

Changes in Housing Wealth and Consumption: Did the Linkage Increase in the 2000s?

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Abstract

This paper shows that the relationship between housing wealth and consumption increased significantly between the 1990s and the 2000s. Likely reasons for this increase include relaxation of credit constraints on existing homeowners (such as lower borrowing costs and relaxed lending standards) and changes in the composition of home ownership. We use three datasets to show that the relationship between housing wealth and consumption has increased. The first is a unique panel of quarterly motor vehicle sales for over 180 markets in the United States between 1989 and 2007. The second contains quarterly data on sales for 28 metropolitan statistical areas (MSAs) in the state of California from 1990-2007. The final dataset is an individual-level dataset, the Survey of Income and Program Participation (SIPP). Using these datasets and various models from the wealth-effects literature, we show that the relationship between housing wealth and consumption grew stronger in the 2000s than it had been in the 1990s, frequently by a large extent. The implications of these results on the future path of aggregate consumption are significant.

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I. Introduction

Policymakers are concerned about the ways in which the troubles in the housing market may affect the broader economy. One channel through which this may occur is the relationship between housing wealth and consumption. This relationship occurs through a variety of channels. The first channel is the traditional “wealth effect,” where unexpected increases in housing wealth are viewed as changes to permanent income. Another channel, as emphasized in Campbell and Cocco (2007) and elsewhere, is the credit channel, where increases in housing wealth, whether expected or unexpected, increase the collateral against which households can borrow.

Unfortunately there is little consensus as to how strong the relationship between housing wealth and consumption is, and estimates of the marginal propensity to consume out of housing wealth vary considerably across studies. A good portion of this dispersion is believed to stem from differences in the types of consumption and wealth data analyzed and also from the differences in the estimation techniques used. Another reason for this dispersion may be that the housing wealth-consumption relationship is not stable over time; Davis and Palumbo (2001) and Poterba (2000) both noted that estimates of the wealth effect are sensitive to the time periods over which data are drawn.

There are several reasons to suspect that the linkage between housing wealth and consumption may have increased notably over the past decade. First, homes have become much more liquid over time; the costs of extracting equity from a home—either through refinancing, home equity lines of credit, or reverse mortgages, to name a few—were significantly lower in the 2000s than in previous decades. As a result, home equity could more easily be used to smooth consumption. Second, the composition of homeowners has shifted over this period; the home ownership rate increased from 64 percent in 1994, to a high of 69 percent in 2004, reflecting large gains in the homeownership rate for groups that are traditionally credit constrained, such as the young. Third, the knowledge and acceptance of tapping home equity for consumption may have increased in the 2000s as a result of a massive advertising campaign by the finance industry that pushed home equity loans, home equity lines of credit, and cash-out refinancing.

To test whether the relationship between consumption and housing wealth has increased in recent years, we develop several new datasets and then estimate consumption equations similar to those used by others in the wealth-effects literature, including Davis and Palumbo (2001), Campbell and Cocco (2007), Case Quigley and Shiller (2005), and Attanasio *et al* (2005) (hereafter referred to ABHL).¹ The first regional dataset is a panel of new motor vehicle retail registrations (which is strongly analogous to sales) in over 180 U.S. markets between 1989 and 2007. While purchases of motor vehicles, at first glance, may

¹ Consumption data at the regional/state/MSA level are difficult to obtain. The consumption data used by Case, Quigley, and Shiller (2005) are similar in many ways to ours but are estimated from a number of sources and are not data that are reported at a quarterly or annual frequency.

appear too specialized to yield useful estimates of the wealth effect, we show that new vehicle sales reflect the broad trends in consumer demand quite effectively.² The second dataset contains quarterly taxable sales in 26 California MSAs from 1990 to 2007. We match both of these regional-level consumption datasets with many of the variables typically used to estimate housing wealth-consumption relationships, such as total income, transfer income, unemployment rates, housing wealth, and financial wealth. The third dataset we exploit is the Survey of Income and Program Participation (SIPP), a dataset that follows families over vary periods of time and periodically gathers information on wealth, income, and motor vehicles.

Using these three datasets to estimate various types of consumption models, we find strong and consistent evidence that the correlation between consumption and housing wealth was much larger in the 2000s relative to the 1990s. The increases are often times large, not uncommonly by more than a factor of 2. Further, some of the estimates of the relationship between housing wealth and consumption were close to 0 in the 1990s and became significant in the 2000s. Although the evidence presented here strongly supports an increase in the magnitude of the relationship, our results, unfortunately, do not address just how large the relationship has become because of data limitations.

A caveat to nearly all attempts that estimate the relationship between wealth and consumption is identification: the correlation between changes in housing wealth and changes in consumption could arise from unobserved shocks that result both in increases in house prices and increased consumption. For instance, house prices may rise because of a change as a result of changes in expectations of future income. In such a case, consumption would also rise, resulting in an observed positive correlation between changes in house prices and changes in consumption. We attempt to address this persistent problem in a variety of ways. First, although there may be a bias, we do not believe that the bias would necessarily increase over time. Again, the contribution of this paper is not the estimates on housing wealth, but the extent to which those estimates increase over time. Second, if one of the reasons for there to be a relationship between housing wealth and consumption is that housing wealth relaxes credit constraints and we further believe that it has become easier to tap home equity, then the relationship between housing wealth and consumption should increase the most in those areas with relatively more credit constrained populations. Indeed, using a variety of measure of credit constraints, we find this to be the case.

The paper proceeds as follows: The next section reviews work on the relationship between housing wealth and consumption and discusses the factors that could cause this relationship to change over time.

² In addition, the motor vehicle data arguably have extremely low measurement error, and they are based on observations of the entire universe rather than a sample.

The second section describes the data used in the analysis, and the third section presents results from a large number of panel-data estimates. Some closing thoughts and a brief discussion of future research follow in the last section.

II. Housing Wealth and Consumption

This section presents a series of stylized facts on housing wealth, housing equity, house prices, and savings over the past 2 decades and then discusses why the propensity to consume out of housing wealth may have increased over time.

II.1 Evidence that Home Equity Extraction has Increased

As shown in Figure 1, real measures of housing wealth, housing equity, and housing debt each soared in the 2000s.³ Boosted primarily by increases in house prices, real housing wealth increased at an annual rate of 6.7 percent between 2000 and 2007, compared to an average increase of 2.5 percent in the 1990s. Real home equity grew at a more modest, though still robust, pace of 4.6 percent in the 2000's, a notable jump from the 1.2 percent increase of the 1990s. Growth in real housing debt by far outpaced in housing wealth and equity, however; real housing debt surged at an average annual rate of 9.2 percent in the 2000's, a sharp swing up from its average rate of 4.4 percent in the 1990s.

Because housing equity did not grow as quickly in the 2000s as did housing wealth, the equity share of housing wealth fell, as shown in Figure 2. The equity share of housing wealth series goes back to 1952, when the equity share of housing stood at 81 percent. From 1952 to 1994, the equity share of housing wealth fell an average of 0.5 percentage point per year. From 2001 to 2006, a period when real house prices rose particularly quickly, the equity share of housing wealth fell an average of 1.3 percent per year.⁴

There are a number of factors that lie behind the patterns in Figure 2. For instance, mortgage interest rates were at low levels during much of the 2000s, resulting in a much lower user cost of capital; the lower user cost could have compelled consumers to take on more mortgage debt. However, the share of income devoted to servicing this mortgage debt also increased rapidly during the 2000s; in 2006Q4, the share of income devoted to servicing debt for homeowners peaked at 18.2 percent, up from 15.3 percent

³ Housing wealth is defined as the market value of owner-occupied housing. Housing equity is defined as housing wealth net housing debt.

⁴ Simple models of the home equity share of housing that include trends, interest rates, and changes in house prices show relatively large residuals in the 2000s.

in early 2000. As shown in Doms and Krainer (2007), these increased mortgage debt burdens occurred for a wide array of households.⁵

In addition to the increases in mortgage debt relative to housing equity, there are several other more direct measures that demonstrate the degree to which consumers extracted equity from their homes. For example, equity lines of credit are one method that consumers can use to extract equity from their homes. As shown in Figure 3, the popularity of home equity lines of credit soared in the 2000s. By the end of 2007, the outstanding balance on home equity loans was \$1.1 trillion. Another method of mortgage equity extraction is cash-out refinancing. According to calculations by Greenspan and Kennedy (2007), the magnitude of cash taken out through this means is similar in magnitude to home equity lines of credit.

II.2 Wealth effects and Borrowing Constraints

Housing wealth likely affects consumption through two main channels: wealth effects and credit constraints.⁶ The traditional “wealth effect” story assumes that unexpected changes in housing wealth are perceived as changes in permanent income, and consumption will adjust in response. The second channel posits that increases in housing equity reduce credit constraints as households are able to borrow against that equity and enjoy the lower rates (especially after tax considerations) afforded by using housing-collateralized debt.

Most papers that examine the linkage between changes in housing wealth and changes in consumption refer to “wealth effects,” most of the time acknowledging that the traditional “wealth effect” story is not factor. With that caveat in mind, the estimates of housing “wealth effects” vary widely, with some studies suggesting a marginal propensity to consume out of housing wealth of nearly 0 (Lettau and Ludvigson 2004) while others suggest a figure as large as 9 percent (Carroll et al 2006).

