Housing Wealth And Consumption: Effects of Total versus Asset Appreciation Return

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Abstract

The total return to housing includes rental plus asset appreciation. Housing wealth shocks should be based on total return but the literature often ignores rental return. Im-Pesaran-Shin panel unit root tests and augmented Dickey-Fuller regressions demonstrate that differences in asset appreciation returns differ by location and there is persistence in differences. Empirical tests show that the effect of a housing return shocks on consumption is much larger when measured using total return rather than just appreciation. This implies that return to housing is important to understanding consumption effects of housing return shocks.

Key words: total return, asset appreciation, capitalization rate, dividend pricing hypothesis, wealth shock, consumption elasticity

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1. Introduction

Economic theory suggests that the total income from durable household assets should include the implicit net rental income. It makes a difference whether a household owns or leases automobiles. Poverty measurement considers implicit income from durables carefully. But, partly due to the lack of information, implicit rental income from durable assets is sometimes neglected. However, in the case of homeownership, implicit rental income is so substantial that it should be considered. The total return to housing investment is the sum of its implicit rental and asset appreciation returns, and it is the basis for valuing real estate investment.

Based on a substantial empirical literature, differences in rates of appreciation return across housing markets have been shown to be persistent and hence predictable. This leaves the problem of dividing the appreciation in the asset price of housing into anticipated and unanticipated components. In the real estate literature, this division has been based on the differences in capitalization rates under the dividend pricing hypothesis. The dividend pricing hypothesis suggests that investors arbitrage away differences in expected risk-adjusted return across housing markets. The capitalization rate functions as a dividend, and the theory implies that expected asset appreciation varies inversely with the capitalization rate.

Empirical research has assessed the relevance of the dividend pricing hypothesis by examining two testable implications of the theory. First, the hypothesis implies that differences in asset appreciation returns are systematically associated with location and hence predictable. Gyourko and Voith (1992), Case and Shiller (1994) find evidence of unequal persistence in appreciation rates across metropolitan areas. Rachlis and Yezer (1985), Archer, Gatzlaff and Ling (1996), Gelfand et. al. (2004), among many others, have confirmed the existence of systematic locational variation both within and across cities in the rates of house price appreciation. Second, the dividend pricing hypothesis implies that higher rental returns are offset by lower appreciation returns. Although measuring the implicit rental returns has been a major challenge for prior work, this negative correlation has been found in several settings. These two elements, rental returns and asset appreciation rate, of housing return have been shown by Meese and Wallace (1994), Capozza and Seguin (1996), Gallin (2008), Eisfeidt and Demers (2018) and Vinson (2019) to vary inversely in panel estimates of housing markets. Accordingly it appears that the dividend pricing hypothesis provides useful insights for understanding housing markets and predicting differences in appreciation rates.

Many papers have ignored the dividend pricing hypothesis when examining how consumption responds to housing wealth shocks by ignoring the role of the rental return. Shocks to appreciation return have been used to measure the link between housing markets and household consumption. There is substantial evidence that positive shocks to the appreciation rate are associated with increases in consumption. Engelhardt (1996), Benjamin, Chinloy and Jud (2004), Bostic, Gabriel and Painter (2009), Calomiris, Longhofer and Miles (2009), Carroll, Otsuka and Slacalek (2011), Case, Quigley and Shiller (2005, 2011) have estimated the elasticity of consumption with respect to housing wealth in the range of 0.03-0.13. These studies all measure shocks to housing wealth using differences in the asset price appreciation rate across locations without considering the rental return component.

Equating shocks to the asset appreciation rate to shocks to the total housing return neglects how the lower implicit rental return compensates for the anticipated high asset appreciation rates in places where large increases in housing price are observed. Under the dividend pricing hypothesis, ignoring differences in risk, the proper measure of shocks to housing returns should be the differences in total return, measured as the sum of the capitalization rate and asset appreciation rate. Recently, Jorda et al. (2019a) and Eichholtz et al. (2020) argued that total return to housing is properly measured as the sum of appreciation and rental return in papers that measure adjustments for risk differentials.

