviate the constraint. Rising house prices increase house equity. Households can choose to sell the house or to refinance their mortgages (taking a loan on the increase of the house value) and taking cash in the process. House appreciation is therefore a determinant of consumption. Households can trade up for better houses, purchase goods and services and accumulate resources for retirement. In addition, even for homeowners who do not refinance, the increase in home equity leads to a rise in consumer confidence.

Wealth effects are, however, more difficult to quantify, since different forces go in opposite directions. Some households choose to move to smaller houses when they get older. These downsizers are better off when house prices increase relative to other prices and can therefore increase their consumption. At the same time, house price appreciation undermines affordability, especially for first-buyers who are struggling to save for the downpayment and qualify for a mortgage. In addition, some households who own small houses want to move to larger houses, and these upsizers might respond to the increase of housing prices by reducing their consumption. Determining the relative magnitude of these effects is difficult.

The Governor of the Federal Reserve Board, Edward M. Gramlich[2] suggested that downsizers generally have higher marginal propensities to consume out of housing wealth than upsizers since downsizers tend to be older and have more time to smooth consumption, whilst upsizers tend to be liquidity constrained. According to that hypothesis, housing prices might have a positive effect on consumption. In the end, the relative response of downsizers and upsizers is an empirical question.

In section 4 we will estimate the wealth effect of changes in housing prices. Before that, we summarize the previous literature dealing with housing effects on consumption that use different data than our own.

Some studies have tried to answer the question of whether housing wealth has an effect in the real economy. McFadden (1994a, 1994b) finds that the impact of house price changes on consumer welfare are quite small (and predicts that house prices will be stable for the generations to come). Lettau and Ludvigson (2001) argue that temporary movements in asset values are often not associated with aggregate consumption movements, and only permanent changes in wealth affect consumption. However, Skinner (1996) suggests that one of the reasons why housing wealth is important for consumption is that there are regional fluctuations in housing prices even when national housing prices are flat.

Bosworth, Burtless and Sabelhaus (1991) argue that capital gains may have contributed to lower savings rates since savings rates of homeowners fell much more than those of nonhomeowners since the 1960s. They claim that the boom in housing prices may have contributed to reduced household savings. They also find that the decline for homeowners is pronounced in the middle age group. Summers and Carroll (1987) also argued that the growth in mortgage debt during the previous eight years has increased consumer spending and depressed private savings. Manchester and Poterba (1989) find that the incidence of second-mortgage borrowing rose from 1.5 percent of all mortgages in 1970 to 10.8 percent in 1987 and was concentrated in the middle age group. Their view is that increased access to second mortgages has reduced personal savings. Some second mortgages are incurred when a home is purchased, but post-acquisition second mortgages have grown faster. An alternative possibility is that households could have used second mortgages to invest in other assets or to repay other debts, although the majority of households used the second mortgages to make home improvements. They find that while net housing equity does not have a significant impact on second mortgage probabilities, accrued capital gains have a significant effect on second mortgage probabilities.

Aoki, Proudman and Vlieghe (2002) apply the financial accelerator mecha-

[2] Remarks by Governor Edward M. Gramlich: "Consumption and the Wealth Effect: The United States and the United Kingdom". Before the International Bond Congress, London, UK. February 20, 2002.

nism[3] proposed by Bernanke, Gertler and Gilchrist (1999) to the household sector and show that fluctuations in house prices significantly affect the value of houses as collateral and influence borrowing conditions for households in the UK. The model is based on the macroeconomic effects of imperfections in credit markets that generate premia on the external cost of raising funds. They find that endogenous developments in credit markets such as variations in collateral or net worth amplify shocks to the economy. Consequently, a positive shock to the economy causes a rise in housing demand that leads to a rise in house prices and an increase in homeowners' net worth. This decreases the external finance premium that leads to a further rise in consumption demand. Muelbauer and Murphy (1993, 1995, 1997) also argue that changes in housing values can change the borrowing opportunities of constrained households via a collateral effect.

2.1. The Standard Model

The theory of consumer behaviour has been described by Friedman (1957), Ando and Modigliani (1963) and Galí (1990) among others. The latter develops a model for time-series analysis of aggregate consumption which dispenses with the assumption of an infinite-lived representative consumer[4]. Therefore the model preserves the main features of the explicitly aggregated life-cycle models (Ando and Modigliani, 1963) but gains the tractability of the infinite-horizon model in terms of its econometric implementation. The life-cycle models account for two factors: (a) finite horizons and (b) a life-cycle profile for individual labor income characterized by retirement in a late stage of the cycle. Therefore they assume the existence of annuity markets whenever there is uncertainty about death.

Galí (1990) proposes a discrete-time, quadratic-utility, open economy version of the overlapping-generations framework in Blanchard (1985) where each consumer born at time s maximizes his expected present discounted value of utility as follows:

$$\max E_t \sum_{j=0}^{\infty} (1+\delta)^{-j} (1-p)^j U(c_{s,t+j}), \tag{2.1}$$

subject to

$$W_{s,t+1+j} = W_{s,t+j}(1+z) + yl_{s,t+j} - c_{s,t+j}, \tag{2.2}$$

[3]The mechanism goes as follows: when house prices fall, households that are moving home have a smaller net worth available for the purchase of the new house. Therefore they will get less favourable mortgage interest rates when renegotiating their mortgage, and have less scope for extracting additional equity to finance consumption.

[4]The infinite-horizon model appears as a special case of the model by a specific configuration of values for those parameters.

$$\lim_{j \to \infty} (1+z)^{-j} W_{s,t+j} = 0, \tag{2.3}$$

for j=0,1,2,..., and where c is consumption, W is nonhuman wealth, and yl is labour income, $x_{s,t}$ is the value of variable x at time t, for a consumer born in period s. δ is the discount rate. $E_t x_{s,t+j}$ denotes the expected value of $x_{s,t+j}$ conditional on the consumer being alive in period t+j, given the information available at time t. Equations 2.2 and 2.3 are the budget constraint and transversality condition, respectively. Individuals are born with zero financial wealth.

Galí (1990) derives from this model the aggregate consumption that is given by

$$c_t = \Omega + \beta yl_t + zW_t + u_t, \tag{2.4}$$

where

$$\beta \equiv \frac{z}{(z+\alpha)}, \qquad \Omega \equiv \frac{\beta\mu(1-\alpha)}{(z+\alpha)},$$

$$u_t \equiv \beta \sum_{j=1}^{\infty} (1+z)^{-j} (1-\alpha)^j (E_t \Delta yl_{t+j} - \mu).$$

and $(1+z) \equiv (1+r)(1+p)^{-1}$, with $(1+r)$ being the pure interest rate and $(1+p)^{-1}$ the annuity rate; α is the rate by which services supplied by an individual consumer is assumed to decline; and $\mu = E(\Delta yl)$is assumed.

Equation 2.4 establishes a linear relationship between aggregate consumption, labour income and nonhuman wealth in line with the life-cycle model of Ando and Modigliani (1963) and its aggregation properties generate a simple relationship between the coefficients of the consumption equation and the underlying structural parameters. The model is constructed based on the maintained hypothesis that the aggregate labour income is a unit-root process with drift and implies that W and c are also unit-root processes, and both u_t and ΔW are stationary. Therefore, the model implies a common trend in c, yl and W.

In this model, an unexpected increase in wealth will raise consumption over the lifetime. Agents will consume more today and save less. Aggregate, planned consumption is explained by labour income and wealth. However, actual consumption is not always equal to planned consumption due to several factors such as adjustment costs, habit formation in consumption and liquidity constraints. Adjustment costs can prevent consumers adjusting their housing services within each period. If habit persistence is in place, households adjust their consumption slowly towards the equilibrium level slowly. Capital restrictions prevent individuals smoothing consumption by borrowing, hence these liquidity constrained consumers follow current consumption more closely. For these reasons we allow adjustment lags in the consumption function. In this sense, consumption will adjust to the planned level with an error correction dynamic specification.

2.2. The Consumption Function incorporating Housing Wealth

In what follows we will estimate aggregrated consumption functions at the state level and investigate the role of housing prices as a proxy for housing wealth. We will follow an Error Correction Model (ECM) for the estimation with each equation:

$$\Delta y_{it} = \alpha_1 \left(\theta_i + \sum_{j=1}^{k} \beta_j x_{jit-1} - y_{it-1} \right) + \sum_{s=1}^{m} \gamma_s \Delta y_{it-s} + \sum_{s=1}^{m} \sum_{j=1}^{k} \gamma_{js} \Delta x_{jit-s} \quad (2.5)$$

with $y_i = \theta_i + \sum_{j=1}^{k} \beta_j x_{ji}$ being the long-run relationship and where x_{jit} stands for labour income and housing prices and y_{it} for consumption.

By using an ECM we maintain the rationality implied by the Euler equation in the long-run, but we relax it in the short-run, where agents and households may be subject to various frictions. The ECM allows one to distinguish between the long-run relationship among the variables of interest and the short-run variation around the equilibrium. Even though the optimization is based on the long-run relationship, modelling the short-run dynamics is necessary for a proper description of the process. The idea is that outside forces drive the common stochastic trends in consumption, income and housing, whilst short-run shocks divert consumption, income and housing prices from their planned time paths. Adding the latter to the ECM improves the fit of the regression.

Unfortunately, there is no series of housing wealth by state available[5]. However, we will calculate a proxy in section 5 to facilitate comparison. Since the major variation in housing wealth comes from changes in housing prices, we estimate the consumption functions using housing prices instead of housing wealth in this section. Another series that is missing at a state level is consumption. We proxy it by Retail Sales (See Appendix 2 for detail description of the data). We calculate real per capita retail sales by deflating by our calculated state CPI and using interpolated state population following Chow and Lin (1971). This is because population estimates by state are only available on an annual basis.

[5] In addition, there are no series of stock wealth and high frequency demand deposits (non-equity financial wealth) by state either. A calculation of a proxy for them will imply too strong assumptions leading to misleading results.

Our long-run equilibrium consumption equation extends from 1975:1 to 1996:4 and uses real per capita retail sales (real per capita consumption, hereafter), real per capita labour income and real housing prices.

The decision whether to pool the data will depend both on the degree of heterogeneity and on the purpose of the exercise. We want to estimate a dynamic consumption model from a panel set of data in which we a have a number of economic units (states in the US) $i = 1, 2, ..., N$ (51 states) and a number of times series observations, $t = 1, 2, ..., T$ (T=88, from 1975q1 to 1996q4). Since both T and N are relatively large, two issues arise. First, time series are usually non-stationary and certain combinations of them are stationary (we deal with this issue in the next two subsections). Second, because of the large T, we can estimate a regression for each state, parameters can vary a lot among states, and so we should think about heterogeneous panels (we deal with this issue below).