Some authors have also noted that estimates of wealth effects are sensitive to the time period examined, but to date, there has been scant attention given to whether the wealth effects have changed over time. There are several reasons to suspect that the housing wealth-consumption relationship has increased, perhaps substantially, over the past decade. The reasons fall into three broad categories: (1) Financial innovation in new debt products, (2) changes in the composition of homeowners, and (3) changes in attitudes towards borrowing.

Consider first the innovations in debt products that have occurred over the past decade. Households face lower costs of extracting equity from their homes than a decade ago—that is, the liquidity of homes

⁵ The savings rate, which fell sharply during the late 1990’s, fell several percentage points in the mid 2000’s, at the height of the housing boom.

⁶ See Davis and Palumbo (2001) for a detailed description of the former and Campbell and Cocco (2006) for a description of the later

as an asset has increased. One example is the costs associated with home equity loans and refinancing; as discussed by Doms and Krainer (2007), the costs of these products fell significantly from the 1990s to the 2000s. Referring back to Figure 3, the use of home equity lines of credit took off in the 2000's, especially in 2004 and 2005. At the same time, the amount of equity available for withdraw also increased notably over this period: Loan-to-value ratios fell considerably, allowing consumers to either extract a greater share of equity during refinancing or when they move.

Another means that consumers can extract equity from homes is by cash-out refinancing, though data on this series is difficult to derive. Greenspan and Kennedy (2005) estimate that the equity extracted via cash-out refinancing is greater than equity extracted via home equity loans during the 2000s. Another class of financial products that made it easier for consumers to extract equity from their homes are reverse mortgages, though these are still relatively few in number. Nonetheless, the availability of reverse mortgages may be important because people perceive that their homes will be more liquid in later years.

The second explanation of why consumption may now be more sensitive to changes in housing wealth than in previous decades addresses the fact that the composition of homeowners has shifted towards households that are more credit constrained and hence more likely to take advantage of increases in their housing wealth. The homeownership rate soared from 64 percent in the mid 1990s, to 69 percent in the mid 2000s. The demographic groups that enjoyed the largest increase in home ownership during this time were the groups that historically have been the most credit constrained, such as younger and highly educated households.

Finally, consumers may have extracted equity from their homes at a higher rate in the 2000s than in the 1990s because the way in which they view their homes as assets has changed. Although no consistent data for these behavioral responses exists, there are several indirect pieces of evidence that suggest this may be true. For example, massive advertising campaign from the financial services industry, such as described in series of New York Times articles, may have made households more willing to extract equity from their homes, *ceteris paribus*.⁷ Several such advertisements are shown in Figure 4.

As a second example, the rapid pace of appreciation in home prices during the housing boom appears to have raised the long run expectations of at least *some* homeowners about the longer-run rate of return from housing—a change that is akin to an increase in expected permanent income. These changes in expectations could have resulted from a blossomed industry touting the virtues of real estate as an investment; an example of the height of the market is shown in Figure 5, a book entitled, “Are You Missing the Real Estate Boom: Why Home Value and Other Real Estate Investments Will Climb Through the End of the Decade--And How to Profit From Them.”

⁷ <http://www.nytimes.com/interactive/2008/07/20/business/20debt-trap.html>

We have elucidated many reasons for why the linkage between housing wealth and consumption may have increased; the extent to which all of these reasons have changed the relationship between house prices and consumption is ultimately an empirical question, which is subject of the next two sections.

III. Data

The datasets typically used in these studies fall into three categories; aggregate data (such as in Carroll et al (2006)), individual household data (such as in Campbell and Cocco (2007)), and regional data (such as in Case, Quigley, and Shiller (2005) and Zhou (2006)). We use two regional datasets and one household dataset. The first dataset includes motor vehicle sales by a unit of geography called designated market areas (DMAs), the second dataset covers taxable sales by metropolitan statistical area (MSA) in California, and the third is motor vehicle purchases by individuals in the Survey of Income Program and Participation.

To set the stage for the data description, nearly all consumption equations are variants of equation (1), where the Greek letters are coefficients to be estimated.

$$(1) \quad C_{i,t} = \gamma_Y Y_{i,t} + \gamma_H H_{i,t} + \gamma_F F_{i,t} + \alpha_i L_i + \beta_i T_t + \varepsilon_{i,t}$$

The main variables in equation (1) are consumption (C), income (Y), housing wealth (H), and financial wealth (F), typically expressed in log levels or log differences. For many of our specifications, we will control for location (L) and time (T), achieving identification through the variation within DMAs.

III.1 Motor vehicle sales by designated market areas (DMAs)

One measure of consumption that is available at a disaggregated level is quarterly motor vehicle registrations from R. L. Polk & Co. These data span 1989Q1 through 2007Q3 and are available at the DMA level. DMAs, which are used to define distinct markets for television stations, are usually larger than metropolitan statistical areas (MSAs) but much smaller than states. A map showing all 200 DMAs in the continental U.S. is provided in Figure 6. One advantage of DMAs over state-level data is that DMAs capture some of the tremendous variation within states, especially in regard to housing wealth. For instance, some large states contain a number of heterogenous housing markets, such as California, which has 13 DMAs that range from the affluent San Francisco Bay area to the more agriculturally based Fresno area. Another advantage of the DMA data is that DMAs are more closely associated with the concept of a “market” than are states. For instance, one area where this is a particular concern are metropolitan areas that span several states, many of which are in the eastern part of the US, such as Philadelphia, Washington D.C., and New York.

New motor vehicle registrations correspond very well to new motor vehicle sales, so we use the terms interchangeably. Sales of new motor vehicles are a statistic followed closely each month by many economists and the business press as a bellwether of consumer spending. One reason motor vehicles are such a good indicator of economic activity is that the pace of sales tends to respond in an exaggerated fashion to many of the economic factors that also affect overall consumer demand.

As shown in the third row of table 1, spending on new motor vehicles represents, on average, only 3 percent of total PCE. However, the contribution of sales of new motor vehicles to the quarterly changes in real PCE spending is much larger than the contribution of less sensitive items, such as food. The correlation between PCE for new motor vehicles and overall PCE between the second quarter of 1990 and the fourth quarter of 2007 is .59, and the correlation between motor vehicles and PCE for goods is .71.⁸ PCE for motor vehicles is modestly correlated with spending for all other goods, with a correlation of about .24 over this period.

Before proceeding, it is worth highlighting that the NIPA estimates of real PCE for new motor vehicles are actually the product of two measures: (1) the volume of unit sales sold to consumers in each period and (2) the real average value of each vehicle sold. Are changes in average expenditures for new vehicles responsible for much of the volatility in consumer spending for motor vehicles? The answer is no. The first column of table 2 shows the share of the variance in quarterly PCE spending for new motor vehicles that stems from changes in average expenditures and from fluctuations in unit sales transactions. A bit more than 96 percent of the variance in consumer outlays for new motor vehicles originates from fluctuations in unit transactions, leaving only a very small role for changes in the real average value per vehicle sold. Over longer periods, however, the quality improvement and mix shifts embedded in the real average expenditures play a much larger role: The second column of table 2 shows that about 57 percent of the average growth rate in PCE for new vehicles between 1990 and 2007 came from the increase in average expenditures, while 43 percent of the average growth rate reflected increases in the number of units sold.

Turning back to the relationship between motor vehicle sales and real PCE, table 1 illustrates the large influence motor vehicles have on headline PCE and more formally measures the contribution of various consumption categories to the volatility of total PCE. The right-most column in table 1 shows the share of the variance in overall PCE spending that is attributable to the type of expenditure listed in each row of the table. Spending on goods, which accounts for, on average, 41 percent of gross consumption outlays and excludes purchases of services, are responsible for 84 percent of the variance of the quarterly changes

⁸ The correlation between motor vehicle spending and total PCE is unchanged at .59 if the spike in sales that resulted from the zero-interest financing incentives offered in 2001Q4 is excluded from the calculation.

in real PCE.⁹ Food expenditures account for 18 percent of the variance of headline consumption, a contribution that is about proportional to its size. In contrast, the contribution of expenditures on new motor vehicles accounts for 36 percent of the variance of real PCE fluctuations, far outpacing the modest size of this sector. As seen in the middle column of table 1, the outsized contribution of motor vehicles reflects the high volatility of auto sales and, as shown earlier in figure 2, their sensitivity to economic conditions.¹⁰

Consumption expenditures for motor vehicles have also changed in ways that are quite similar to other spending aggregates when measured across the wealth-accumulation episodes that have occurred since 1990, where the two notable wealth-accumulation episodes include (1) the stock market boom between 1995 and 1999 studied by Davis and Palumbo (2001), and (2) the steep rise in home prices between 1999 and 2005 (a period we will refer to as the “Real estate boom”). Table 3 shows the average growth rates of annual levels of spending across these periods for the same four spending categories shown in table 1. As shown in the first line, outlays for all goods and services expanded, on average, 3.3 percent between 1990 and 2007, but growth slowed to 2.6 percent in the period that included the 1990 recession. Growth in PCE spending stepped up to an average rate of 4.3 percent during the stock market boom, and the pace of growth then eased back to 3.3 percent during the real estate boom. Spending on all goods—shown in the second line of table 3—has a similar, though more volatile, pattern over these periods. Expenditures on new vehicles are even a bit more volatile across these periods, as shown in the third line of table 3, but the growth patterns are consistent with those of headline PCE: Spending for new motor vehicles grew at an average annual rate of 2.8 percent between 1990 and 2007 but contracted during the period including the 1990 recession. Vehicle spending then expanded 7.7 percent during the stock market boom and 4.8 percent during the real estate boom. For comparison, expenditures on food stepped up by a much smaller magnitudes during the stock market and housing booms.