Thus the 2% (US Census 2010) capitalization rate in San Francisco and the 12% (US Census 2010) capitalization rate in Cleveland do not prompt a massive capital outflow from West to Midwest, because the asset appreciation rate in San Francisco is expected to be 7% (Zillow 2020) and that in Cleveland -2% (Zillow 2020), in order to equalize the total return to real estate investors in the national market. Treating the difference in observed appreciation rates between these two cities as unexpected produces a biased estimate of the unanticipated component of return to housing investment. Furthermore that bias is systematically related to a host of factors that distinguish San Francisco and Cleveland.

The innovation in this paper is that shocks to total return, as well as its division between the capitalization and asset appreciation rates, are constructed and related to household consumption. The principal finding is that consumption responds more to shocks to the total return to housing than to a similarly-sized increase in the rental or asset appreciation return. This implies that the capitalization rate component is important both because households respond to total return and because differences in appreciation return are not shocks but anticipated by homeowners in areas where the capitalization rates are unusually high or low. Encompassing tests performed by forcing total return and asset appreciation return into the same consumption equation, show that the estimated effect of total return is positive and significant while asset appreciation return is not significant. The empirical tests demonstrate that the marginal propensity to consume from a $1 shock to total housing wealth is about 11-18 cents.

The next section of this paper reviews both the literature on total return to housing investment and its division into the capitalization and asset appreciation rates. Research on the consequences of shocks to asset appreciation rates compared to other wealth shocks is also discussed. Section three explains how the capitalization rate and asset appreciation return across US metropolitan areas are constructed. Specific properties of the relation among components of the total return using the estimates of these rates are developed in section four. Finally the relation between total return and its rental and asset appreciation components and consumption is estimated in section five. Section six concludes.

2. Literature Review

This paper contributes to two strands of literature: evaluating the prediction of the dividend pricing model that rent-to-price ratios, or capitalization rates (CAP rates), are related to future asset price returns, and the effect of housing wealth shocks on consumption.

According to the present value relation, the expected total return on an asset is the sum of the dividend yield and the expected asset price appreciation rate. Campbell and Shiller (1998b) developed the dividend-price ratio model as a dynamic version of Gordon's (1962) asset pricing model. According to the dividend yield decomposition presented in this research, the log dividend–price ratio reflects expected future long-term returns and dividend growth, and this decomposition holds for both nominal and real variables. Campbell (2003) demonstrated that the variables that predict returns and dividend growth are ratios of stock prices to factors such as dividends, earnings, moving average of earnings, or the book value of equity.

Fama and French (1988 a,b) and Poterba and Summers (1988) showed that there is a forecastable component of stock returns, and that this component is important when returns are measured over long periods. Campbell and Shiller (2001) tested various simple efficient-market models of the financial market using dividend-price ratios based on aggregate data for the US and twelve other countries, and found the dividend-price ratios to be useful in predicting future stock price changes. Engsted and Pedersen (2010) documented that, for the US stock market, inflation reinforces real return predictability and it changes the effects of real dividend growth in the manner predicted by the dividend-price ratio. A non-exhaustive list of papers analyzing the use of dividend-price ratio to predict stock returns includes Stambaugh (1999), Valkanov (2003), Lewellen (2004) and Campbell and Yogo (2006), Cochrane (2008), Asimakopoulos and Asimakopoulos (2017), and Piatti and Trojani (2020). The central finding is that dividend return is consequential for predicting total return.

Housing is typically a composite good: the structure, a depreciating capital good which delivers a flow of consumption services over a long period of time; and land, an asset that does not depreciate. In the case of housing, the total return is the sum of the capitalization rate and asset appreciation return. The capitalization component is analogous to a dividend yield and has been shown to be informative with respect to expectations about the future growth rate of housing prices. The asset appreciation return is commonly measured as the real house price appreciation rate for owner-occupied housing.

The user cost approach and the rental equivalence approach are the two main existing approaches used to measure housing service flow. Poterba (1984) pointed out that a house's real price equals the present value of its future net service flow discounted at the homeowner's real after-tax interest rate. The full ex ante user cost consists of normal maintenance expenditures plus property taxes plus depreciation expenses (loss of value of the dwelling unit due to the effects of aging and wear and tear that is not offset by normal maintenance expenditures) plus waiting costs (the costs of forgone interest due to the funds tied up in an owned dwelling) and anticipated capital gains or losses due to housing market specific inflation over the given time period. On the other hand, the rental equivalence approach values the services yielded by a dwelling using the observed market rent for the same sort of dwelling for the same period of time (if such a rental value exists). Blackley and Follain (1996) examined the link between rents and user cost, and found that increases in user cost are not fully matched by increases in rents. Verbrugge (2008) showed the large divergence of rents and user cost, and suggested there are both practical and theoretical reasons to prefer a rent-based approach to homeowner cost measurement. Accordingly the rent-based approach is used here.