Ando and Modigliani's model does not imply that there is a cointegrating relationship among consumption, labour income and wealth. Rather, it says that consumption is linearly related to labour income and wealth. As seen above, Galí (1990) however, shows that consumption, income and wealth share a common trend. Therefore, if variables under study are unit root, estimates would be not consistent unless consumption is cointegrated with income and wealth variables.

3. Housing Prices in the United States

3.1. House Price Inflation versus CPI Inflation

One of the most interesting features of Figure 1.3 is that annual home price inflation is currently well above consumer price inflation. In addition, differentials in house price inflation tend to be persistent. One explanation for this is that house price changes are persistent themselves. Asset prices are expected to adjust automatically to the new information on the fundamental value, yet housing prices appear to adjust gradually. Krainer (2002) points to two possible reasons. First, housing markets might be inefficient because either the market does not clear automatically or housing price expectations are backward-looking. And second, house prices themselves depend on persistent variables such as employment growth and changes in personal income.

Cecchetti et al. (2000) find that price level divergences across the US cities are temporary although persistent. They show that the relative price levels among cities mean revert at an exceptionally slow rate due to a combination of transportation costs, differential speeds of adjustment to small and large shocks, and the inclusion of non-traded good prices in the overall price index.

Table 3.1 explores this idea for both real house price inflation and CPI inflation for the US state data and gives the highest and lowest 10 and 20-year rate of housing price real appreciation and CPI[6] inflation in each state. It shows big fluctuations in real state housing prices and, most importantly, big differences among states in the same period. These localized price declines/increases affect household networth and contribute to the stress on financial institutions. For instance, while Massachusetts had the highest housing price inflation rate of 11.42, North Dakota had the lowest (4.23) during the period 1975-1985. At the same time, the highest CPI inflation rate was Ohio with 7.64 and the lowest New York with 6.35. The difference between the maximum and minimum is larger for the 1975-85 period than for the 1986-96 and, as expected, decreases as the sample increases. As Cecchetti et al. (2000) point out, inflation differences seem to reverse themselves since the high inflation during the period 1986-96 is preceded by a relatively low rate during the previous decade (as the New York case shows). House price changes, however, behave in a different way. While on average the difference between the state with the highest and the lowest inflation rate is 0.35 percentage points for the whole period, the same average for changes in housing prices is 4.09 percentage points. The speed of adjustment for CPI rates is slow, and it takes over 20 years for state CPI rates to converge. The speed of convergence of housing prices, however, is too slow suggesting that real house price differentials

Index	Sample	Maximum	State	Minimum	State	Differential
Real House Price	1975-1985	11.42	Massachusetts	4.23	North Dakota	7.19
Inflation	1986-1996	7.10	Oregon	.51	Alaska	6.59
	1975-1996	7.55	California	3.47	North Dakota	4.09
CPI	1975-1985	7.64	Ohio	6.35	New York	1.29
Inflation	1986-1996	3.90	New York	2.90	Texas	1.00
	1975-1996	5.31	Washington	4.96	Michigan	.35

Table 3.1: House Price Inflation and CPI Inflation Rates

it seems the series are non-stationary.

Univariate unit-root tests like those of Dickey and Fuller have proved to have extremely low power and tend to be biased towards failing to reject the

null of unit root in small samples, hence we will use the Im, Pesaran and Shin (2003) (IPS) test, which proceeds as follows:

1. First we will eliminate the common time effect θ_t by substracting the cross-sectional mean from the data $(q_{i,t})$ as follows:

$$\tilde{q}_{i,t} = q_{i,t} - (1/N) \sum_{i=1}^{N} q_{i,t} \tag{3.1}$$

θ_t stands for the common time effect, that is, macroeconomic shocks that induce cross-sectional dependence. The latter cannot be introduced in a univariate regression, but it can be fully taken into account by substracting the cross-sectional mean of the variable under study. In this way, it will take into account the cross-sectional dependence asymptotically[7].

2. We then calculate the Augmented Dickey-Fuller-GLS test[8] by Elliot, Rothenberg, and Stock (1996) of each state by regressing $\Delta\tilde{q}_{i,t}$ on $\tilde{q}_{i,t-1}$, a constant, a trend and lagged values of $\Delta\tilde{q}_{i,t}$.

$$\Delta\tilde{q}_{i,t} = \alpha_i + \beta_i \tilde{q}_{i,t-1} + \sum_{j=1}^{k_i} \gamma_{ij} \Delta\tilde{q}_{i,t-j} + \epsilon_{i,t} \tag{3.2}$$

where α_i accounts for the heterogeneity among states - reasons for such heterogeneity being different tax rates and income levels. Note that these regressions implicitly allow for θ_t on the right-hand side since we have adjusted series $q_{i,t}$ by substracting the estimated common macro effect through $(1/N)\sum_{i=1}^{N} q_{i,t}$.

[7] Cecchetti, Mark and Sonora (2000) also control for residual dependence across individuals and calculate the p-values of the IPS test from a parametric bootstrap consisting of 2000 replications using the estimated error-covariance matrix in the data-generating process.

[8] DF-GLS test is a modified augmented Dickey-Fuller test where the times series is transformed via a generalized least squares regression (GLS) prior to performing the test.

The null hypothesis is that each series has a unit root, $H_o : \beta_i = \beta = 0$ for all i. The interpretation is as follows: the closer the estimate of β is to zero, the closer to a stationary process $\Delta\tilde{q}_{i,t}$ is, implying that $\tilde{q}_{i,t}$ is a unit root non-stationary process. The alternative hypothesis is $H_a : \beta_i < 0$ for some i, allowing for heterogeneity across states.

$\Delta \ln hp$	Levels	
State	$\bar{t}$	$lags$
Alabama	-1.752	11
Alaska	-2.261	8
Arizona	-3.873	9
Arkansas	-1.881	9
California	-2.007	8
Colorado	-2.654	8
Connecticut	-2.539	9
Delaware	-2.415	9
District of Columbia	-1.742	5
Florida	-3.703	10
Georgia	-2.283	10
Hawaii	-1.794	1
Idaho	-1.965	8
Illinois	-1.453	2
Indiana	-0.929	7
Iowa	-1.920	11
Kansas	-1.503	5
Kentucky	-0.875	3
Louisiana	-2.550	5
Maine	-1.560	6
Maryland	-2.051	4
Massachusetts	-2.157	10
Michigan	-0.990	6
Minnesota	-1.293	6
Mississippi	-1.399	8
Missouri	-3.185	9
Montana	-2.388	10
Nebraska	-2.373	11
Nevada	-1.129	1
New Hampshire	-2.415	8
New Jersey	-1.733	11
New Mexico	-2.683	10
New York	-2.593	7
North Carolina	-1.926	8
North Dakota	-0.903	5
Ohio	-2.487	11
Oklahoma	-2.348	5
Oregon	-2.435	7

State	Levels $\bar{t}$	$lags$
Pennsylvania	-2.268	6
Rhode Island	-2.670	10
South Carolina	-1.438	11
South Dakota	-2.063	10
Tennessee	-1.874	5
Texas	-1.515	3
Utah	-2.868	9
Vermont	-1.535	11
Virginia	-1.596	8
Washington	-2.677	6
West Virginia	-1.408	9
Wisconsin	-1.624	1
Wyoming	-2.032	11
Average	-2.034	

Note: IPS test. 5% Critical Value:-2.36 from Im, Pesaran, and Shin (2003, table 2).
Sample Period: 1975:1-1996:4

Table 3.2: Panel Unit-Root Test for log Housing Prices

In order to determine the lag length (k_i) of equation 3.2 we follow Ng and Perron (1995). They suggest a sequential t-test algorithm for choosing k. For instance, let us suppose that we start with $k_i = 6$. If the absolute value of the t-ratio for γ_{i6} is less than 1.96, we reset $k_i = 5$ and reestimate the equation. The process stops when the estimated coefficient with the longest lag exceeds 1.96.

3. We calculate the IPS test statistic $\bar{t}$ by averaging the univariate ADF test t_i:

$$\bar{t} = (1/N)\sum_{i=1}^{N} t_i. \tag{3.3}$$

4. The null hypothesis is that each series has a unit root and there exists cross-sectional independence among them. Since the asymptotic distributions of the t-bar statistics are nonstandard and do not have analytic expressions, we will use the critical values tabulated by IPS using Monte Carlo simulations.

Table 3.2 shows the results of the IPS test for the whole period sample. The results provide evidence towards the existence of a stochastic trend in the series of interest. In most of the cases we cannot reject the null hypothesis of unit root.

The IPS test $\bar{t}$ is -2.03 and the critical value -2.36, hence we cannot reject the null of a unit root in housing prices. The interpretation of failing to reject the null hypothesis is interpreted as implying that housing prices are trended, in this instance upwards. Relative house prices do not converge to a common trend. Since housing prices could wander apart indefinitely, they may become arbitrarily high or low. Hence the issue of possible cointegration arises.

4. Methodology

The aim of this section is modelling the consumption-house prices linkage in order to shed light on how closely the two variables are actually correlated.

4.1. Integration

As a first step, we test the consumption series for integration as we did for housing prices series. Table 4.1 shows the IPS test results for real per capita consumption and real per capita labour income. These tests give unambiguous results, unit roots appear to be present for the log levels of the series in all three cases.

	Levels
Variable	$\bar{t}$
C	-2.157
Y	-2.068
HP[1]	-2.034

Note: IPS test. 5% Critical Value: -2.36 from Im, Pesaran and Shin (2003, table 2).
Sample Period: 1975:1-1996:4
[1]Later on we will show that housing wealth has a $\bar{t}$ of -2.118

Table 4.1: Panel Unit-Root Tests

Since both the independent and dependent variables are non-stationary, we now test whether a combination of them is stationary - a test of whether C, Y and HP are cointegrated.

4.2. Cointegration in Heterogeneous Panels

We follow Pedroni (1999) in testing the null of no cointegration in heterogeneous panels. The advantage of this test is that it allows for heterogeneity among individuals, both in the long-run cointegrating vector and the short-run dynamics from the cointegrating vectors. In addition it allows for multiple regressors.

We first compute the OLS residuals $e_{i,t}$ from each cointegration regression:

$$y_{i,t} = \alpha_i + \delta_i t + \sum_{j=1}^{k} \beta_{ji} x_{1i,t} + e_{i,t} \tag{4.1}$$

estimated from state i.

$t = 1, ..., T, T$ being the number of observations over time; $i = 1, ..., N$, N being the number of states; $j = 1, ..., K$, K being the number of regressors.