Turning to income, personal income measures are produced by BEA at the MSA and county levels at an annual frequency and at the state-level at a quarterly frequency. We compute various measures of personal income at the DMA level using the county and MSA data, and we use changes in non-farm payroll employment to interpolate quarterly changes in personal income excluding government transfers.

To estimate nominal housing wealth in each DMA in each period, $H_{i,t}$, we do the following: First, we take the sum of house values reported by all households living in owner-occupied housing in each

⁹ PCE goods are shown separately in the table in response to concerns raised by Wilcox (1992) about mixing the different methodologies used to construct various components of PCE. As a share of real PCE expenditures on goods, new motor vehicles represents about 7 percent of the average level of spending and 50 percent of the variance of quarterly changes.

¹⁰ The contribution of vehicle expenditures to the variance of PCE falls from 36 percent to 27 percent if the spike in sales that resulted from the zero-interest financing incentives offered in 2001Q4 is excluded.

DMA in the Decennial Census and the American Community Surveys in 1990, 2000, 2005, and 2006— $H_{i,t} = \sum_{j \in i} H_{j,i,t}$. Then, to interpolate a quarterly pattern of housing wealth between these dates we assume that housing wealth grows according to changes in house prices, $\Delta HPI_{i,t}$, and net changes in the housing stock, $N_{i,t}$, as shown in equation (2).¹¹

$$(2) \quad \Delta H_{i,t} = H_{i,t} + H_{i,t} \cdot \Delta HPI_{i,t} + N_{i,t}$$

$N_{i,t}$ is unobserved, so we estimate $N_{i,t}$ in a variety of ways using changes in employment, homeownership rates, and other variables. At a quarterly frequency, the variable that contributes the most to the variance in (2) is the HPI. Therefore, in our empirical work that estimates quarterly change models, we often use $\Delta HPI_{i,t}$.

The other variables we have constructed at the DMA level include the unemployment rate, the age distribution of the population, and the share of first lien mortgage loans that classified as “sub prime.”¹²

To get a better perspective on the cross-section heterogeneity of the variables used in this study, Figure 7 presents box-whisker plots of the changes in house prices, employment, income, and motor vehicle sales. The charts show the distribution across the DMAs of the log changes (Q4/Q4) for each variable in each year; the length of each “whisker” depicts the distance between the 10th and 90th percentiles, a measure we interpret as signaling a higher degree of dispersion across the regions of the country. A rather fascinating aspect of the house price panel is that the variance of house price changes increased dramatically in 2003, 2004, and 2005. As the figure clearly shows, some areas of the country experienced very sharp increases in home prices while other areas did not.

III.2 Taxable sales by metropolitan statistical areas (MSAs)

Our second dataset consists of taxable sales for MSAs in the State of California from 1990Q1 through 2007Q1. These data represent all consumer sales for which sales taxes were paid during this period,

¹¹ Changes in the housing stock include newly-constructed housing units, units converted from rentals to ownership, and net depreciation. Net depreciation includes renovations.

¹² One variable that we explored extensively was financial wealth. However, we have low hopes for accurately identifying financial wealth effect in our panel data analysis. Short run changes in financial wealth could be strongly correlated across DMAs: when equity markets increase, the portfolios increase in all DMAs. In Zhou (2007), for instance, the cross-state changes in financial wealth look very strongly correlated. By contrast, house price changes vary tremendously across states, DMAs, and MSAs.

which is likely a large share of total consumer sales.¹³ The data are available for 28 MSAs, and we match them with the same measures of income, housing wealth, and other variables that were described above. Whisker plots of these data are provided in Figure 8.

III.3 Survey of Income and Program Participation (SIPP)

The final dataset we use comes from the Survey of Income and Program Participation (SIPP), a series of interviews that track approximately 40,000 households over time. The survey collects information on income and program participation, and it also collects data on several specialized topics that are relevant to our study. For example, the interviews included questions about assets and liabilities in 1996, 2001, and 2004, which included houses and motor vehicles. These data allow us to track annual measures of household wealth for the periods 1996-1999, 2001-2003, and 2004-2005, which we then match to demographic and income information contained in the main part of the survey, including the household's location, the age and education of the household head (averaged with that of his/her spouse or partner, where applicable), the household's status as a homeowner or renter, and total household income.^{14 15}

The information collected in the "assets and liabilities" questions includes the values and ages of the household's cars and their total wealth. If they are homeowners, the survey also asks about their property value, home equity, and outstanding mortgage debt.^{16 17} From this information we estimated new car purchases by comparing the model year of the household's newest car with the calendar year in which the interview was conducted.¹⁸ The total value of a household's fleet is the sum of the values of the vehicles. These data are then transformed into year-over-year log changes, and the same transformation is done to

¹³ One consumer item that is not subject to sales tax is food, but it is difficult to know what percent of consumer sales are not covered by sales tax, as it is impossible to know total consumer sales for the State of California.

¹⁴ For the 1996 and 2001 panels, the survey did provide MSA codes for households living within Metropolitan Statistical Areas. We merged this information with our MSA-level housing price index. (Households were clustered by MSA in our analysis to allow for correlation within metropolitan areas.) The housing price index was then used to generate a secondary measure of the year over year change in house values, which has the added benefit of being available for both homeowners and renters.

¹⁵ We excluded households that live in mobile homes as well as those who neither own nor rent their residences. Also excluded were households that moved, experienced a change in household reference person or homeowner/renter status during the year, or for which information was missing.

¹⁶ Only observations for which household property value and mortgage debt were not statistically imputed were used in the analysis.

¹⁷ Observations on cars were available for all years but the reference year 1996 (that covered by the first "assets and liabilities" topical module of the 1996 panel.)

¹⁸ After 1997, a new car purchase was determined to have occurred when the model year of a household's newest car lagged one year behind the current year but was not present in that prior year's interview.

mortgage debt, property value, and total household income, and non-housing wealth, which we defined as total household wealth less home equity.¹⁹

IV. Estimates of the Relationship between Housing Wealth and Consumption

For each measure of consumption, we estimated the relationship between consumption and housing wealth using a variety of models that are prevalent in the wealth effects literature. The models differ in their treatment of trends in the data, in the periods of time over which the models are estimated, and in the ways in which wealth is measured. For most specifications, the data suggest that the relationship between housing wealth and consumption was stronger after 2000 than it was in the 1990s.

We first present results that use motor vehicle sales by DMA and taxable sales by MSA as the measures of consumption, and we estimate the relationship both in first-differences as well as in the context of an error correction model. We then show results that use the SIPP data.

IV.1 Estimates based on Motor Vehicle Sales and Taxable Sales: First Differences

Using the data described in section III, the first set of results we present are a variety of first difference models for the DMA and MSA data.²⁰ We estimate the basic model in Equation (3)²¹.

$$(3) \quad \Delta \log(C_{i,t}) = \gamma_Y \Delta \log(Y_{i,t}) + \gamma_H \Delta \log(H_{i,t}) + \gamma_F \Delta \log(F_{i,t}) + \alpha_i L_i + \beta_t T_t + \varepsilon_{i,t}$$

The hypothesis we wish to test with Equation (3) is whether γ_H increased over time. There are a variety of methods that can be used to test whether parameters change over time, but given that we have a panel of relatively short duration, we take a simple approach and test whether γ_H in the 2000's exceeds γ_H of the 1990s.²² We do not mean to imply that there was necessarily a jump-shift in γ_H from 1999 to 2000,

¹⁹ When log changes were not sensible or well defined, we did the following: Observations on households with year over year changes of more than 100 log points in mortgage debt, property value, household income, or non-housing wealth were omitted from the analysis, as these were likely to have been errors in reporting. For changes in the total value of the household's cars, a different cutoff was necessary, as larger movements in car values could be brought about when a vehicle was bought or sold. Households that went from zero cars to having a positive car value were counted as having a car value change of 200 log points, whereas those that got rid of their car wealth (going from a positive value to zero) were counted as experiencing a change of -200 log points. Observations with car value changes above or below these cutoffs were treated as being at these upper or lower limits, respectively. Households which did not own cars in either year were treated as having a change in car value of zero.

²⁰ Due to inadequate data on income and house prices, the sample of DMAs used in this study is 187; the excluded DMAs are very small and most are not part of an MSA.

²¹ Equation (3) is very similar to the models estimated by Case, Quigley, and Shiller (2005), Gan (2008), and Campbell and Cocco (2007).

²² We also examined a variety of different break points, such as 1998, 1999, 2001, and 2002. We generally found that the 2000 break point produced the clearest set of results.

we only mean to imply that, on average, γ_H in the 2000s appears to be larger than the average γ_H in the 1990s.