In the context of asset pricing, rent is a dividend from owning a house, and price is a discounted sum of future rents. Empirical research provides two types of evidence supporting the application of the dividend pricing model to the housing market. First, many studies have analyzed the predictive power of the rent-price ratio on future price changes, in spite of problems of attenuation bias due to difficulties of unmatched price and rent samples. Second, there are many studies testing the persistent differences in appreciation rates across housing markets that have not been arbitraged away.

Many studies have analyzed the predictive power of the rent-price ratio on future asset price changes using data from individual housing markets rather than national aggregates. Phillips (1988) applied pooled-tenure hedonic estimates of rent-price ratio to generate the capitalization rates and found a weak inverse relation between capitalization rates and future house price appreciation. Meese and Wallace (1994) tested 16 submarkets in the San Francisco MSA and found a negative relation between rental and appreciation return. Clark (1995) used decennial census data and found a significant and negative relation between rent-price ratio and subsequent changes in rents, suggesting that house prices will be higher in areas that subsequently have larger increases in rents. Capozza and Seguin (1996) analyzed decadal house value appreciation rates using census data from 64 US MSAs, and found that they could be predicted by rent-price ratios at the beginning of the decade. Gallin (2008) uses the BLS rental series and finds that previous rent-price ratios are significantly, but positively, correlated with the future 4-year-ahead national house price appreciation rates. Hattapoglu and Hoxha (2013) examined the Houston housing market and showed there is a negative relation between the lagged appreciation rate and subsequent rent-price ratio. Eisfeldt and Demers (2018) construct city-level returns for the largest 30 cities from 1986 to 2014, and found rental yields monotonically decline with house price tier while house price appreciation monotonically increases with price tier. Overall, when the U.S. capitalization rates are disaggregated spatially, they appear to be negatively related to subsequent asset price appreciation.

Outside the residential housing market in the US, there are many studies on return predictability and rent-price ratios. Kallberg, Liu and Anand (2003) tested the dividend pricing model in the U.S. REIT market over 1973-2001 and found that it cannot be rejected if share repurchase is included as part of dividends. Plazzi, Torous and Valkanov (2006) examined the commercial real estate sector, and found that the rent–price ratio does not have predictive power for future rent growth for apartment, retail and industrial properties, but that it does predict future returns for these types of property, compared to no predictive power for either rent growth or returns for office properties. Hendershott and MacGregor (2005) used micro data from the U.K. office and retail market, and showed that expected real rent growth predicted future real rent-price ratios over 1977-2001. Hwang, Quigley and Son (2006) found strong supportive evidence for the dividend pricing hypothesis in South Korea both before and after the Asian Financial Crisis. Bracke (2015) found a significant negative relation between rent growth and the rent-price ratios in Central London areas. Eichholtz et al. (2020) constructed historical total return and risk estimates for Paris and Amsterdam, and found the long-term real return to housing is entirely due to the rental yields with real capital gains around zero.

In an alternative approach, empirical research supports the dividend pricing model applied to housing through tests for persistent differences in appreciation rates across housing markets that have not been arbitraged away. Gyourko and Voith (1992) and Case and Shiller (1994) find evidence of unequal persistence in appreciation rates across MSAs. Rachlis and Yezer (1985), Archer, Gatzlaff and Ling (1996), and Gelfand et. al. (2004), among many others, have confirmed the systematic locational variation in the rates of house price appreciation. Clark and Coggin (2009) found mixed evidence for the convergence of regional house price. Guren (2018) pointed out that house prices exhibit substantial momentum and positive autocorrelation. Kang et. al. (2020) employed multi-source big geo-data in the machine learning framework to provide evidence of house price appreciation persistency with respect to locations. According to the consumption capital asset pricing model, expected return should be equal across assets that have similar correlation with the market portfolio. Housing, as an asset class for investors should have the expected return equated across areas. The simple arbitrage argument means that areas where expected appreciation is higher should have lower capitalization rates to equalize expected return across housing markets.