We the we calculate the Panel Cointegration Statistic (Group t-Statistic) as the sum of the individual ADF t-statistic (τ_i) :

$$\tilde{Z}^*_{t_{N,T}} = N\bar{\tau} = \sum_{i=1}^{N} \tau_i \tag{4.2}$$

with a distribution expressed as

$$\frac{\frac{1}{\sqrt{N}}\tilde{Z}^*_{t_{N,T}} - \mu\sqrt{N}}{\sqrt{\nu}} = \frac{\sqrt{N}\bar{\tau} - \mu\sqrt{N}}{\sqrt{\nu}} \xrightarrow{D} N(0,1)$$

where μ and ν are functions of the moments of the underlying Brownian motion functionals that can be found in Table 3 (Pedroni, 1999).

Table 4.2 shows the results of the test. These are one-sided statistics with a critical value of -1.64, thus large negative values imply rejection of the null of no cointegration. The table shows that in all cases, with or without intercept and trend included, we can reject the null of no cointegration. Cointegration estimates are robust to the presence of measurement error and endogeneity of the regressors, hence the superconsistency result. So there is evidence that C, W and Y are cointegrated and that they form a meaningful regression relationship.

Pedroni Group t-statistic	With housing prices		With housing wealth	
	t	p-value	t	p-value
Standard case	-12.452	0.000	-12.988	0.000
Heterogeneous Intercept Included	-8.444	0.000	-8.902	0.000
Heterogeneous Trends and Intercepts Included	-4.758	0.000	-4.935	0.000

Note: t-value calculated following Pedroni (1999)

One-tailed test at 5 percent level on the Normal distribution. Critical value: -1.64

Table 4.2: Cointegration IPS Test

4.3. Estimation and Results

In this section we deal with the estimation of a consumption function in which the regressors are non-stationary and there exists cointegration among variables. We consider three estimators: the Mean Group (MG) Estimator, the Pooled Mean Group (PMG) Estimator and the Dynamic Seemingly Unrelated Regression (DSUR) Estimator.

4.3.1. Mean Group Estimator

One way to estimate panel data models is to estimate the separate equations for each group of individuals and study the distribution of the mean of the estimated coefficients across groups. Since T is large (88 observations) we can estimate an Autoregressive Distributed Lag ($ARDL(p, q, q, ..., q)$) model for each group separately as follows:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} x_{i,t-j} + \mu_i + \varepsilon_{it} \tag{4.3}$$

where x_{it} is the vector of regressors for each equation i and μ_i the constant for each equation. (We include in one of the models seasonal dummies). We allow for different lag order for each state and use the Schwarz Bayesian Criterion (SBC) to select the right lag order.

In what follows we work with the more convenient re-parameterization of the ARDL model of the form of an ECM as equation 2.5 above. Pesaran and Smith (1995) show that this MG estimator gives consistent estimates of the average of the parameters. The drawback is that it does not take into account the fact that some parameters might be the same across groups.

Table A.2 and A.3 present the MG estimated results (the first table does not include seasonal dummies whilst the second one does). The first column of the tables shows the lag orders for each group selected by the SBC, and the second, third and fourth illustrate the labour income elasticity, housing price elasticity and the adjustment coefficient of equation 2.5 respectively. Table A.2 illustrates how labour income and housing elasticities seem to differ among states. Housing prices are significant in half of the states, probably due in part to the fact that synergies among states are not taken into account (the DSUR below will correct for that). By synergies we mean special links between states: for instance, many people working in Washington DC live in Virginia, where they can find better schools for their children and cheaper accommodation. Moreover, the coefficient of adjustment (α) is negative and significant, thus supporting the cointegration hypothesis and indicating the presence of lags in the response of consumption to income and wealth. Table A.3 reestimates the long-run coefficients, including seasonal dummies.

Mean Group Estimate Summary	β_1	β_2	α
(without seasonal dummies)			
MG	.76 (13.51)	.20 (5.18)	-7.21 (-12.03)
No. of states with correct sign	50	44	51
No. of states with correct sign and significant coefficients	38	22	35
(with seasonal dummies)			
MG	.87 (10.21)	.16 (3.0)	-.30 (11.59)
No. of states with correct sign	49	37	51
No. of states with correct sign and significant coefficients	37	19	48

Table 4.3: Mean Group Estimates

Table 4.3 summarizes the main findings of the MG estimation (Tables A.2 and A.3). β_1 is the coefficient of the log of real labour income, β_2 is the coefficient of real housing prices, and α is the adjustment coefficient. The first row of the table shows the MG estimator. The housing price elasticity is 0.20 and is very significant. The value of all MG elasticities decreases when seasonal dummies are introduced, leading to a value of the housing price elasticity of 0.16. The table also shows how many states have coefficients with the correct sign and are significant. The coefficient on housing prices seems to be significant less frequent, however at least more than half of the coefficients that have the correct sign are significant.

By looking at the short-run results, the significance of the estimates shows that consumption responds also to current period changes in labour income and wealth (available from the author under request).

4.3.2. Pooled Mean Group Estimator

An intermediate estimator between the MG estimator above and a pooled estimator (fixed or random effects estimator) where coefficients and error variances are constrained to be same while the intercepts are allowed to differ across groups, is the PMG developed by Pesaran, Shin and Smith (1999). It allows the intercepts, short-run coefficients and error variances to differ across groups, but the long-run coefficients are restricted to be identical among groups.

We use the MG estimates as initial estimates of the long-run parameters for the pooled maximum likelihood function and the Newton-Raphson algorithm since it considers the first and the second derivative of the log-likelihood function.

Table 4.4 illustrates the results. The housing price elasticities vary from 0.19 to 0.22 depending of the lag structure chosen when seasonal dummies are not

ARDL	Seasonal Dummies	Pooled Mean Group	Restricted DSUR
SBC	no	.224(19.680)	
SBC	yes	.195(11.797)	
1,1,1	no	.213(16.711)	
1,1,1	yes	.191(10.829)	
0,3,3	no	.186(19.093)	
0,3,3	yes	.208(29.181)	
3lags3leads	no		.166(34.21)
3lags3leads	yes		.186(51.00)

Table 4.4: Pooled Estimates of the Long-Run Housing Price Elasticity

included. If included, the elasticity ranges from 0.19 to 0.20.

4.3.3. Dynamic Seemingly Unrelated Regression (DSUR) Estimator

Following Mark, Ogaki and Sul (2003) we consider N cointegrating regressions where N is fixed. Each equation has a triangular representation,

$$y_{it} = x_{it}'\beta_i + \bar{u}_{it} \tag{4.4}$$

$$\Delta x_{it} = e_{it} \tag{4.5}$$

A problem can arise in equation 4.4, since there exists correlation between the equilibrium error of equation i and leads and lags of first differences of the regressors of all other equations $j = 1, ..., N$. Therefore we need to adjust for possible spillover effects among states by including leads and lags not only of Δx_{1t} but also leads and lags of Δx_{2t} through Δx_{Nt} (z_t').

To purge endogeneity we project $\bar{u}_{it}$ on z_t:

$$\bar{u} = z_t'\delta_i + u_t \tag{4.6}$$

where $z_t' = (z_{1t}', ..., z_{Nt}')\,, i = 1, ..., N.$ and $z_{it}' = \left(\Delta x_{it+p}', ..., \Delta x_{it-p}'\right)$
and substitute the projection of $\bar{u}_{it}$ into equation 4.4 gives:

$$y_{it} = x_{it}'\beta_i + z_t'\delta_i + u_{it} \tag{4.7}$$

We then apply SUR to the above equation. This is the representation of the DSUR. This model can be used in small to moderate systems where the number of time periods, T, is substantially larger than the number of equations, N - as it is in our case. The model is estimated using the asymptotically efficient, feasible generalized least-squares algorithm.

The main attraction of the DSUR is that it takes into account the long-run cross-sectional dependence in the equilibrium errors in estimation and is asymptotically efficient. The test for cross-sectional dependence we estimate the innovation covariance matrix of the consumption function. The last row of Table 4.5 show whether the off-diagonal elements in the innovation covariance matrix can be restricted to zero using the Breusch and Pagan test of independence of the residuals. Clearly the null is rejected.

Table 4.5 shows the elasticities of labour income and housing prices with or without seasonal dummies included. Most of the housing price elasticities are significantly different from zero and differ quite a lot among states. The average is 0.23 (0.17) when seasonal dummies are (are not) included.

In addition, we also calculate a restricted DSUR by assuming that $\beta_1 = \beta_2 = \beta$ and stack the equation together:

$$\tilde{y}_t = \tilde{x}_t \beta + u_t \tag{4.8}$$

The results are shown in last column of Table 4.4. The elasticity ranges between 0.17 and 0.19 depending whether seasonal dummies are included.