The first set of regressions we estimate take the form of Equation (4).

$$(4) \quad \Delta \log(C_{i,t}) = \alpha_i D_i + \beta_i T_t + \gamma_H \Delta \log(H_{i,t}) + \gamma_Y \Delta \log(Y_{i,t}) + \gamma_F \Delta \log(F_{i,t}) + \gamma_C \Delta \log(C_{i,t-1}) + \varepsilon_{i,t}$$

D_i are geography-specific fixed effects (DMA's for the motor vehicle sales, and MSA's for taxable sales), T_t are time fixed effects. One lag of the dependent variable is included as a regressor, and the Δ denotes quarterly first differences.

The results for the DMA sample are presented in Table 4 and the MSA results are presented in Table 5. The first columns in Tables 4 and 5 show the results when the regression is estimated over the entire time period, the second columns show results when the models are estimated using data from the 1990s, and the third columns show results when the models are estimated using data from the 2000s. For both measures of consumption, γ_H is significant and positive when estimated over the entire sample, and, as shown in columns 2 and 3, γ_H^{2000s} is significantly greater than γ_H^{1990s} in both cases. In fact, the relationship appears to be significant and positive only for the sub-sample that begins in 2000.

As a check on robustness, we repeated the analysis using the “unpredicted” portion of the changes in housing wealth, a distinction that is sometimes made in the housing wealth effects literature.²³ We define the change in “unpredicted” housing wealth as $\Delta \eta_{i,t}$, which is the residual from a model of house prices shown in Equation (5).

$$(5) \quad \Delta \log(HPI_{i,t}) = \alpha_i D_i + \beta_i T_t + \lambda_H \Delta \log(HPI_{i,t-1}) + \lambda_Y \Delta \log(Y_{i,t}) + \lambda_{U1} unemployment_{i,t} + \lambda_{U4} unemployment_{i,t-4} + \lambda_P \Delta \log(P_{i,t-1}) + \eta_{i,t}$$

The unexpected changes in house prices are the portion of those changes that cannot be explained by lagged house prices, income, unemployment, and population.

The results are contained in Columns 4 though 6 of Tables 4 and 5, and they are similar to the results in Columns 1-3. We modify (5) to also include future values of income growth, unemployment, and population to obtain a different version of $\Delta \eta_{i,t}$. The reason for including leads of these variables is that the change in house prices at time t may reflect expectations for the economy, and it is this argument that is often waged against models like (4). A similar result holds for Columns 7-9 as was found in the previous columns: γ_H^{2000s} is significantly greater than γ_H^{1990s} in both the DMA and MSA case.

²³ The permanent income hypothesis states that a true “wealth effect” response to a change in housing wealth should only occur if the change is unpredicted.

As discussed earlier, one reason why an increase in housing wealth may be related to changes in consumption arises from the relaxation of credit constraints. Deriving measures of “credit constraints” is problematic. For each of the MSAs and DMAs, we constructed a variety of measures of the demographics of the populations that could be related to credit constraints. For instance, we computed the share of first lien mortgages that were denied, following Mian and Sufi (2008). Another measure we computed was the average credit score of the residents in each geographic area; the correlation between the credit score variable and the denial rate is 0.60. Tables 6 and 7 present the results for when we estimate equation (4) by whether areas had above or below average mean credit scores.²⁴ Turning first to the results in Table 6, γ_H increases from the 1990s to the 2000s, but the increase is not statistically significant. However, the increase for the low credit score areas is significant and is also very large. A similar story appears in Table 7 that repeats the analysis for the MSA sample; the increase in γ_H for the low credit score sample of MSAs is much larger than that of the high credit score areas.

IV.2 Estimates based on Motor Vehicle Sales and Taxable Sales: Error Correction Model

Another approach we took to the regressions, which has been used by many in the literature for estimating MPCs out of wealth, was cointegration analysis. This method is based in standard life-cycle theory, which states that consumption should be proportional to total lifetime resources—the sum of human wealth (current and expected future labor income) and financial wealth. It is common to use current income as a proxy for human wealth, which then yields an estimable relationship between consumption, income, and wealth as shown in Equation (6).

$$(6) \log(C_{i,t}) = \alpha_i D_i + \beta_i T_i + \gamma_H \log(H_{i,t}) + \gamma_Y \log(Y_{i,t}) + \gamma_F \log(F_{i,t}) + \gamma_C \log(C_{i,t-1}) + \varepsilon_{i,t}$$

We use dynamic OLS to estimate the coefficients of the error correction model. Specifically, we include 2 leads, 2 lags, and the contemporaneous first difference of the independent variables as stationary regressors. We also examined several alternative specifications, such as dividing income into transfer and other income. The results presented discussed below are robust to a wide set of specifications.

The results using the DMA are presented in Table 9. The first 3 columns report the results using different measures of housing wealth; the results are generally robust to how housing wealth is measured. In column 5, we also include housing wealth interacted with a dummy for the 2000s. The coefficient on this variable is twice as large as the original, similar to the results in tables 4-6.

Equation (6) describes the relationship between consumption and housing wealth that holds in the long run. In the short run, actual consumption might deviate from planned consumption because

²⁴ The results are similar when also segment the sample by denial rates.

consumers may adjust their spending with a lag in response to news about their income or wealth (e.g. if it takes time to make buying decisions in response to good news). To test whether these short-run dynamics may have changed over time, we calculate the gap between actual and planned consumption (using the predicted level of consumption from the life cycle equation), as shown in Table 9, and find the value of the gap is useful in predicting future changes in spending. The coefficient on the gap between actual and target spending growth is significant and has the expected (negative) sign: Given a negative percentage point consumption error in a quarter (so actual consumption is below planned), the results suggest that consumption tends to grow more quickly – by an additional 0.6 percentage point ($.6 = .15 \times 4$) at an annual rate – to close the gap.

IV.3 Estimates Based on SIPP Data

As described in the data section, we use the 1996, 2001, and 2004 panels. In particular, we use homeowners that stay in their home for 2 consecutive years. In modeling whether or not households purchase a new car, we control age, education, income, and characteristics of the existing cars that the household has. In the spirit of S,s models of adjustment, we include a variable that measures the value of cars relative to a household's income--this crude measure is a form of gap between the desired level of the motor vehicle stock and the current stock. We also include the age of the newest car in the household as well as the age squared. Additional explanatory variables include the log change in income, income and wealth quintile dummies, and state of residence dummy variables.

The results are presented in Table 10. The first column is a simple probit of whether the household acquired a new vehicle within the past year. The first variable in the table is the log change in housing wealth. The second and third columns split the sample by time, pre and post 2000. We estimated many specifications using the full sample, and generally speaking, some of the coefficients on housing wealth for the post 2000 sample is statistically greater than 0, sometimes not. However, in nearly all other specifications, the coefficient for the log change in house value is larger in the post-2000 sample than the pre-2000 sample.

For the DMA and MSA results, we computed several measures that might be related to credit constraints. For the SIPP, we split the sample by age, and, more specifically, we split the sample by whether the head of the household is less than 45 years old. We find that the likelihood of purchasing a new car is most strongly related to housing wealth for younger households in the 2000's. For older households, the changes in house values have little relationship with purchasing a new car in the SIPP sample.

IV.4 Summary of results

Using 3 different datasets we find a consistent pattern that the relationship between changes in housing wealth and consumption has increased over time. However, the datasets we examined also suggest that changes in the housing wealth-consumption relationship are not occur uniformly across the population. In the disaggregated regional datasets, the biggest changes occurred in areas where credit constraints were most likely to have been binding in the 1990s. Similarly, for the SIPP data, the most dramatic changes in the relationship appear to have been concentrated in younger households.

V. Implications for Personal Consumption Expenditures

The results in the previous section suggest that the relationship between housing wealth and consumption changed notably in the 2000s. In this section we calculate what various marginal propensities to consume (MPC) out of housing wealth might imply for the path of future consumption, given the substantial declines in housing wealth that most people are expecting over the next couple of years. The objective of this exercise is to gain some insight into the potential magnitudes of the direct effects to the U.S. economy from a downturn in housing wealth.

Table 11 presents estimates of the MPC that are taken from the literature, and, based on our results that suggest that the MPC out of housing may have increased significantly in the 2000s, we also include MPC's that are 25, 50, and 100 percent greater than each of these baseline levels. We first try an MPC of one percent, a modest level that is our lower bound estimate.²⁵ The second level for the MPC that we include in the exercise is 3½ percent, a level taken from FRB/US model at the Federal Reserve Board; this estimate is mostly based on historical data, mostly of which are before 2000.

The columns of the table correspond to a range of values of the decline in real housing wealth. There is lack of agreement about the decline in house values, so we chose a range from 15 to 25 percent. Macroeconomic Advisors, a consulting firm, forecasts that real house prices (as measured by OFHEO) will fall a total of 15-3/4% from 2007 until 2010. However, using the national Case-Shiller index, the fall is likely to be greater, as it has already fallen over 22 percent in real terms. As can be seen in the table, there is tremendous variation in the drag on consumption that a downturn in housing may have. At one extreme, if the MPC for housing wealth has increased to a level that is twice as large as the FRB/US estimate and real house prices fall 25 percent, then the loss of housing wealth would reduce the rate of change in real consumption by 3.2 percentage points. On the other hand, if the true housing MPC is much smaller, then the drag to consumption will be proportionally smaller.

²⁵ Although many studies find an MPC that is much higher than one percent, there are several who argue that the MPC out of housing wealth is either low or should be low.