This paper also adds to the literature on the effects of housing wealth shocks on consumption. Existing literature on the wealth effect on consumption has found that consumption responds differently depending on the type of wealth. Iacoviello (2004), Lettau and Ludvigson (2004), Piazzesi et al. (2004), Case et al. (2005) and Lustig and Van Nieuwerburgh (2004) have explored the independent roles of financial wealth and housing wealth shocks on consumption. Because housing serves as both an instrument for saving and as a consumption good, it therefore may affect household consumption expenditure differently than financial wealth. Engelhardt (1996) provided a direct test of the link between house price appreciation and consumption and found a marginal propensity to consume out of real capital gains in owner-occupied housing of about 0.03. Benjamin, Chinloy and Jud (2004) estimated that a $1 increase in real estate wealth is associated with an increase in current year consumption of 8 cents whereas the financial wealth effect on consumption is only 2 cents. Carroll, Otsuka and Slacalek (2011) found the immediate marginal propensity to consume from $1 change in housing wealth is about 2 cents while the final eventual effect is about 9 cents. Bostic, Gabriel and Painter (2009) estimated the elasticity of consumption spending with respect to housing wealth shocks to be about 0.06 over 1989-2001 for homeowners. However, Calomiris, Longhofer and Miles (2009) reported that housing wealth has a small and non-significant effect on consumption after controlling for the endogeneity bias resulting from the correlation between housing wealth and permanent income. Case, Quigley and Shiller (2011) revisited their own estimates in Case, Quigley and Shiller (2005), using an extended panel of observations on state-quarter level over 1978-2009, and found the elasticity of consumption with respect to house value shocks ranging from 0.03 to 0.13. In sum, estimates of the effect of housing wealth shocks on consumption vary substantially across these studies. Overall the evidence favors a modest positive link between differences in house price appreciation and household consumption.

3. Data

The total return to real estate is the sum of the implicit rental return and asset appreciation return. A major challenge in testing the effects of differences in total return is the lack of data on capitalization rates for residential housing. This section discusses how a panel of MSA-level total return on housing was constructed.

3.1 Capitalization Rates

The American Housing Survey (AHS) is used to generate the capitalization (CAP) rates, i.e. the rent-to-price ratio, at the MSA level over 1985-2013. The AHS started in 1973 and data is collected every other year. The AHS changed the narrative of the questionnaires significantly in 1985, and removed individual household responses on housing value questions in the Public Use File (PUF) after 2015. As a result, this study uses AHS PUF for 1985-2013. It provides a panel data set of detailed property-level information, including house price (asset price of owner-occupied homes, and rental price of renter-occupied units), housing quality characteristics, geographic location and information on occupants.

There are several advantages of using AHS data for the purpose of measuring house price changes over space and time. First, the AHS covers a large number of housing units in both the owner-occupied and rental markets. This facilitates the construction of MSA-level rent-price ratios. Most center city housing is rental in the largest cities, this portion of the housing market has been long ignored due to data limitations.[2] Second, the AHS provides information on both the housing units that transact and those that did not. This reduces the likelihood of sample selection bias. Kiel (1994) found that homeowners were more likely to trade their house if their house had higher-than-average appreciation in the past. Consequently houses with repeat sales may be fundamentally different. Third, the panel data feature of the AHS makes it relatively easy to control for quality characteristics of the housing units, hence avoiding omitted variable bias.

There are two common issues with the AHS data: the accuracy of self-reported house values, and the lack of objective information on neighborhood characteristics. Goodman and Ittner (1992) found that the average homeowner over-values his/her house by 6%. Kiel and Zabel (2003) found a similar over-valuation of 5.1% but showed that the difference between sales prices and owners' valuations is unrelated to particular characteristics of the house, occupants, or the neighborhood. The missing objective information on the neighborhood and community is not unique to AHS. The transaction data sources used to generate Case-Shiller home price indices

[2] There is a stream of literature using BLS rent index to construct rent-price ratios (Case and Shiller 1990; Davis, Lehnert and Martin, 2008). Campbell, Davis and Gallin (2009) pointed out that BLS rent index may not capture some of the unobserved trends in the implicit rental prices of owner-occupied housing. Recently Ambrose, Coulson and Yoshida (2015) have demonstrated substantial biases that resulted from procedures used to construct the BLS rent index.

and FHFA house price indices do not contain neighborhood characteristics either. When the AHS is used as a panel, the effects of measurement errors associated with neighborhood and unobserved physical characteristics as well as owner perceptions should be differenced away.