State	(1)				(2)			
	lags leads	β_1	β_2	R^2	lags leads	β_1	β_2	R^2
Alabama	3,3	.777(19.37)	.477(11.97)	.63	3,3	.795(23.64)	.546(14.80)	.84
Alaska	3,3	.092(1.69)	.180(6.10)	.40	3,3	.100(2.55)	.178(8.17)	.69
Arizona	3,3	.248(2.99)	.352(5.90)	.37	3,3	.159(2.29)	.318(6.27)	.65
Arkansas	3,3	.545(10.46)	.034(.68)	.47	3,3	.615(15.04)	.130(3.35)	.77
California	3,3	.473(3.09)	-.245(-5.92)	.50	3,3	.423(3.62)	-.245(-8.05)	.74
Colorado	3,3	1.016(16.19)	-.197(-5.17)	.53	3,3	1.001(19.12)	-.160(-5.21)	.76
Connecticut	3,3	.663(12.55)	.437(16.33)	.81	3,3	.573(12.61)	.468(20.30)	.91
Delaware	3,3	.380(3.31)	.337(5.33)	.64	3,3	.213(2.42)	.460(9.68)	.77
DC	3,3	-.080(-1.65)	.037(1.18)	.46	3,3	-.089(-1.90)	.037(1.26)	.49
Florida	3,3	.694(14.97)	.709(5.07)	.70	3,3	.746(24.36)	.885(9.12)	.88
Georgia	3,3	.576(13.23)	.528(5.46)	.54	3,3	.541(13.98)	.585(6.87)	.77
Hawaii	3,3	.067(.66)	.583(15.74)	.75	3,3	.074(.90)	.550(18.26)	.89
Idaho	3,3	.759(8.22)	.443(8.10)	.43	3,3	.707(8.80)	.383(8.16)	.61
Illinois	3,3	.470(3.63)	.099(1.42)	.42	3,3	.306(3.39)	.218(4.41)	.77
Indiana	3,3	.401(6.04)	.412(7.71)	.57	3,3	.408(8.21)	.483(11.81)	.81
Iowa	3,3	.822(16.91)	.029(1.15)	.56	3,3	.834(22.50)	.062(3.34)	.83
Kansas	3,3	1.10(10.66)	.310(5.28)	.41	3,3	1.162(15.09)	.373(8.63)	.77
Kentucky	3,3	1.446(33.96)	-.173(-3.70)	.84	3,3	1.420(43.49)	-.095(-2.29)	.95
Louisiana	3,3	.604(8.75)	.293(8.90)	.50	3,3	.600(12.30)	.309(13.30)	.78
Maine	3,3	.992(11.37)	.036(.88)	.62	3,3	.922(12.51)	.042(1.30)	.84
Maryland	3,3	1.289(14.97)	-.989(-11.68)	.52	3,3	1.163(18.08)	-.813(-13.59)	.80
Massachusetts	3,3	.736(8.96)	.130(3.96)	.77	3,3	.704(13.94)	.142(7.14)	.92
Michigan	3,3	1.445(18.65)	-.276(-5.50)	.70	3,3	1.410(24.42)	-.274(-7.77)	.88
Minnesota	3,3	.551(12.59)	.490(6.38)	.43	3,3	.609(19.64)	.772(14.45)	.87
Mississippi	3,3	.648(16.93)	.522(16.04)	.54	3,3	.733(23.63)	.607(21.07)	.75
Missouri	3,3	.838(15.64)	.006(.11)	.57	3,3	.815(18.13)	.043(.90)	.81
Montana	3,3	.672(5.57)	.234(6.19)	.42	3,3	.624(5.52)	.282(8.07)	.58
Nebraska	3,3	.784(15.05)	.326(8.35)	.47	3,3	.858(21.36)	.462(14.79)	.80
Nevada	3,3	-.070(-.57)	.161(1.77)	.17	3,3	-.094(-.87)	.315(4.04)	.49
New Hampshire	3,3	1.046(17.64)	.202(6.01)	.76	3,3	.939(23.63)	.232(11.61)	.90
New Jersey	3,3	-.004(-.04)	.265(5.67)	.50	3,3	-.080(-1.11)	.308(9.83)	.78
New Mexico	3,3	.742(10.44)	.755(15.99)	.52	3,3	.757(12.89)	.804(20.28)	.79
New York	3,3	.475(4.60)	.076(1.71)	.48	3,3	.421(5.66)	.105(3.47)	.75
North Carolina	3,3	1.080(23.34)	-.041(-.44)	.76	3,3	1.055(29.60)	.055(.78)	.92
North Dakota	3,3	1.108(15.15)	.108(3.39)	.56	3,3	1.202(19.59)	.126(4.65)	.77
Ohio	3,3	1.053(11.59)	.060(1.30)	.58	3,3	.995(14.79)	.074(2.27)	.83

Oklahoma	3,3	-.044(-.52)	-.085(3.39)	.18	3,3	.032(.45)	.099(4.60)	.43
Oregon	3,3	1.580(12.18)	-.106(-2.23)	.37	3,3	1.467(13.19)	-.046(-1.13)	.68
Pennsylvania	3,3	.751(9.05)	.243(5.68)	.62	3,3	.587(8.98)	.330(10.67)	.82
Rhode Island	3,3	.104(1.31)	.313(10.94)	.59	3,3	.014(.19)	.335(12.11)	.81
South Carolina	3,3	.864(29.71)	.072(1.07)	.80	3,3	.872(42.77)	.148(3.01)	.94
South Dakota	3,3	.940(16.81)	-.143(-2.94)	.63	3,3	.933(20.30)	-.137(-3.58)	.83
Tennessee	3,3	1.278(46.76)	.171(3.58)	.86	3,3	1.265(68.64)	.211(6.18)	.97
Texas	3,3	.982(11.71)	.393(10.79)	.35	3,3	1.102(15.64)	.444(14.42)	.77
Utah	3,3	.232(3.29)	.213(7.82)	.49	3,3	.241(4.18)	.255(11.20)	.78
Vermont	3,3	.718(8.46)	.203(3.60)	.55	3,3	.670(8.39)	.182(3.37)	.76
Virginia	3,3	.492(9.56)	.198(3.18)	.58	3,3	.503(12.05)	.159(3.05)	.85
Washington	3,3	.971(10.62)	.068(1.36)	.68	3,3	.750(11.28)	.179(4.73)	.94
West Virginia	3,3	-.079(-1.24)	.000(.01)	.12	3,3	-.026(-.48)	.002(.09)	.26
Wisconsin	3,3	.373(4.44)	.092(2.09)	.27	3,3	.371(5.73)	.157(4.50)	.71
Wyoming	3,3	-.76(-4.83)	.483(9.63)	.59	3,3	-.791(-5.66)	.503(10.84)	.63
Seasonal Dummies	no				yes			
B-P test independence	chi2(1275) = 30733.553				chi2(1275) = 11066.492			
of residuals	p-value=0.000				p-value=0.000			
Average	3,3	0.644(10.67)	0.173(4.17)		3,3	0.620(13.72)	0.227(6.27)	

Table 4.5: Unrestricted DSUR Estimates

4.3.4. Aging of Population and Homeownership

Venti and Wise (1991, 2001, 2002), McFadden (1994a, 1994b), Hoynes and McFadden (1997), Mankiw and Weil (1989), Hurd (1997), and Bosworth et al. (1991) studied the effect of changes in the housing equity of the aged on consumption and wealth and came to different conclusions. Therefore, the empirical evidence on the effects of an aging population on consumption and wealth is not clear cut. It is not clear whether demographic characteristics have a positive or negative effect on consumption. In the same vain, it is not clear whether increases (decreases) in elderly home equity arising from capital gains (losses) are translated into consumption. In our model the differences among house price coefficients imply that there exist different behaviour among states. There are two variables that can potentially explain these differences: different rates of aging of population and homeownership among states. The percentage of the population age 65 and older rose sharply after 1975 and will continue to rise for the next forty years. Table A.4 illustrates the proportion of population aged 45 years or more (and 65 years or more). There appears to be a pattern: States with negative or insignificant housing coefficients are states with a relatively low proportion of households with heads aged 45 years or more. This is the case of California, Alaska, Colorado and Georgia (among others).

The second factor that could explain the difference in coefficients is homeownership rates in each state. The greater the proportion of households who are homeowners, the more the wealth effect dominates at the aggregate level[9]. Table A.5 shows homeownership rates for 1986, 1990 and 1996. States with lower homeownership rates are the states with negative or insignificant housing price coefficients. DC, Illinois, Massachusetts, Nevada are examples.

In what follows, we try to give further evidence on the changes in consumption after retirement and the possible effects on consumption of converting housing equity into liquid assets. To this end, we include the proportion of population aged 45 or more in the long-run relationship to control for aging population and the results are shown in Table A.6 and A.7 using both Mean Group and DSUR estimations, respectively. β_3 is the coefficient of the aging variable that happens to be significant for at least half of the states. Housing coefficients, however, still differ widely among states. Consequently, we conclude that after controlling for different rates of aging populations, there are big differences in the response of consumption to housing prices. Moreover, it is not possible for us to shed more light on the earlier discussions in the literature about the sign of the demographic impact on consumption via housing wealth. Around half of the significant coefficients of the aging population variable are positive and the other half are negative.

5. Compare and Contrast

As mentioned in the Introduction, Case et al. (2001) follow a roughly similar procedure. They estimate regressions relating consumption to income, stock wealth and housing wealth for a panel of the 50 US states and District of Columbia. They deflate all variables by the national GDP deflator and test for unit roots in the time series, rejecting the hypothesis of unit roots in the data for most of the series. They use three different specifications including fixed effects and adding a serial correlation correction and a lagged dependent variable and estimate the regression in differences[10]. The estimated effect of housing market wealth on consumption in their work ranges from 0.05 to 0.09.

[9] The homeownership rate at the US is 68 per cent in the first quarter of 2003, an increase of 4 percentage points from 1993 due basically to the affluent baby boomers and the entrance in the market of minority middle class (immigrants). New finance alternatives have allowed low-wealth households to qualify for loans to become homeowners.

[10] The use of differences avoids the pitfall of spurious correlation due to common trending series, however it tends to lead to the omission of the long-run relationship that may exist among levels of these variables.

Pesaran and Smith (1995) show that fixed effects, instrumental variables or Generalized Method of Moments estimators can be inconsistent and produce misleading estimates of the average values of the parameters in dynamic panel data models when T is large and the slope coefficients are not identical, as is usually the case. Therefore a more suitable estimator that imposes weaker homogeneity correlate with interest rates and income expectations. Capital gains due to real state wealth prices contain important forward-looking aspects. Net wealth is composed by financial saving, amortization of loans and/or capital gains. It is therefore interesting to see whether the results change when housing wealth is used instead of housing prices.

In order to make a comparison with Case at al. (2001) we reestimate our model using housing wealth instead of housing prices (although we do not include stock market wealth since stock market indexes are nationally driven). Following Case et al. (2001) we impute the aggregate value of owner-occupied housing to proxy for housing wealth as follows:

$$W_{it} = R_{it} N_{it} HP_{it} W_{io} \tag{5.1}$$

where

W_{it}=aggregate value of owner occupied housing in state i in quarter t

R_{it}=homeownership rate in state i in quarter t

N_{it}=number of households in state i in quarter t

HP_{it}=quarterly conventional mortgage home price index for state i in quarter t

W_{io}=median house value for state i in the base year 1990

(See Appendix 2 for a detailed description of the data)

We test housing wealth for unit roots and we cannot reject the null hypothesis of unit root (footnote of Table 4.1). We then test for cointegration between real retail sales, real labour income and real housing wealth and we can reject the null of hypothesis of no cointegration (last two columns of Table 4.2). In this specification, housing wealth directly affects consumption through its market value, which provides a source of purchasing power to cope with fluctuations in income.

Table 5.3 shows the PMG housing wealth estimates of the cointegrating relation, the estimated elasticity ranges from 0.15 to 0.21 depending on whether seasonal dummies are included. These findings are very similar to the estimated effect of housing prices on consumption in the previous section.

In a nutshell, these results give support to our previous findings and imply that the estimated elasticity of housing wealth is more than twice the estimated elasticity in Case et al. (2001).