VI. Conclusion

Using three different measures of consumption and a variety of different models, this paper showed that the relationship between housing wealth and consumption has increased significantly between the 1990s and the 2000s. This increased linkage could have occurred for a number of reasons, including the relaxation of credit constraints on existing homeowners, changes in the composition of homeownership, and behavioral changes. The implications of this result for a forecasted path of future consumption are significant.

Many interesting questions remain unanswered and could be the focus of future research. For instance, how do the coincident decline in house values and the tightening of credit constraints affect the results? Are the results symmetric? Do consumers respond to a shock to housing wealth in ways other than a reducing their consumption? For instance, to what extent will consumers increase their labor supply following a wealth shock.

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Table 1**Fluctuations in Real Personal Consumption Expenditures (PCE)**

1990 through 2007

| | Share of PCE (percent) | Standard deviation (quarterly percent change, annual rate) | Share of PCE volatility (percent) |
|--------------------------------|---------------------------|--|---|
| Goods and services | 100 | 1.8 | 100 |
| .. Goods | 41 | 3.6 | 84 |
| .. New motor vehicles | 3 | 29.5 | 36 |
| <i>Memo:</i> .. <i>Food</i> | 14 | 2.6 | 18 |

* Data are from the *National Income and Product Accounts*. Share of PCE volatility attributable to each component is calculated as 100 less the variance of growth contribution of PCE excluding each component relative to the variance of total PCE. Components are excluded from PCE using a formula that accounts for chain weights.

Table 2**Components of Consumption Expenditures for New Light Vehicles**

Contributions of unit sales and real average values

| | Contributions to Variance of quarterly changes (percent) <i>1990 to 2007</i> | Average Contributions to annual growth (percent) <i>1990 to 2007</i> |
|--------------------|---|---|
| Unit transactions | 96.1 | 43.1 |
| Real average value | 3.4 | 57.2 |
| Covariance | 0.4 | -- |

* Columns may not sum to 100 due to rounding. Data are from the *National Income and Product Accounts*. Contributions to annual growth calculated from annual averages.

Table 3**Growth in Real Personal Consumption Expenditures (PCE)**

Average annual rate of increase (percent), various periods

| | 1990 — 2007 <i>entire sample</i> | 1990 — 1995 <i>pre stock market boom</i> | 1995 — 1999 <i>stock market boom</i> | 1999 — 2005 <i>Real estate boom</i> |
|--------------------------------|-------------------------------------|---|---|--|
| Goods and services | 3.3 | 2.6 | 4.3 | 3.3 |
| .. Goods | 3.8 | 2.6 | 5.3 | 4.0 |
| .. New motor vehicles | 2.8 | -1.2 | 7.7 | 4.8 |
| <i>Memo:</i> .. <i>Food</i> | <i>2.1</i> | <i>1.1</i> | <i>2.0</i> | <i>2.7</i> |

* Calculations based on annual averages. Data are from the *National Income and Product Accounts*.

Table 4: Log Change of Quarterly Motor Vehicle Sales Regressions, by DMA, 1990-2007

| | Unadjusted house prices | | | House prices adjusted by current and past economic conditions | | | House prices adjusted by current, past, and future economic conditions | | |
|------------------------|-------------------------|----------------------|----------------------|---|----------------------|----------------------|--|----------------------|----------------------|
| | (1) Full Sample | (2) Year<2000 | (3) Year>=2000 | (4) Full Sample | (5) Year<2000 | (6) Year>=2000 | (7) Full Sample | (8) Year<2000 | (9) Year>=2000 |
| Log change in: | | | | | | | | | |
| House prices | 0.159*** (0.054) | 0.052 (0.078) | 0.336*** (0.081) | 0.257*** (0.061) | 0.172* (0.093) | 0.392*** (0.083) | 0.195*** (0.064) | 0.140 (0.093) | 0.280*** (0.097) |
| Income | 0.720*** (0.153) | 1.081*** (0.348) | 0.575*** (0.157) | 0.742*** (0.155) | 0.986*** (0.361) | 0.594*** (0.160) | 0.776*** (0.159) | 1.013*** (0.360) | 0.611*** (0.166) |
| Financial assets | -0.075*** (0.024) | -0.228 (0.171) | -0.074*** (0.021) | -0.077*** (0.024) | -0.139 (0.182) | -0.076*** (0.021) | -0.077*** (0.025) | -0.141 (0.182) | -0.076*** (0.021) |
| Constant | -0.051*** (0.007) | 0.013 (0.009) | 0.037*** (0.006) | 0.004 (0.007) | 0.001 (0.009) | 0.077*** (0.006) | -0.030*** (0.007) | 0.001 (0.009) | 0.041*** (0.007) |
| Lag dependent variable | -0.419*** (0.008) | -0.422*** (0.010) | -0.418*** (0.012) | -0.422*** (0.008) | -0.428*** (0.011) | -0.415*** (0.012) | -0.424*** (0.008) | -0.428*** (0.011) | -0.420*** (0.013) |
| Observations | 13450 | 7698 | 5752 | 12690 | 7093 | 5597 | 12147 | 7093 | 5054 |
| Number of DMAs | 186 | 186 | 186 | 181 | 181 | 181 | 181 | 181 | 181 |
| R-squared | 0.392 | 0.298 | 0.537 | 0.395 | 0.300 | 0.533 | 0.399 | 0.300 | 0.548 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable in all regressions is the quarterly log change in motor vehicle sales. Fixed effects and time dummies are included in all models.

Table 5: Log Change of Quarterly Taxable Sales Regressions, by California MSA, 1990-2007

| | Unadjusted house prices | | | House prices adjusted by current and past economic conditions | | | House prices adjusted by current, past, and future economic conditions | | |
|------------------------|-------------------------|----------------------|----------------------|---|----------------------|----------------------|--|----------------------|----------------------|
| | (1) Full Sample | (2) Year<2000 | (3) Year>=2000 | (4) Full Sample | (5) Year<2000 | (6) Year>=2000 | (7) Full Sample | (8) Year<2000 | (9) Year>=2000 |
| Log change in: | | | | | | | | | |
| House prices | 0.104** (0.043) | 0.005 (0.062) | 0.199*** (0.061) | 0.069 (0.050) | -0.071 (0.071) | 0.231*** (0.071) | 0.077 (0.052) | -0.055 (0.072) | 0.249*** (0.077) |
| Income | 0.885*** (0.096) | 0.602*** (0.163) | 0.940*** (0.118) | 0.966*** (0.094) | 0.664*** (0.169) | 0.980*** (0.115) | 0.951*** (0.096) | 0.660*** (0.169) | 0.931*** (0.118) |
| Financial assets | -0.221*** (0.085) | -0.294** (0.144) | -0.163 (0.102) | -0.219** (0.088) | -0.288* (0.162) | -0.175* (0.102) | -0.226** (0.089) | -0.291* (0.162) | -0.179* (0.103) |
| Constant | -0.002 (0.005) | 0.016*** (0.005) | 0.017*** (0.004) | -0.012*** (0.004) | 0.061*** (0.016) | 0.021*** (0.004) | -0.002 (0.005) | 0.062*** (0.016) | 0.006 (0.005) |
| Lag dependent variable | -0.297*** (0.023) | -0.314*** (0.030) | -0.311*** (0.036) | -0.308*** (0.023) | -0.339*** (0.031) | -0.309*** (0.036) | -0.305*** (0.024) | -0.339*** (0.031) | -0.308*** (0.039) |
| Observations | 1848 | 1064 | 784 | 1736 | 952 | 784 | 1652 | 952 | 700 |
| Number of DMAs | 28 | 28 | 28 | 28 | 28 | 28 | 28 | 28 | 28 |
| R-squared | 0.369 | 0.379 | 0.372 | 0.355 | 0.361 | 0.372 | 0.354 | 0.361 | 0.374 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable in all regressions is the quarterly log change in taxable sales. Fixed effects and time dummies are included in all models.

Table 6: Log Change of Quarterly Motor Vehicle Sales Regressions, by DMA and by Credit Scores, 1990-2007

| | (1) Baseline | High Credit Areas | | | Low Credit Areas | | |
|------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | | (2) All years | (3) Year<2000 | (4) Year>=2000 | (5) All years | (6) Year<2000 | (7) Year>=2000 |
| Log change in: | | | | | | | |
| House prices | 0.195*** (0.064) | 0.217** (0.103) | 0.235 (0.151) | 0.198 (0.154) | 0.218*** (0.081) | 0.149 (0.117) | 0.358*** (0.121) |
| Income | 0.776*** (0.159) | 0.379 (0.260) | 0.379 (0.579) | 0.246 (0.271) | 1.028*** (0.204) | 1.339*** (0.453) | 0.940*** (0.210) |
| Financial assets | -0.077*** (0.025) | 0.103 (0.167) | 0.143 (0.282) | 0.042 (0.208) | -0.085*** (0.024) | -0.323 (0.236) | -0.083*** (0.020) |
| Constant | -0.030*** (0.007) | -0.001 (0.012) | -0.001 (0.014) | -0.016 (0.012) | -0.056*** (0.009) | -0.033** (0.015) | 0.036*** (0.008) |
| Lag dependent variable | -0.424*** (0.008) | -0.392*** (0.012) | -0.390*** (0.016) | -0.402*** (0.019) | -0.431*** (0.011) | -0.434*** (0.015) | -0.429*** (0.017) |
| Observations | 12147 | 5631 | 3279 | 2352 | 6516 | 3814 | 2702 |
| Number of dma | 181 | 84 | 84 | 84 | 97 | 97 | 97 |
| R-squared | 0.399 | 0.430 | 0.312 | 0.582 | 0.402 | 0.327 | 0.535 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable in all regressions is the quarterly log change in motor vehicle sales.