The method adopted to estimate capitalization rates is the pooled-tenure hedonic estimation approach developed by Phillips (1988). This method pools value for owner occupied units with rent for rental units in a single regression of the following form.

$$log(P_{i,t,m}) = \alpha_{i,t,m} + \beta_{t,m} * OWN_{i.t.m} + X_{i,t,m}\gamma' + \varepsilon_{i.t.m} \tag{1}$$

$$CAP_{t,m} = Rental\ Price\ /\ Asset\ Price = exp(-\ \beta_{t,m}) \tag{2}$$

The dependent variable, $log(P_{i,t,m})$ is the log of market value for owner-occupied unit *i* in year *t* and MSA *m*, or the log of annual rent for rental unit *i* in year *t* and MSA m. $OWN_{i.t.m}$ is a dummy variable indicating if housing unit *i* is owner-occupied in year *t* and MSA m. $X_{i,t,m}$ is a vector of housing quality characteristics, including metro status dummy (center city or suburb), structure type of the building, age of the unit and its unit size in square feet, number of bedrooms, number of bathrooms, number of half bathrooms, garage dummy, basement dummy, type of air system, type of heating system, and housing adequacy score.

Regressions are estimated for each MSA and year separately to generate a panel of different βestimates by MSA and year. The β parameter estimates reflect the average percentage difference in $log(P_{i,t,m})$ between owner-occupied units and rental units, controlling for differences in specified housing quality characteristics. Then the capitalization rate can be calculated as the antilog of the estimated value of β.

Figure 1 presents the distribution of capitalization rates by year when all MSAs are pooled. For the US housing market in general, the average capitalization rate has stayed relatively stable over the three decades. A detailed list of MSA-level capitalization rates and standard errors by year is provided in an online appendix. The geographical variation in individual city capitalization rates is large. Nationwide, the average capitalization rate ranges from 6% to 9% over 1985-2013. However capitalization rates differ significantly across markets. Figure 2 illustrates the capitalization rates over time in the 10 biggest cities based on GDP. Among these 10 biggest MSAs in the US, Houston, TX and Dallas, TX have the highest capitalization rates over the time period of 1985-2013, ranging from 7.5% to 12%. San Francisco, CA and Los Angeles, CA have the lowest capitalization rates in most of the years during the sample period, ranging from 3% to 6%. This is consistent with other research which also finds sizable differences in CAP rates for the subset of the years and metropolitan areas that is examined here.[3]

3.2 Asset Price Appreciation Rates

The FHFA house price index (HPI) is used to measure the asset price appreciation rate. This index is a weighted, repeat-sales index measure of the change over time in single-family house prices. The sample used in this study covers quarterly purchase-only indexes for 124 MSAs over 1975q1 - 2019q1. The FHFA HPI dataset contains 404 MSAs, of which 124 MSAs are in the

[3] Phillips (1988) found that, from 1974 to 1979, the capitalization rate of Atlanta, GA increased from 5.9% to 8.2% while that of Chicago, IL fell from 8.2% to 5.4% but that of Boston, MA remained around 6%. In May 2019, Zillow reported the capitalization rates in every US city with a population over 250,000 using median home value and median annual rent. The list started from San Francisco, CA with a capitalization rate of 2%, and went up to Detroit, MI at 19%. Such differences either imply massive imperfections in house pricing or compensating differences in expected appreciation.

AHS dataset. Figure 4 illustrates the distribution of MSA-level annual average appreciation rates by year using FHFA HPI. Figure 5 shows the annual average appreciation rates of FHFA HPI in the biggest 10 cities in the US. Los Angeles, CA has the most volatile appreciation rates, ranging from -13% to 24% over time, with a mean of 5.5% and a standard deviation of 10%. San Francisco, CA follows on the volatility list, with the appreciation rates ranging from -8% to 20%, mean of 6.5% and a standard deviation of 9%. Dallas, TX has the smallest standard deviation of 3%, with the range of appreciation rates from -4.8% to 6.3% and the mean at 2%.