6. Conclusion

We have analysed the effect of housing prices on consumption using variables suggested by the life-cycle model. Since housing prices are locally driven we study the

ARDL	Seasonal Dummies	Pooled Mean Group
SBC	no	.200(24.03)
SBC	yes	.165(12.01)
1,1,1	no	.212(20.41)
1,1,1	yes	.185(12.52)
0,3,3	no	.202(17.226)
0,3,3	yes	.153(25.99)

Table 5.3: Pooled Estimates of the Long-Run Housing Wealth Elasticity

housing wealth effect using state level data for the 50 US states and the District of Columbia. We found unit roots in housing prices and a cointegrating relationship between consumption, income and housing wealth at the state level. Due to the considerable heterogeneity in state level behaviour, fixed effects estimators that constrain intercepts, short-run coefficients and error variances lead to misleading inferences. We therefore use three different estimation methods that allow for heterogeneity among states and calculate the elasticity of housing prices. We find that differences in the aging of populations and homeownership play a role in the link between consumption and housing prices, although they do not explain the different response of consumption to housing prices among states. We find evidence of a strong housing wealth effect with elasticities ranging from 0.15 to 0.23.

A. Appendix

A.1. US States and Regions

State	State Code	Census Regions	CPI Index
Alabama	AL	South	South:Urban:All Items, NSA
Alaska	AK	West	West: Urban: All Items, NSA
Arizona	AZ	West	West: Urban: All Items, NSA
Arkansas	AR	South	South:Urban:All Items, NSA
California	CA	West	Los Angeles-Riverside-Orange: All Items, NSA
Colorado	CO	West	West: Urban: All Items, NSA
Connecticut	CT	Northeast	NY-NJ,NY-CT-PA: All Items, NSA
Delaware	DE	South	Phila-Wilmington-Alt City: All Items, NSA
District of Columbia	DC	South	South:Urban:All Items, NSA
Florida	FL	South	South:Urban:All Items, NSA
Georgia	GA	South	Atlanta, GA: All Items, NSA
Hawaii	HI	West	West: Urban: All Items, NSA
Idaho	ID	West	West: Urban: All Items, NSA
Illinois	IL	Midwest	Chicago-Gary-Kenosha, IL-IN-WI:All Items, NSA
Indiana	IN	Midwest	Chicago-Gary-Kenosha, IL-IN-WI:All Items, NSA
Iowa	IA	Midwest	Midwest: Urban: All Items, NSA
Kansas	KS	Midwest	Midwest: Urban: All Items, NSA
Kentucky	KY	South	South:Urban:All Items, NSA
Louisiana	LA	South	South:Urban:All Items, NSA
Maine	ME	Northeast	Northeast: Urban: All Items, NSA
Maryland	MD	South	Phila-Wilmington-Alt City: All Items, NSA
Massachusetts	MA	Northeast	Boston-Brockton-Nashua: All Items, NSA
Michigan	MI	Midwest	Detroit-Ann Arbor-Flint, MI: All Items, NSA
Minnesota	MN	Midwest	Midwest: Urban: All Items, NSA
Mississippi	MS	South	South:Urban:All Items, NSA
Missouri	MO	Midwest	Midwest: Urban: All Items, NSA
Montana	MT	West	West: Urban: All Items, NSA
Nebraska	NE	Midwest	Midwest: Urban: All Items, NSA
Nevada	NV	West	West: Urban: All Items, NSA
New Hampshire	NH	Northeast	Boston-Brockton-Nashua: All Items, NSA
New Jersey	NJ	Northeast	NY-NJ,NY-CT-PA: All Items, NSA
New Mexico	NM	West	West: Urban: All Items, NSA
New York	NY	Northeast	NY-NJ,NY-CT-PA: All Items, NSA
North Carolina	NC	South	South:Urban:All Items, NSA
North Dakota	ND	Midwest	Midwest: Urban: All Items, NSA
Ohio	OH	Midwest	Cleveland-Akron, OH: All Items, NSA

(continued)	State Code	Census Regions	CPI Index
Oklahoma	OK	South	South:Urban:All Items, NSA
Oregon	OR	West	West: Urban: All Items, NSA
Pennsylvania	PA	Northeast	Phila-Wilmington-Alt City: All Items, NSA
Rhode Island	RI	Northeast	Northeast: Urban: All Items, NSA
South Carolina	SC	South	South:Urban:All Items, NSA
South Dakota	SD	Midwest	Midwest: Urban: All Items, NSA
Tennessee	TN	South	South:Urban:All Items, NSA
Texas	TX	South	Dallas-Fort Worth, TX: All Items, NSA
Utah	UT	West	West: Urban: All Items, NSA
Vermont	VT	Northeast	Northeast: Urban: All Items, NSA
Virginia	VA	South	South:Urban:All Items, NSA
Washington	WA	West	Seattle-Tacoma-Bremerton: All Items, NSA
West Virginia	WV	South	South:Urban:All Items, NSA
Wisconsin	WI	Midwest	Chicago-Gary-Kenosha, IL-IN-WI:All Items, NSA
Wyoming	WY	West	West: Urban: All Items, NSA

Table A.1: State Consumer Prices' Sources

A.2. Data Sources

The panel data used is a balanced panel spanning from 1975:1 to 1996:4 for 50 US states and District of Columbia.

A.2.1. Real per Capita Retail Sales

This is our proxy for Real per Capita Consumption. We construct the series from:

- Monthly Retail Sales for the period 78:01-96:12 for 20 states (CA, FL, GA, IL, IN, LA, MA, MD, MI, MN, MO, NC, NJ, NY, OH, PA, TN, TX, VA, WI) from the US Census Bureau (please note that the monthly retail sales series have been discontinued)
- Monthly Retail Sales for the period 87:01-96:12 for 7 states (AZ-CO-CT-DE-KS-KY-WA) from the US Census Bureau and partial interpolation using the Chow-Lin Method for the period 75:1-87:4.
- For the rest of the 23 states full interpolation was computed.

The series used by the Chow-Lin Method is order to calculate the interpolations are the Monthly Retail Sales from 78:01-96:12 for 9 Census Divisions from the US Census Bureau and the Annual Retail Sales from 63-96 from the Sales and Marketing Management magazine for 50 states.

The series is deflated by the calculated state CPI described below and made per capita using the interpolated state population estimates.

A.2.2. Real Housing Prices

Real housing prices were calculated from the Quarterly Conventional Mortgage Home Price Index (CMHPI) by Freddie Mac. They were deflated by the calculated state CPI described below.

A.2.3. Real per Capita Labour Income

Real per Capita Labour Income was calculated from the quarterly labour Income by the Bureau of Economic Analysis. The series is deflated by the calculated state CPI described below and made per capita using the interpolated state population estimates.

A.2.4. State Consumer Prices

State CPI was calculated by matching monthly CPIs of the 4 Census Regions by the Bureau of Labor Statistics and monthly or quarterly CPIs for 26 Metropolitan Statistical Areas (MSAs) and Primary Metropolitan Statistical Areas (PMSAs) and Cities, with the closest state. The CPIs used are listed in Table A.1.

A.2.5. Population Estimates

State Population Estimates were interpolated from annual resident population estimates by the US Census Bureau. The Chow-Lin method used Monthly US Population Estimates by the US Census Bureau.

A.2.6. Real per Capita Housing Wealth

Real per capita Housing Wealth was calculated following Case et al. (2001). Apart from the housing prices describe above, we used:

Homeownership Rates State Quarterly Homeownership Rate were interpolated from Annual Homeownership Rates by the Housing Vacancies and Homeownership, Annual Statistics of the US Census Bureau, Table 13. The Chow-Lin method used the quarterly US Homeownership Rates by the US Census Bureau, Table 5.

Total Number of Households State Quarterly Estimates of Total Households were interpolated from the State Intercensal Estimates of Total Households by the US Census Bureau. The Chow-Lin method used the Quarterly Estimates of Total Households for the US by the US Census Bureau, Series H-111.

House Median Value Median house value from the 1990 Census of Population and Housing, US Bureau of the Census.

The series is deflated by the calculated state CPI described below and made per capita using the interpolated state population estimates.

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State	MG Estimator				
	$ARDL$	β_1	β_2	α	R^2
Alabama	2,0,0	.820(12.01)	.475(4.43)	-1.00(NA)	.43
Alaska	0,0,0	.076(.35)	.247(1.91)	-.462(-4.58)	.39
Arizona	0,0,2	.014(.047)	.051(.204)	-.440(-3.70)	.42
Arkansas	0,0,0	.831(5.18)	.358(1.88)	-.622(-4.57)	.50
California	2,0,0	1.259(1.71)	-.248(-1.40)	-.378(-3.90)	.48
Colorado	2,0,1	1.030(9.72)	-.107(-1.38)	-1.00(NA)	.34
Connecticut	2,1,0	.633(4.436)	.421(4.501)	-.663(-4.718)	.51
Delaware	2,1,0	.595(1.28)	.266(.91)	-.406(-3.26)	.56
DC	2,1,0	.056(.22)	-.184(-.92)	-.161(-3.45)	.38
Florida	2,1,0	.732(7.03)	.499(1.39)	-.549(-4.58)	.55
Georgia	0,0,0	.662(4.78)	.394(.94)	-.488(-3.77)	.55
Hawaii	3,2,0	.122(.48)	.546(6.06)	-1.00(NA)	.39
Idaho	2,0,0	1.022(3.02)	.612(2.68)	-.354(-3.58)	.30
Illinois	0,0,0	.286(1.00)	.247(1.26)	-.648(-4.50)	.70
Indiana	2,0,0	.618(6.14)	.511(4.89)	-1.00(NA)	.49
Iowa	0,0,0	.987(5.39)	.093(.76)	-.489(-4.15)	.47
Kansas	0,0,0	1.096(7.57)	.300(3.16)	-1.00(NA)	.52
Kentucky	2,0,0	1.419(20.34)	-.026(-.22)	-1.00(NA)	.50
Louisiana	0,0,0	.600(6.07)	.306(6.23)	-1.00(NA)	.47
Maine	2,2,1	1.049(6.87)	.069(.78)	-1.00(NA)	.45
Maryland	2,0,0	1.232(3.90)	-.821(-2.51)	-.497(-4.00)	.58
Massachusetts	2,1,0	.864(5.56)	.107(1.57)	-1.00(NA)	.58
Michigan	3,1,0	1.486(13.58)	-.239(-2.37)	-1.105(-6.51)	.63
Minnesota	2,0,0	.689(8.55)	.690(3.77)	-1.00(NA)	.56
Mississippi	2,1,0	.766(6.34)	.651(5.38)	-.625(-4.96)	.44
Missouri	2,0,0	.875(6.16)	.023(.11)	-.568(-4.24)	.49
Montana	0,0,0	.963(2.93)	.247(2.13)	-.447(-5.08)	.22
Nebraska	3,0,0	.903(9.20)	.352(3.45)	-1.00(NA)	.45
Nevada	0,0,0	.440(.74)	.697(1.49)	-.329(-3.26)	.32
New Hampshire	3,0,0	1.053(10.66)	.219(3.20)	-1.00(NA)	.55
New Jersey	0,0,0	.213(.72)	.278(1.82)	-.571(-4.09)	.58
New Mexico	0,0,0	.695(2.71)	.444(2.22)	-.503(-3.68)	.30
New York	2,0,1	.438(1.16)	.109(.59)	-.425(-3.47)	.58
North Carolina	3,2,0	1.100(13.77)	.029(.14)	-1.00(NA)	.50
North Dakota	2,0,0	1.447(5.97)	.261(1.91)	-.493(-4.60)	.48
Ohio	0,0,0	1.326(7.203)	.044(.36)	-.726(-5.31)	.57