Fixed effects and time dummies are included in all models.

High credit areas are those with above average credit scores. Low credit areas are those with below average credit scores.

Table 7: Log Change of Quarterly Taxable Sales Regressions, by MSA and by Credit Scores, 1990-2007

| | (1) | High Credit Areas | | | Low Credit Areas | | |
|------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | | (2) | (3) | (4) | (5) | (6) | (7) |
| | Baseline | All years | Year<2000 | Year>=2000 | All years | Year<2000 | Year>=2000 |
| Log change in: | | | | | | | |
| House prices | 0.077 (0.052) | 0.049 (0.099) | -0.075 (0.155) | 0.093 (0.125) | 0.064 (0.067) | -0.050 (0.086) | 0.304*** (0.114) |
| Income | 0.951*** (0.096) | 1.244*** (0.160) | 0.598* (0.360) | 1.310*** (0.182) | 0.513*** (0.157) | 0.510** (0.206) | 0.608** (0.259) |
| Financial assets | -0.226** (0.089) | -0.282** (0.120) | -0.237 (0.229) | -0.261* (0.134) | -0.163 (0.141) | -0.410 (0.250) | -0.015 (0.177) |
| Constant | -0.002 (0.005) | 0.001 (0.007) | 0.021*** (0.007) | -0.016*** (0.006) | 0.013** (0.007) | 0.023*** (0.006) | -0.000 (0.007) |
| Lag dependent variable | -0.305*** (0.024) | -0.370*** (0.034) | -0.381*** (0.044) | -0.385*** (0.055) | -0.269*** (0.036) | -0.287*** (0.047) | -0.259*** (0.057) |
| Observations | 1652 | 826 | 476 | 350 | 826 | 476 | 350 |
| Number of dma | 28 | 14 | 14 | 14 | 14 | 14 | 14 |
| R-squared | 0.354 | 0.432 | 0.413 | 0.468 | 0.344 | 0.360 | 0.326 |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable in all regressions is the quarterly log change in taxable sales.

Fixed effects and time dummies are included in all models.

High credit areas are those with above average credit scores. Low credit areas are those with below average credit scores.

Table 8: Log Quarterly Motor Vehicle Sales Regressions, by DMA, 1990-2007

| | (1) | (2) | (3) | (4) | (5) |
|-----------------------|-----------------------|-----------------------|----------------------|------------------------|-----------------------|
| Log house, 1 | 0.156*** (0.00975) | 0.148*** (0.00972) | | | 0.0413*** (0.0143) |
| Log house, 2 | | | 0.100*** (0.0108) | | |
| Log house, 3 | | | | 0.0898*** (0.00699) | |
| Log house,1 post 1999 | | | | | 0.0893*** (0.0148) |
| Log financial assets | | 0.0781*** (0.0128) | 0.129*** (0.0128) | 0.0844*** (0.0132) | 0.0546*** (0.0157) |
| Log income | 1.136*** (0.0168) | 1.036*** (0.0253) | 1.011*** (0.0237) | 1.132*** (0.0233) | 1.051*** (0.0332) |
| Constant | -6.400*** (0.120) | -8.142*** (0.333) | -5.573*** (0.375) | -4.176*** (0.310) | -6.136*** (0.535) |
| Observations | 13419 | 13393 | 13393 | 13239 | 13393 |
| Number of dma | 186 | 186 | 186 | 184 | 186 |
| R-squared | . | . | . | . | . |

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Each column are the estimates for linear regression of the log of motor vehicle sales.

2 leads and 2 lags of the first differences in the regressions are included.

Each model has fixed and time effects.

Table 9

Adjustment Dynamics: Log Change in Motor Vehicle Sales

| | (1) | (2) |
|-------------------------------------|----------------------|----------------------|
| Log of sales gap (actual-predicted) | -0.252*** (0.009) | -0.155*** (0.008) |
| Lagged log of housing wealth | | 0.172*** (0.033) |
| Lagged log of financial wealth | | 0.086 (0.082) |
| Constant | 0.012*** (0.001) | 0.047*** (0.007) |
| Observations | 12707 | 12707 |
| Number of dma | 186 | 186 |
| R-squared | 0.338 | 0.570 |
| Standard errors in parentheses | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | |

Table 10: Probits of New Car Purchases Using Data from the SIPP, 1997-99, 2002-2002, 2005

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---------------------|---------------------|---------------------|---------------------|----------------------|----------------------|---------------------|-----------------------|-----------------------|
| | Full sample | Year<2000 | Year>2000 | Age<45 | Age<45, Year<2000 | Age<45, Year>2000 | Age>=45 | Age>=45, Year<2000 | Age>=45, Year>2000 |
| Log change in house value | 0.009 (0.006) | -0.002 (0.009) | 0.014 (0.007)* | 0.038 (0.012)** | 0.012 (0.020) | 0.050 (0.012)** | -0.001 (0.006) | -0.007 (0.012) | 0.003 (0.007) |
| Age | 0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) | -0.001 (0.000)* | -0.002 (0.001) | -0.001 (0.001) | -0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) |
| Education | -0.001 (0.001) | 0.001 (0.001) | -0.002 (0.001)** | 0.001 (0.001) | 0.002 (0.002) | -0.000 (0.002) | -0.001 (0.001) | 0.001 (0.001) | -0.002 (0.001)** |
| Log change in income | 0.014 (0.004)** | 0.036 (0.010)** | 0.002 (0.005) | 0.017 (0.007)* | 0.050 (0.017)** | -0.002 (0.008) | 0.012 (0.006)* | 0.029 (0.012)* | 0.004 (0.006) |
| Income quintile dummies (lowest is omitted) | | | | | | | | | |
| quintile 2 | 0.099 (0.009)** | 0.080 (0.015)** | 0.110 (0.009)** | 0.106 (0.031)** | 0.139 (0.056)* | 0.098 (0.028)** | 0.095 (0.012)** | 0.067 (0.018)** | 0.108 (0.011)** |
| quintile 3 | 0.143 (0.011)** | 0.108 (0.021)** | 0.161 (0.012)** | 0.156 (0.030)** | 0.168 (0.051)** | 0.157 (0.030)** | 0.136 (0.014)** | 0.095 (0.025)** | 0.156 (0.013)** |
| quintile 4 | 0.195 (0.014)** | 0.151 (0.024)** | 0.217 (0.012)** | 0.199 (0.027)** | 0.212 (0.047)** | 0.201 (0.026)** | 0.195 (0.018)** | 0.142 (0.029)** | 0.220 (0.016)** |
| quintile 5 | 0.261 (0.012)** | 0.195 (0.022)** | 0.298 (0.017)** | 0.282 (0.039)** | 0.286 (0.060)** | 0.291 (0.039)** | 0.250 (0.019)** | 0.166 (0.028)** | 0.293 (0.017)** |
| Car age | -0.021 (0.001)** | -0.029 (0.002)** | -0.015 (0.002)** | -0.025 (0.002)** | -0.037 (0.004)** | -0.016 (0.003)** | -0.020 (0.002)** | -0.025 (0.003)** | -0.015 (0.002)** |
| Car age squared | 0.001 (0.000)** | 0.001 (0.000)** | 0.001 (0.000)** | 0.001 (0.000)** | 0.002 (0.000)** | 0.001 (0.000)** | 0.001 (0.000)** | 0.001 (0.000)** | 0.001 (0.000)** |
| Value of cars to income | 0.086 (0.019)** | 0.015 (0.031) | 0.126 (0.014)** | 0.057 (0.025)* | -0.042 (0.042) | 0.132 (0.036)** | 0.092 (0.021)** | 0.030 (0.033) | 0.121 (0.017)** |
| Observations | 40445 | 15781 | 24664 | 13693 | 5629 | 8021 | 26752 | 10109 | 16643 |

Robust standard errors in parentheses

* significant at 5%; ** significant at 1%

The dependent variable is 1 if a new car was purchased within the past year, 0 otherwise. Year and state dummies are included. Errors are clustered by MSA.