3.3. Total Return to Housing

The total return to housing for each MSA is the sum of the capitalization rate generated using the AHS and the subsequent asset appreciation rate from the FHFA HPI. This panel covers 124 MSAs over 1985-2013. Table 1 reports the means and standard deviations of the total return to housing and its two components in each year and in various time periods. Figure 6 displays the series of total return to housing and its components by year. The average capitalization rate has stayed stable over the full sample period. The average asset appreciation rate was relatively stable and lower than the capitalization rate before 2000. In terms of volatility, the total return to housing is similar to the asset price appreciation rate, while the capitalization rate is less volatile than the asset appreciation rate.

In a recent study by Eisfeldt and Demers (2008), supportive evidence is found to complement the findings in this paper. House returns are generated for 30 largest US cities using AHS and CoreLogic data, and exhibit two stylized facts. Average annual city-level rental yields and house price appreciation rates are stable, at 4.5% and 4.2%, respectively, but house price appreciation rates have higher volatility than rental yields.

In the next section, empirical tests are conducted to examine the correlation between current year's CAP rates and the asset appreciation rates of the subsequent year. The dividend pricing hypothesis suggests that current higher rental returns are offset by subsequent lower appreciation returns. Figure 7 presents the scatterplots of MSA-level CAP rates and subsequent asset appreciation rates for 1985, 1995, 2005 and 2013. Casual observation indicates total return varies over the years and higher CAP rates are associated with lower appreciation. The negative correlation between these two components is strongest in 2005.

4. Dividend Pricing Model

Campbell and Shiller (1988 a,b) developed the dividend-price ratio model as a dynamic version of Gordon's (1962) asset pricing model. The log dividend-price ratio can be written as an expected discounted value of all future returns and dividend growth rates discounted as the constant rate.

$$\delta_t = d_{t-1} - p_t \simeq E_t \sum_{j=0}^{\infty} \rho^j (r_{t+j} - \Delta d_{t+j}) + \frac{c-k}{1-\rho} \tag{3}$$

In the above equation, δ_t is the log dividend-price ratio, as the difference between the log dividend in last period, d_{t-1}, and the log asset price in this period, p_t. r_t is an ex post discount rate. Δd_t is the growth rate of the dividend. Their model defines the log of the sum of the asset price and the previous dividend as a constant k, plus a weighted average of the log asset price and the log dividend with weights $\rho$and $1 - \rho$. $\rho$is close to but a little smaller than 1. The constant term $c$is the deviation between beginning-of-period rational expectation of return and the ex ante return over the period. This paper will focus on empirical tests of properties of the relation between the two components of the total return using the estimates of these rates across US MSAs, under this dividend pricing model framework.

4.1 Tests for Persistence

The dividend pricing model, as applied to housing, argues that the total return to housing is properly measured by the sum of its rental and appreciation returns. Based on a substantial empirical literature, differences in rates of return across housing markets have been shown to be persistent and hence predictable. This leaves the problem of dividing the appreciation in the asset price of housing into anticipated and unanticipated components.

A number of tests for persistence of appreciation rates across housing markets are conducted here over these 124 MSAs, to determine if differences in appreciation rates across housing markets are persistent. To obtain an estimate of the degree of persistence, a standard test is applied to estimate the speed with which the asset appreciation return converges to its long run level.

$$y_{i,t} = \alpha + \sum_{n=1}^{N} \beta_{i,n} y_{i,t-n} + MSA_i + Time_t + \varepsilon_t \tag{4}$$

In Equation (4), y_t and y_{t-n} are the current period and n-lagged period values of the asset appreciation return. MSA_i and $Time_t$ represents MSA fixed effects and the time trend. Following the literature on panel unit root tests that allow for cross-sectional dependence (Pesaran, 2007; Haurin, Jong and Zhang, 2013), Im-Pesaran-Shin (IPS) tests are conducted with a time trend and subtracting the cross-sectional means. There are three main reasons to use the IPS panel unit root test. First, house prices in different MSAs are affected by common factors such as interest rates and business cycles. Second, the IPS test allows for panel-specific intercept, trend and autoregressive coefficients. Third, the IPS test assumes a large N and a small T, which is the case here.