Oklahoma	2,0,0	-.180(-.39)	.083(.67)	-.305(-3.02)	.34
Oregon	3,0,1	.888(1.70)	.229(.951)	-.303(-3.19)	.40
Pennsylvania	2,1,0	1.078(2.83)	.048(.20)	-.495(-3.56)	.60
Rhode Island	0,0,0	.512(.72)	.008(.022)	-.246(-2.12)	.35
South Carolina	2,0,0	.913(20.14)	.158(1.11)	-.105(-6.16)	.69
South Dakota	1,0,0	1.142(3.98)	.026(.08)	-.319(-3.34)	.41
Tennessee	2,0,0	1.325(51.80)	.201(3.26)	-1.944(-9.39)	.70
Texas	2,0,0	1.019(7.91)	.418(7.43)	-1.109(-6.91)	.63
Utah	0,1,0	.486(4.74)	.315(5.52)	-1.00(NA)	.36
Vermont	1,0,0	1.153(2.27)	-.337(-.78)	-.322(-2.99)	.41
Virginia	2,0,0	.531(4.88)	.215(1.46)	-1.00(NA)	.54
Washington	2,0,1	.710(11.90)	.235(7.20)	-2.43(-11.86)	.76
West Virginia	0,0,1	.284(.77)	.093(.57)	-.175(-2.35)	.45
Wisconsin	2,0,0	.468(3.56)	.246(2.49)	-1.00(NA)	.54
Wyoming	3,0,0	.240(.18)	.530(1.58)	-.13(-2.48)	.06
Seasonal Dummies			no		
Average (MG)		.764(13.506)	.204(5.183)	-.721(-12.03)	

Table A.2: Mean Group Estimation without Seasonal Dummies

.

State	MG Estimator				
	$ARDL$	β_1	β_2	α	R^2
Alabama	3,0,0	.870(7.89)	.538(3.07)	-.298(-4.07)	.87
Alaska	1,0,3	.062(.24)	.270(1.91)	-.217(-3.64)	.84
Arizona	2,0,2	-.027(-.08)	-.002(-.01)	-.257(-3.33)	.74
Arkansas	3,0,0	.856(5.06)	.380(1.94)	-.302(-3.99)	.88
California	2,1,0	3.682(1.02)	-.898(-1.03)	-.051(-1.05)	.89
Colorado	1,1,0	1.099(5.97)	-.098(-.74)	-.314(-3.86)	.81
Connecticut	2,1,0	.669(4.57)	.408(4.31)	-.351(-4.033)	.86
Delaware	2,1,0	.812(1.56)	.108(.33)	-.250(-2.91)	.84
DC	2,0,3	.077(.36)	-.159(-.95)	-.128(-3.99)	.72
Florida	2,0,1	.637(5.94)	.073(.19)	-.345(-4.62)	.84
Georgia	1,0,1	.619(2.61)	-.132(-.16)	-.167(-2.00)	.85
Hawaii	3,0,0	.729(1.03)	.307(1.24)	-.179(-2.32)	.85
Idaho	2,0,2	1.242(2.73)	.830(2.52)	-.142(-2.60)	.81
Illinois	2,0,0	.340(.92)	.116(.45)	-.271(-3.02)	.91
Indiana	2,0,0	.618(4.34)	.501(3.50)	-.386(-4.47)	.86
Iowa	3,0,0	1.129(5.19)	.201(1.39)	-.202(-3.45)	.89
Kansas	3,0,0	.988(6.24)	.251(2.56)	-.496(-4.88)	.88
Kentucky	2,0,0	1.481(14.87)	-.058(-.37)	-.347(-4.53)	.89
Louisiana	2,0,2	.681(4.57)	.344(4.88)	-.373(-3.67)	.87
Maine	3,0,0	1.124(4.25)	-.058(-.38)	-.343(-4.28)	.86
Maryland	2,0,0	1.009(1.91)	-.581(-1.04)	-.157(-2.22)	.89
Massachusetts	3,0,0	.956(4.26)	.039(.37)	-.381(-3.76)	.89
Michigan	3,0,0	1.483(9.52)	-.213(-1.54)	-.416(-5.41)	.89
Minnesota	1,0,2	.647(9.60)	.695(4.70)	-.589(-5.35)	.91
Mississippi	2,1,0	.611(3.93)	.495(3.24)	-.232(-3.25)	.87
Missouri	2,2,0	.818(4.31)	-.238(-.80)	-.235(-2.93)	.85
Montana	2,0,3	1.369(3.84)	.256(2.55)	-.267(-4.81)	.80
Nebraska	3,0,0	.740(3.29)	.253(1.13)	-.222(-2.92)	.89
Nevada	1,0,0	1.014(1.10)	1.135(1.56)	-.114(-2.22)	.84
New Hampshire	3,0,0	1.068(12.62)	.229(4.12)	-.621(-6.58)	.89
New Jersey	1,0,1	.062(.16)	.321(1.63)	-.268(-2.84)	.85
New Mexico	2,0,0	.687(1.87)	.320(1.06)	-.175(-2.42)	.82
New York	3,1,0	.280(.41)	.070(.21)	-.121(-1.77)	.89
North Carolina	1,0,0	.987(6.94)	-.159(-.42)	-.257(-3.24)	.91
North Dakota	3,0,0	1.263(4.60)	.303(1.84)	-.201(-4.04)	.89
Ohio	3,1,0	1.122(3.43)	.084(.44)	-.240(-2.67)	.89

Oklahoma	3,1,2	.077(.23)	.130(1.46)	-.202(-3.83)	.86
Oregon	1,1,1	1.333(1.92)	.251(.87)	-.124(-2.53)	.85
Pennsylvania	1,0,0	1.261(3.46)	-.105(-.45)	-.247(-3.79)	.93
Rhode Island	1,0,0	1.773(.49)	-1.008(-.42)	-.041(-.63)	.84
South Carolina	1,1,0	.925(17.71)	.123(.76)	-.494(-4.93)	.91
South Dakota	3,0,3	1.366(3.90)	.600(1.35)	-.135(-2.84)	.87
Tennessee	2,0,0	1.338(35.31)	.240(2.60)	-.736(-8.19)	.90
Texas	1,0,0	1.162(8.15)	.488(7.24)	-.506(-6.00)	.89
Utah	1,1,0	.555(2.61)	.271(2.30)	-.235(-3.29)	.85
Vermont	3,0,0	1.065(1.85)	-.228(-.47)	-.146(-2.48)	.83
Virginia	3,0,0	.572(4.97)	.165(1.06)	-.548(-5.60)	.85
Washington	2,2,0	.866(9.85)	.139(2.95)	-1.00(NA)	.91
West Virginia	2,0,0	.105(.37)	.038(.28)	-.127(-2.88)	.81
Wisconsin	2,0,0	.498(2.67)	.277(2.01)	-.411(-3.86)	.85
Wyoming	0,0,0	-.441(-.46)	.596(2.36)	-.106(-3.14)	.66
Seasonal Dummies			yes		
Average (MG)		.868(10.21)	.155(2.97)	-.294(11.589)	

Table A.3: Mean Group Estimation with Seasonal Dummies

.

State	45+			65+		
	1975	1986	1996	1975	1986	1996
Alabama	30.15	31.28	34.27	10.44	12.29	13.09
Alaska	16.51	17.53	25.28	2.34	3.21	5.12
Arizona	29.20	30.16	32.75	9.99	12.40	13.38
Arkansas	32.93	33.41	35.53	12.76	14.46	14.47
California	29.75	27.96	29.32	9.72	10.54	11.07
Colorado	26.30	26.33	31.78	8.30	9.06	10.14
Connecticut	32.66	32.97	35.33	10.49	13.01	14.36
Delaware	29.02	30.66	33.10	8.63	11.46	12.86
District of Columbia	30.86	30.37	34.60	10.26	12.01	13.90
Florida	37.70	38.02	39.08	15.88	17.86	18.55
Georgia	27.30	27.49	29.95	8.67	9.87	9.98
Hawaii	25.58	27.66	33.48	6.63	9.92	12.96
Idaho	28.32	28.09	31.53	9.57	11.22	11.43
Illinois	31.08	30.68	32.65	10.36	12.06	12.55
Indiana	29.78	30.81	33.41	9.98	11.98	12.67
Iowa	32.74	33.44	36.03	12.71	14.82	15.23
Kansas	32.64	31.63	33.46	12.57	13.53	13.70
Kentucky	30.28	30.68	34.10	10.76	12.04	12.64
Louisiana	27.48	27.57	31.53	9.20	10.13	11.48
Maine	31.96	31.87	35.39	11.89	13.21	13.97
Maryland	28.80	29.61	32.14	8.35	10.50	11.44
Massachusetts	32.86	32.01	34.29	11.77	13.36	14.14
Michigan	28.89	29.95	32.92	9.02	11.33	12.47
Minnesota	29.97	29.86	32.24	11.23	12.44	12.45
Mississippi	29.11	29.37	31.99	10.79	11.94	12.35
Missouri	32.99	32.74	34.39	12.57	13.70	13.89
Montana	29.80	30.36	35.69	10.07	12.16	13.22
Nebraska	31.96	31.65	33.83	12.59	13.77	13.92
Nevada	27.98	29.64	33.00	7.27	10.03	11.51
New Hampshire	30.24	29.26	31.80	10.87	11.43	12.08
New Jersey	33.22	33.28	34.93	10.53	12.76	13.73
New Mexico	25.70	27.25	31.24	7.96	9.78	11.13
New York	33.31	32.64	34.30	11.43	12.78	13.35
North Carolina	28.90	30.57	33.49	9.07	11.45	12.60
North Dakota	30.54	30.18	34.22	11.50	13.10	14.54
Ohio	30.75	31.66	34.23	9.99	12.24	13.43