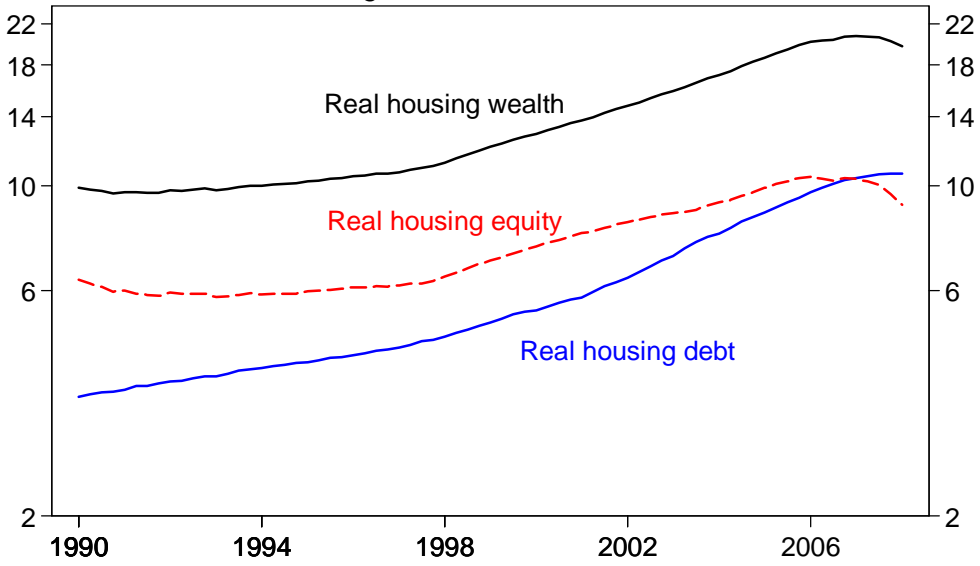
Table 11: Estimates of the Direct Restraints to Consumption Growth from a Decline in Housing Wealth

| Assumed housing wealth effect | | Assumed decline in real housing wealth (in percent) | | |
|-------------------------------|-----|---|------|------|
| | | 15.0 | 20.0 | 25.0 |
| Modest | 1.0 | 0.3 | 0.4 | 0.5 |
| 25% greater | 1.3 | 0.4 | 0.5 | 0.6 |
| 50% | 1.5 | 0.5 | 0.6 | 0.8 |
| 100% | 2.0 | 0.6 | 0.8 | 1.0 |
| FRB/US | 3.5 | 1.1 | 1.4 | 1.8 |
| 25% greater | 4.4 | 1.3 | 1.8 | 2.2 |
| 50% | 5.3 | 1.6 | 2.1 | 2.7 |
| 100% | 7.0 | 2.1 | 2.9 | 3.6 |

The assumed housing wealth effect is in percent.
The numbers in the table are in percentage points of consumption

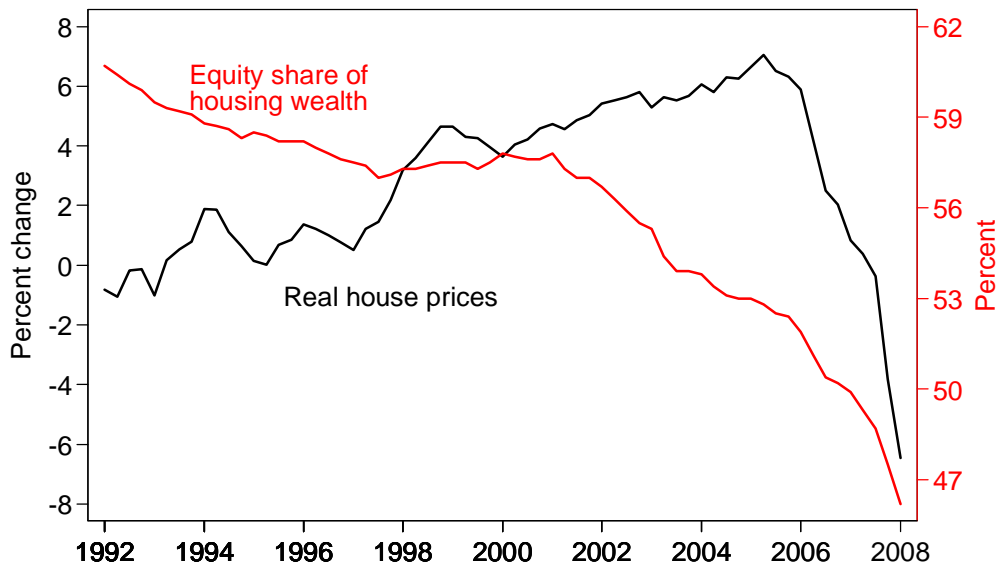
Figure 1: Real Housing Wealth, Equity, and Debt
1990Q1-2008Q1

Levels, 2008 trillions, log scale



Source: Board of Governors

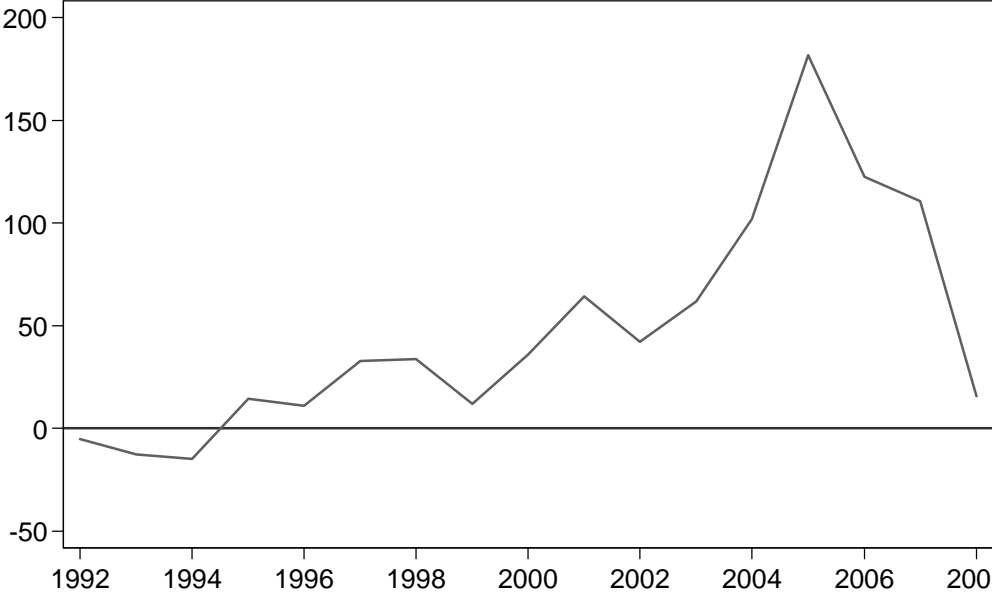
Figure 2: Equity Share of Housing Wealth and
Year-Over-Year Change in Real House Prices,
1990Q1-2008Q1



Source: Board of Governors and OFHEO.

Figure 3: Net Issuance of Home Equity Loans

Billions of 2008 dollars



Source: Board of Governors.

Figure 4: Examples of Home Equity Advertisements



Home Equity Loans

You can use the money you've earned for - ANYTHING!

A photograph of a man and a woman standing on a boat, looking at each other. The boat is white with a red interior.

Tap into the Money...

With a home equity loan or line of credit today.

us bank
The Real Service Connection

A photograph of a two-story house with a brown roof and a yellow facade. A banner is hanging across the front of the house. The banner features the text 'Tap into the Money...' and 'With a home equity loan or line of credit today.' The us bank logo is in the bottom right corner of the banner.