Table 2 reports the results on tests of $ln(\Delta HPI_{i,t,k})$, the percentage change in the house price index of MSA i at period t from k quarters before. Table 3 shows the results on tests of $\Delta HPI_{i,t,k}$, the cumulative appreciation in house price index of MSA i from period $t-k$ to period t. In both tables, $k = 1, 4, 8, 20$, representing quarterly appreciation, yearly appreciation, bi-annual appreciation and 5-year appreciation respectively. The null hypothesis of all panels containing unit roots can be rejected at 1% significance level in almost all models, which provides evidence that some panels are trend stationary. These results suggest that house price appreciation, during the period of 1975-2019, could be predicted. The past literature assumes that the expected appreciation rate is equal in each city. But the rational expectations assumption and the dividend pricing hypothesis imply that differences in asset appreciation rates are systematically associated with location and hence predictable. Results found in this paper confirm that.

The result is consistent with the many studies in the literature that examine local housing markets during different time periods. Malpezzi (1999) applied Levin-Lin-Chu panel unit root tests (Levin, Lin, and Chu 2002) and found that a unit root can be rejected for real house price changes over 1979-1996. Mikhed and Zemcik (2009) conducted IPS panel unit root tests of house price appreciation rates over several different time periods across 22 US metropolitans, and found that the null hypothesis of a unit root could be rejected for 1978-2007. Haurin, Jong and Zhang (2013) also used IPS panel unit root tests on state level house prices, and found the house price series to be trend stationary with structural breaks. Capozza, Hendershott and Mayer (2002) explored the cyclical behavior of real house price in 62 MSA over 1979-1995 and showed patterns of serial correlation and mean reversion that varied across cities.

To better understand the stationary of house price appreciation in different MSAs, augmented Dickey-Fuller regressions (ADF1981) are estimated for each MSA using its full time series. Two sets of models are tested: (1) ADF tests with 0-2 lags, a trend and no constant term, (2) ADF tests with 0-2 lags, a constant term and no trend. Following Bogin, Doerner and Larson (2019), a deterministic constant term is included but not a trend in the main results, because "it is difficult to justify a model with real house prices trending upward ad infinitum."

Figure 8 illustrates the distribution of MacKinnon approximate p-values of ADF tests for unit roots on MSA-level quarterly HPI appreciate rates, with 0, 1 and 2 ADF lag terms respectively. Without the lag term, the null hypothesis of a unit root can be rejected at 1% significance level for all MSAs. Including 1 lag term, a unit root can be rejected at 1% significance level for all cities except for 7 MSAs (Augusta, GA-SC, Baton Rouge, LA, Corpus Christi, TX, Eugene, OR, Houston, TX, New Orleans, LA, and Raleigh, NC). While when 2 lags are included, the unit root null hypothesis can still be rejected in about half the MSAs.

Figure 9 presents the results of same ADF regressions on MSA-level HPI quarterly cumulative appreciation. Similar patterns can be observed. These results suggest, in agreement with the literature noted above, that differences in the real house price appreciation are stationary and hence predictable. However, MSAs differ in the level of persistence.

An alternative test of persistence in the differences of MSA-level housing price appreciation rates is the traditional full panel model with time and MSA fixed effects, as shown in equation (5).

$$\Delta log(HPI_{i,t,k}) = \alpha + \beta\Delta log(HPI_{i,t-k,k}) + Time_t + MSA_i + \varepsilon_{i,t} \quad (5)$$

where $\Delta log(HPI_{i,t,k})$ is the cumulative change in log value of house price index of MSA i from period $t - k$ to period t.$\Delta log(HPI_{i,t-k,k})$ is the change in log HPI from period $t - 2k$ to period $t - k$. $Time_t$ and MSA_i represent time and the MSA fixed effects. The data is in quarterly so $k = 1, 4, 8, 20$ in various models. Lee, Seslen and Wheaton (2015) examined the relation between house price and its subsequent changes across locations within MSAs and undertook a panel regression of demeaned change in price against demeaned prices. Following their method, a similar test, Equation (6), is conducted with change in log HPI against the level of log HPI.

$$\Delta log(HPI_{i,t,k}) = \alpha + \beta log(HPI_{i,t-k}) + Time_t + MSA_i + \varepsilon_{i,t} \quad (6)$$

where $log(HPI_{i,\,t-k})$ is the level of house price index of MSA i in period $t - k$. Both equation (5) and (6) are tested.

Regression estimates for equation (5) are shown in Table 4. In almost all models (except for the Pesaran's test of cross sectional independence with $k = 1$) , the cross-sectional dependence and first-order autocorrelation in this panel can be rejected at 1% significance level. The F-statistics of the tests on the MSA dummies are significant at the 1% significance level, suggesting that the differences in asset price appreciation rates are systematically associated with location. This is consistent with the dividend pricing hypothesis, given that capitalization rates vary substantially with location.