(continued)	45+			65+		
	1975	1986	1996	1975	1986	1996
Oklahoma	32.29	31.32	34.62	12.23	12.44	13.57
Oregon	31.35	31.32	35.22	11.21	13.31	13.45
Pennsylvania	34.81	35.05	37.33	11.66	14.62	15.91
Rhode Island	34.77	33.58	35.06	12.18	14.55	15.78
South Carolina	26.87	28.67	33.03	8.14	10.53	12.10
South Dakota	32.19	31.76	33.79	12.56	14.10	14.47
Tennessee	30.49	31.52	34.27	10.52	12.24	12.59
Texas	27.93	26.58	29.40	9.41	9.44	10.19
Utah	23.28	22.00	24.81	7.44	8.03	8.80
Vermont	29.57	29.25	33.56	11.03	11.80	12.23
Virginia	28.38	28.94	32.09	8.59	10.33	11.23
Washington	29.80	29.29	32.18	10.18	11.62	11.63
West Virginia	33.29	33.88	38.37	11.70	13.66	15.23
Wisconsin	30.79	31.11	33.56	11.22	13.05	13.30
Wyoming	27.24	26.45	32.81	8.83	8.56	11.23
Mean	30.01	30.18	33.28	10.26	11.88	12.77
Variance	10.77	9.98	6.50	4.30	4.79	4.07
Highest	37.7	38.02	39.08	15.88	17.86	18.55
Lowest	16.51	17.53	24.81	2.34	3.21	5.12

Table A.4: Aging Population

.

State	1986	1990	1996
Alabama	70.3	68.4	71
Alaska	61.5	58.4	62.9
Arizona	62.5	64.5	62
Arkansas	67.5	67.8	66.6
California	53.8	53.8	55
Colorado	63.7	59	64.5
Connecticut	68.1	67.9	69
Delaware	71	67.7	71.5
District of Columbia	34.6	36.4	40.4
Florida	66.5	65.1	67.1
Georgia	62.4	64.3	69.3
Hawaii	50.9	55.5	50.6
Idaho	69.8	69.4	71.4
Illinois	60.9	63	68.2
Indiana	67.6	67	74.2
Iowa	69.2	70.7	72.8
Kansas	66.4	69	67.5
Kentucky	68.1	65.8	73.2
Louisiana	70.4	67.8	64.9
Maine	74	74.2	76.5
Maryland	62.8	64.9	66.9
Massachusetts	60.3	58.6	61.7
Michigan	70.9	72.3	73.3
Minnesota	68	68	75.4
Mississippi	70.4	69.4	73
Missouri	67.8	64	70.2
Montana	64.4	69.1	68.6
Nebraska	68.3	67.3	66.8
Nevada	54.5	55.8	61.1
New Hampshire	64.8	65	65
New Jersey	63.3	65	64.6
New Mexico	67.8	68.6	67.1
New York	51.3	53.3	52.7
North Carolina	68.2	69	70.4
North Dakota	69.2	67.2	68.2
Ohio	68.2	68.7	69.2

(continued)	1986	1990	1996
Oklahoma	69.7	70.3	68.4
Oregon	63.9	64.4	63.1
Pennsylvania	72.3	73.8	71.7
Rhode Island	62.2	58.5	56.6
South Carolina	70.3	71.4	72.9
South Dakota	65.9	66.2	67.8
Tennessee	67.4	68.3	68.8
Texas	61	59.7	61.8
Utah	68	70.1	72.7
Vermont	69.8	72.6	70.3
Virginia	68.2	69.8	68.5
Washington	65.1	61.8	63.1
West Virginia	76.4	72	74.3
Wisconsin	66.5	68.3	68.2
Wyoming	72	68.9	68
Mean	65.5	65.5	66.8
Variance	47.1	42.9	44.7
Highest	76.4	74.2	76.5
Lowest	34.6	36.4	40.4

Table A.5: Homeownership Rates

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State	MG Estimator					
	$ARDL$	β_1	β_2	β_3	α	R^2
Alabama	2,0,0,3	0.129(0.33)	0.465(1.06)	1.722(1.45)	-0.530(-3.62)	0.72
Alaska	3,0,0,2	-0.508(-2.30)	0.422(4.66)	0.749(4.73)	-0.703(-5.67)	0.70
Arizona	0,0,0,0	0.726(3.29)	0.289(1.93)	-0.330(-0.65)	-	0.44
Arkansas	2,0,1,3	-0.591(-1.23)	0.550(1.96)	6.497(3.36)	-0.604(-3.57)	0.76
California	1,0,2,2	0.813(3.27)	-0.038(-0.62)	0.314(0.79)	-1.258(-11.08)	0.66
Colorado	0,0,1,3	2.617(4.84)	-0.064(-0.81)	-0.768(-1.84)	-	0.74
Connecticut	3,0,0,3	1.612(2.82)	0.021(0.09)	-3.538(-1.84)	-0.698(-4.49)	0.73
Delaware	3,0,0,3	3.223(3.30)	-0.548(-1.40)	-5.215(-3.17)	-0.537(-2.82)	0.77
DC	3,0,0,3	0.185(0.86)	-0.193(-1.39)	-1.611(-3.29)	-0.341(-3.58)	0.61
Florida	1,0,0,2	1.049(13.55)	0.873(3.50)	1.175(2.46)	-1.263(-10.70)	0.63
Georgia	2,3,0,3	-0.164(-0.21)	0.749(0.76)	2.495(1.48)	-0.356(-1.96)	0.73
Hawaii	2,0,0,3	1.687(2.91)	-0.106(-0.62)	-0.173(-0.36)	-0.596(-3.48)	0.73
Idaho	3,0,1,3	-1.358(-1.79)	1.488(9.28)	3.607(2.68)	-0.754(-5.12)	0.69
Illinois	3,0,0,3	1.246(8.02)	0.066(0.64)	-3.135(-11.62)	-1.902(-6.02)	0.88
Indiana	2,0,0,3	0.362(0.72)	0.391(1.09)	0.416(0.30)	-0.663(-3.31)	0.70
Iowa	3,0,1,3	0.365(1.57)	0.648(7.69)	0.979(1.24)	-1.269(-5.58)	0.82
Kansas	0,0,0,3	1.102(3.26)	0.287(1.20)	-1.106(-1.27)	-	0.63
Kentucky	2,0,0,3	0.735(1.44)	0.440(0.97)	1.009(0.75)	-0.577(-3.74)	0.78
Louisiana	3,0,0,3	0.589(1.51)	0.350(3.43)	0.178(0.23)	-0.741(-3.95)	0.76
Maine	3,0,0,3	1.320(1.77)	-0.113(-0.43)	-1.525(-1.71)	-0.831(-4.16)	0.75
Maryland	3,0,0,3	1.694(6.78)	-0.770(-4.07)	-1.670(-2.66)	-0.823(-3.93)	0.81
Massachusetts	3,0,3,2	1.099(5.35)	0.010(0.12)	-0.446(-0.91)	-1.817(-7.39)	0.85
Michigan	3,2,0,2	1.473(26.60)	0.021(0.44)	-0.427(-2.58)	-2.464(-11.69)	0.89
Minnesota	3,0,0,3	0.360(2.73)	0.208(0.62)	0.819(1.31)	-1.069(-4.45)	0.79
Mississippi	2,0,1,3	1.347(2.10)	0.813(3.12)	-2.777(-1.26)	-0.513(-4.22)	0.69
Missouri	0,0,0,3	0.823(4.07)	-0.001(-0.05)	-1.156(-1.27)	-	0.68
Montana	3,0,0,3	1.391(1.79)	0.390(2.80)	-0.591(-0.77)	-0.516(-3.44)	0.63
Nebraska	2,0,0,3	-0.196(-0.37)	0.435(1.13)	1.488(0.73)	-0.640(-4.09)	0.77
Nevada	2,0,0,3	-5.005(-1.57)	0.803(0.74)	6.852(1.62)	-0.222(-2.17)	0.65
New Hampshire	3,1,0,3	0.947(3.49)	0.160(1.29)	-0.844(-1.22)	-1.383(-6.65)	0.81
New Jersey	3,2,1,2	-0.144(-0.68)	0.403(5.32)	0.707(1.10)	-1.954(-7.40)	0.82
New Mexico	2,0,0,3	1.293(0.96)	0.782(3.87)	-0.523(-0.35)	-0.458(-2.74)	0.70
New York	3,0,0,2	0.279(1.02)	0.292(2.78)	0.943(1.11)	-1.641(-6.13)	0.72
North Carolina	2,0,0,3	0.594(1.02)	0.736(1.22)	0.135(0.10)	-0.551(-2.89)	0.73
North Dakota	2,2,0,3	1.980(1.59)	0.535(2.84)	-2.116(-0.93)	-0.489(-3.80)	0.74
Ohio	2,0,0,3	0.582(1.44)	-0.120(-0.37)	1.800(1.61)	-0.609(-3.18)	0.80

Oklahoma	3,0,0,3	-1.750(-1.28)	0.822(2.55)	3.209(1.55)	-0.297(-3.28)	0.65
Oregon	3,0,0,3	-0.019(-0.06)	0.318(6.62)	0.978(1.52)	-1434(-5.20)	0.81
Pennsylvania	2,0,0,3	-0.760(-0.13)	0.009(0.00)	-1.465(-0.12)	-0.141(-0.71)	0.74
Rhode Island	2,0,0,0	0.795(1.05)	-0.276(-0.78)	-4.895(-1.73)	-0.387(-2.47)	0.38
South Carolina	3,0,0,3	0.716(4.57)	0.449(1.50)	0.391(1.62)	-1.015(-4.49)	0.83
South Dakota	3,0,2,3	0.395(2.78)	0.521(4.06)	1.020(1.02)	-1.445(-5.77)	0.81
Tennessee	3,1,0,2	1.002(17.93)	0.423(8.15)	1.321(6.14)	-2.627(-13.05)	0.89
Texas	3,0,1,3	-0.026(-0.10)	0.099(1.53)	1.087(3.04)	-1.512(-5.66)	0.82
Utah	0,0,0,3	0.132(0.28)	.248(3.80)	0.751(1.03)	-	0.71
Vermont	2,0,3,3	1.391(1.71)	-0.521(-1.55)	-1.958(-1.97)	-0.449(-2.87)	0.76
Virginia	3,0,0,2	0.934(4.99)	0.054(0.38)	0.179(0.59)	-1.362(-6.84)	0.78
Washington	3,0,0,3	0.721(9.33)	0.248(5.20)	-0.234(-1.42)	-2.289(-8.05)	0.86
West Virginia	3,0,0,3	-1.338(-1.42)	0.457(2.14)	1.998(1.30)	-0.223(-2.90)	0.69
Wisconsin	3,0,0,2	0.734(2.87)	-0.078(-0.38)	1.200(1.07)	-1.283(-5.27)	0.74
Wyoming	3,0,0,3	-1.293(-1.47)	1.202(4.08)	0.649(1.15)	-0.207(-3.74)	0.50
Seasonal Dummies				no		

Table A.6: Mean Group Estimation controlling for Aging Population

.