Figure 5: Example of Changes in Future House Price Appreciation

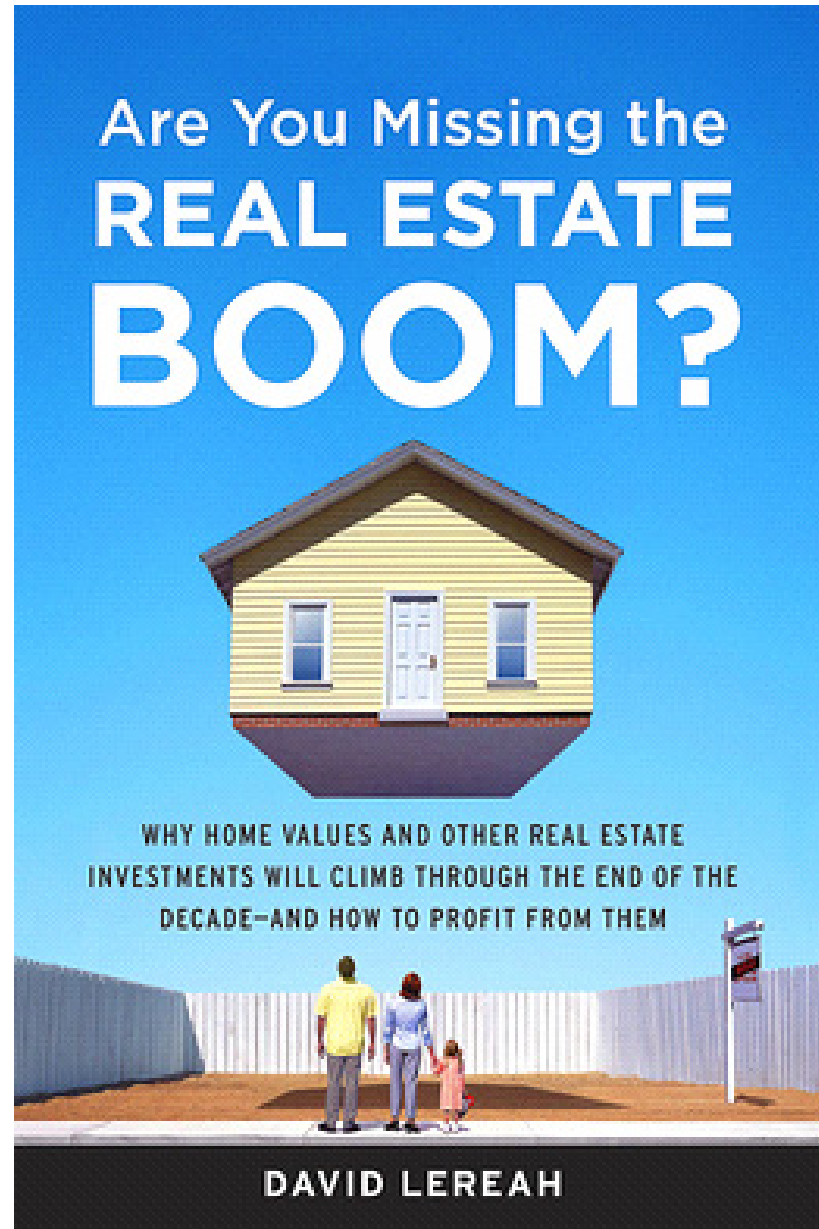
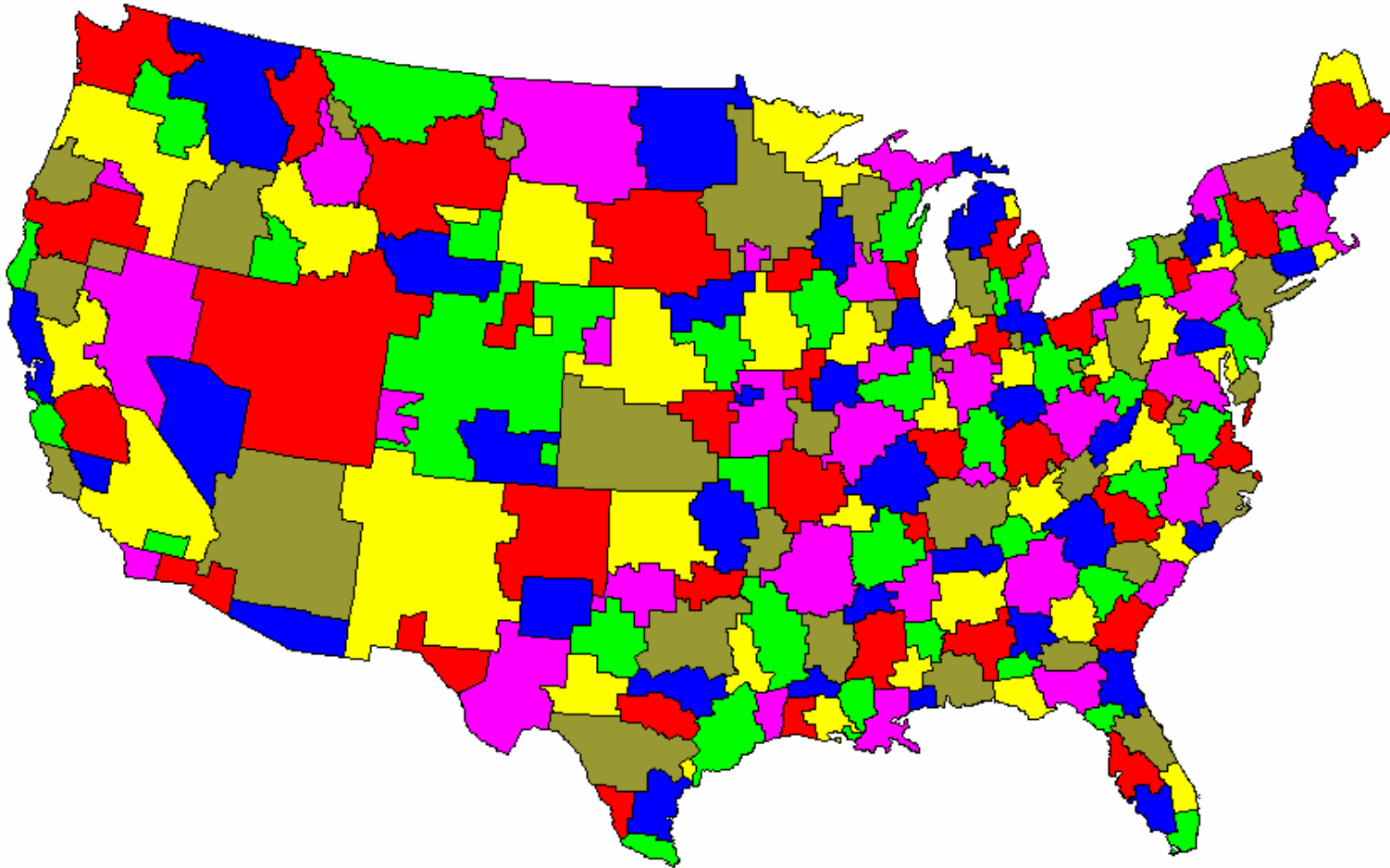


Figure 6: Map of Designated Market Areas



Source: http://en.wikipedia.org/wiki/List_of_television_stations_in_North_America_by_media_market

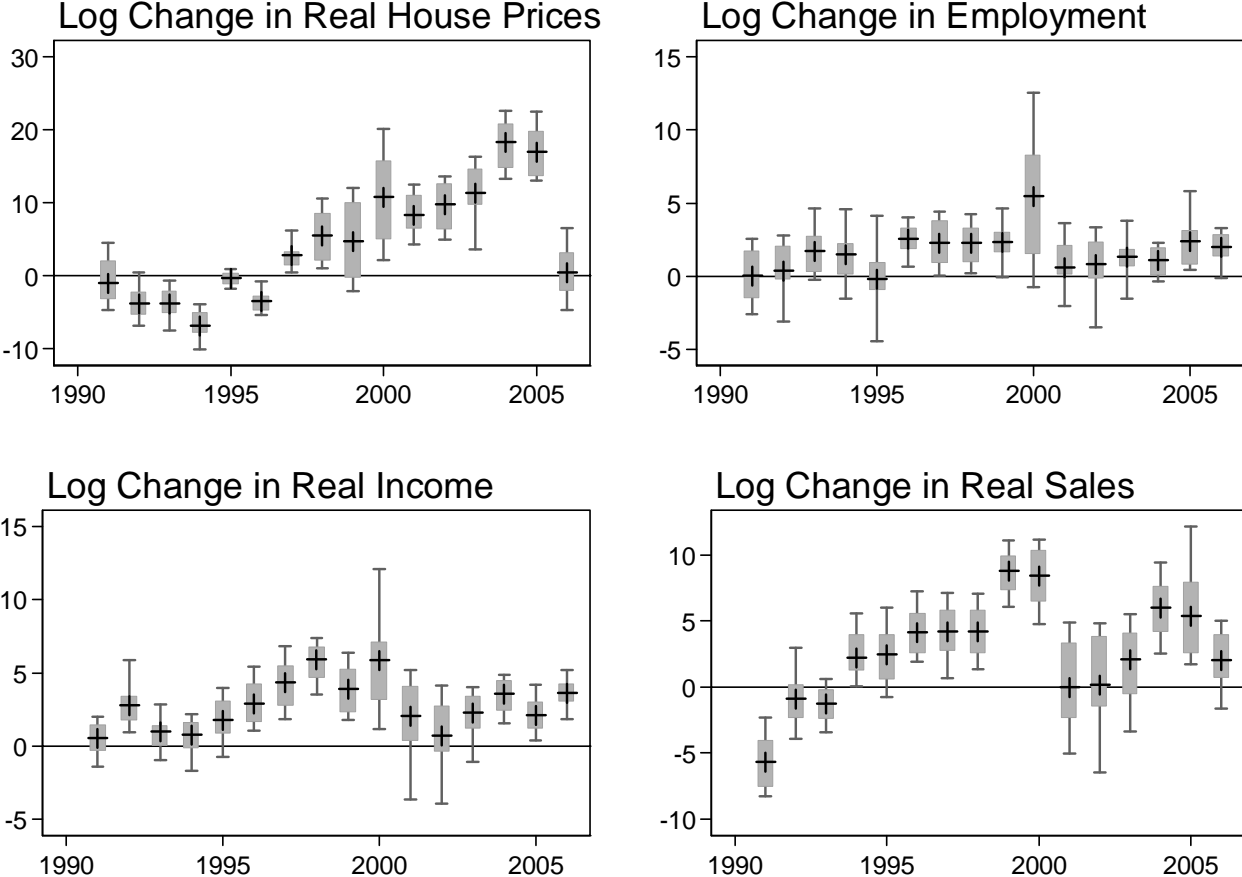
Figure 7

Time-series Variance across Designated Market Areas for Key Variables



Note: House prices, employment, and income show year-over-year percent change, using fourth quarter data. Motor vehicle sales show the percent change from the previous year, using the yearly average over the 4 quarters. 2007 data for motor vehicle sales uses the average of only the first 3 quarters. The whiskers show the 90th and 10th percentiles, and the box edges represent the 75th and 25th percentiles. The plus symbol indicates the mean.

Figure 8: Time-series Variance across California MSAs for Key Variables



Note: House prices, employment, and income show year-over-year percent change, using fourth quarter data. Motor vehicle sales show the percent change from the previous year, using the yearly average over the 4 quarters. The whiskers show the 90th and 10th percentiles, and the box edges represent the 75th and 25th percentiles. The plus symbol indicates the mean.