State	lags leads	β_1	β_2	β_3	$\bar{R}^2$
Alabama	3,3	0.318(2.12)	0.236(1.55)	2.010(3.97)	0.78
Alaska	3,3	-0.685(-3.92)	0.391(6.33)	0.896(8.54)	0.73
Arizona	3,3	0.888(7.62)	-0.025(-0.22)	-1.411(-3.70)	0.51
Arkansas	3,3	0.038(0.20)	-0.146(-1.57)	2.900(3.47)	0.68
California	3,3	1.091(5.29)	0.094(1.55)	-0.012(-0.03)	0.75
Colorado	3,3	2.882(8.88)	-0.239(-4.34)	-0.860(-2.91)	0.77
Connecticut	3,3	1.781(7.34)	0.034(0.34)	-3.727(-4.50)	0.84
Delaware	3,3	2.849(7.21)	-0.266(-2.03)	-3.375(-4.40)	0.84
DC	3,3	-0.059(-0.69)	-0.008(-0.18)	-1.382(-5.60)	0.56
Florida	3,3	0.985(11.33)	1.265(6.10)	0.858(1.78)	0.75
Georgia	3,3	0.865(7.76)	0.721(4.20)	1.549(3.97)	0.82
Hawaii	3,3	2.314(6.28)	-0.201(-1.79)	0.285(0.92)	0.86
Idaho	3,3	-3.893(-7.43)	1.757(18.07)	7.625(8.26)	0.81
Illinois	3,3	1.801(5.04)	-0.262(-1.37)	-3.962(-7.14)	0.82
Indiana	3,3	0.183(0.88)	0.505(2.98)	1.000(1.66)	0.68
Iowa	3,3	1.080(7.05)	0.914(10.67)	-1.780(-3.16)	0.76
Kansas	3,3	1.3(a)-6483			

Ik.9li1(y1(3389(as)-8.1(3)11(64)-7.56)183)-1187.7(3)0(-164-()-15.87.797()183w983 (-13-1187.7556)183w98385.183285.

1(0.1)10.9504-1.2(.7)-1838(0)-6.In-1(.5)10.(.98)10.9(32)-1838(1.00)1029(0()7.2(3010.9(.)3(66)10.9())-151651.1(.)3.2(77)]TJ0-1.4403JT+M)i9(o)1061

(15.4((31(3)-193015.4(3.353)-19302(.6)867(7990)-1600..4(3.73)-1930553)-19302(133)-193015.4(3.033)-19302(.6)590.3.2(.7193015.4(3.73)-1930603)-

Oklahoma	3,3	-2.283(-5.05)	0.292(3.98)	4.084(6.10)	0.49
Oregon	3,3	0.288(1.08)	0.473(10.92)	-0.634(-1.13)	0.70
Pennsylvania	3,3	1.025(3.44)	0.335(3.49)	0.200(0.26)	0.76
Rhode Island	3,3	0.953(6.54)	-0.161(-3.31)	-4.852(-8.91)	0.81
South Carolina	3,3	0.746(7.13)	0.393(2.11)	0.593(2.96)	0.89
South Dakota	3,3	0.426(3.63)	0.612(6.86)	1.008(1.26)	0.76
Tennessee	3,3	1.064(10.42)	0.388(5.26)	1.449(3.05)	0.92
Texas	3,3	0.408(1.86)	0.047(0.74)	0.503(1.57)	0.43
Utah	3,3	1.219(4.36)	0.052(1.27)	-0.513(-1.19)	0.71
Vermont	3,3	1.948(6.59)	-0.336(-2.50)	-2.547(-5.97)	0.78
Virginia	3,3	0.837(5.95)	-0.003(-0.03)	0.537(1.60)	0.73
Washington	3,3	1.161(7.13)	0.184(2.66)	-0.882(-2.90)	0.82
West Virginia	3,3	-1.413(-5.88)	0.469(5.69)	1.879(4.38)	0.41
Wisconsin	3,3	0.627(2.99)	-0.706(-2.32)	3.852(2.96)	0.58
Wyoming	3,3	-1.764(-5.00)	1.042(8.31)	0.529(2.22)	0.70
Seasonal Dummies			no		
B-P test independence			chi2(1275) = 23897.822		
of residuals			p-value=0.000		

Table A.7: Unrestricted DSUR Estimates controlling for Aging Population

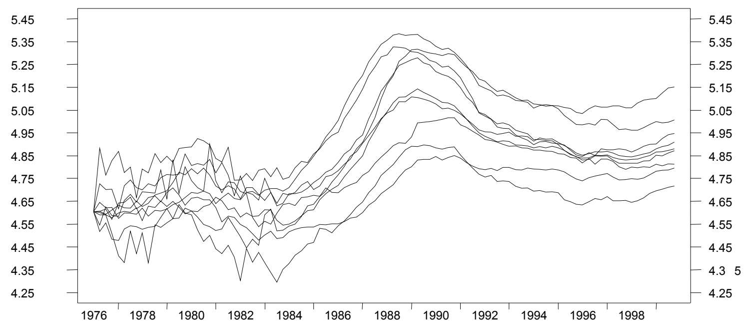

Figure A.1: Log of State Real Housing Prices in the Northeast Region

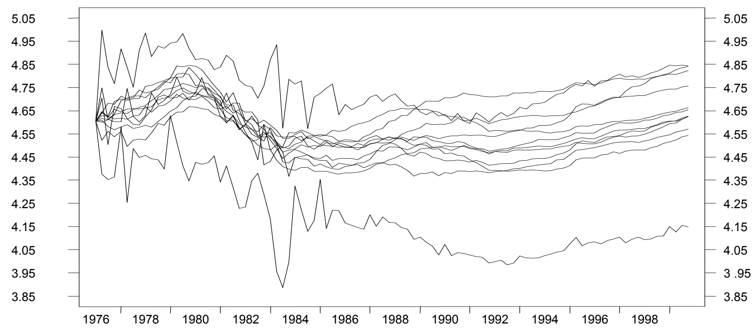

Figure A.2: Log of State Real Housing Prices in the Midwest Region

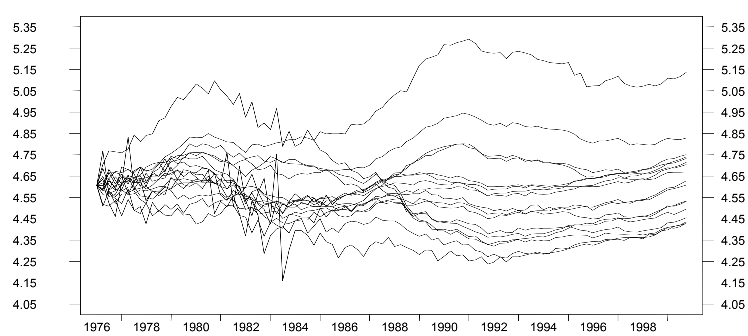

Figure A.3: Log of State Real Housing Prices in the South Region

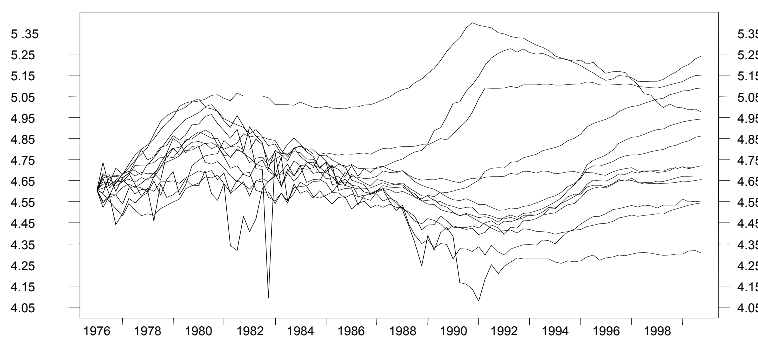

Figure A.4: Log of State Real Housing Prices in the West Region

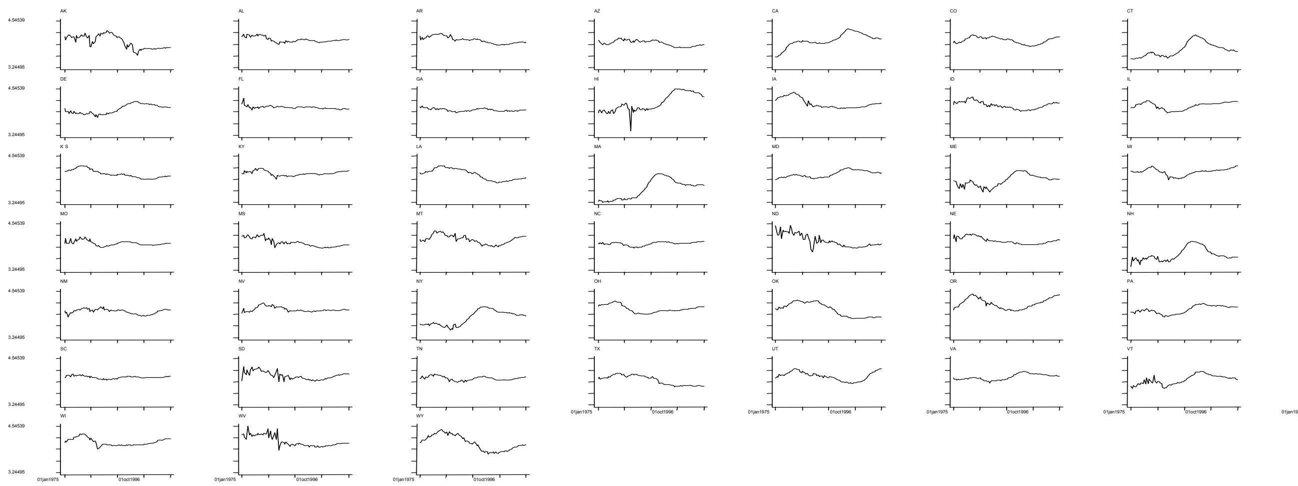

Figure A.5: Log of Real Housing Prices in all States