The coefficients of the MSA dummies identify MSAs with persistently high and low rates of appreciation. Table 5 presents the summary of statistics and the top and bottom 10 MSAs in terms of the MSA dummy coefficient estimates using the model in equation (5). The coefficient estimates of the MSA dummies represent the additional asset appreciation, over a quarter ($k = 1$), a year($k = 4$), two years ($k = 8$) and five years ($k = 20$) respectively, of a certain MSA compared to the reference MSA, Akron, OH. MSAs that have persistently high appreciation rates tend to keep the momentum in both short and long run, specifically the MSAs in California, New York, Boston, and Honolulu. However, MSAs with generally low appreciation rates are not always at the bottom of the appreciation list. MSAs with small coefficients in terms of quarterly asset appreciation rates ($k = 1$) tend to be different from the ones in terms of 5-year asset appreciate rates ($k = 20$). These results demonstrate the asymmetry in the persistence of asset price appreciation rates. MSAs with high appreciation returns tend to have the greatest momentum, while MSAs with low appreciation returns tend to experience mean reversion.

Estimates of Equation (6) are presented in Table 6. Consistent with Table 4, Table 6 also provides evidence of the systematic locational variation in asset appreciation rates. Moreover, the coefficient of lagged HPI is statistically significant and negative. This result provides evidence of the predictability of the differences in asset price appreciation rates. Thus the differences in asset appreciation rates are not shocks but are, or at least should be, anticipated. This is fully consistent with the dividend pricing hypothesis provided capitalization rates vary accordingly across cities.

It is natural to ask if there is persistence in total housing returns, when the rental return component is included on top of the asset appreciation return, and how tests for persistence in total return compare to the appreciation return results just presented. It should be noted that there is an issue of directly comparing the test for persistence in total return to housing with the test for persistence in asset appreciation rate, because the measure for total return to housing constructed in this paper is for every other year. However, tests for the persistence in the total return to housing could provide some useful insights of housing market dynamics. IPS panel unit root tests and the traditional full panel model with time and MS fixed effects are applied.

First, IPS panel unit root tests are applied again to examine the stationary of total return on housing, with a time trend and subtracting the cross-sectional means. Given that this is a bi-annual data set over 1985-2013, models including 0-1 lags for ADF regressions are tested, using average annual total return to housing based on the capitalization rates from the AHS and the average annual asset appreciation rates from the FHFA HPI. The results are presented in Table 7. Both models rejected the null hypothesis of all panels containing unit roots at the 1% significance level, suggesting that some panels are trend stationary. Augmented Dickey-Fuller regressions on total return on housing series are estimated for each MSA to understand the differences in total housing return across different locations. Results of the p-values from ADF tests with 0-1 lags, a constant term and no trend are shown in Figure 10. Compared to inland MSAs, coastal MSAs have a higher probability of rejecting the null hypothesis of a unit root in total housing return. Compared with the results on Figure 9, without the lag term, the null hypothesis that the panels of total return to housing have unit roots can be rejected at 1% significance level for 21 MSAs. In sum, these tests are more likely to reject the null hypothesis of a unit root in asset price appreciation rates than in the total return to housing. There is more persistence and predictability in differential appreciation rates than in rates of total return.

Second, the traditional full panel model with time and MSA fixed effects is applied to test the systematic locational variation in the total return to housing, as shown in Equation (7), where $R_{i,t}$ is the total return to housing of MSA i in period $t - k$.

$$R_{i,t} = \alpha + \beta^* R_{i,t-2} + Time_t + MSA_i + \varepsilon_{i,t} \tag{7}$$

The results of the above equation are comparable to the results of Equation (5) when $k = 8$.The mean and standard deviation of the coefficient estimates of MSA dummy variables are 0.04% and 0.38%, when total return to housing is regressed on the total return 2 years ago. Compared to the mean and standard deviation of 1.70% and 1.57% of the MSA dummy estimates for asset price appreciation rate test, the variance in persistent differences in total return to housing across housing markets is much less than that in asset appreciation return.

Overall the evidence for persistence in appreciation rates for virtually all MSAs presented here is compelling as suggested in the previous literature. This alone implies that at least a portion of differences in appreciation return is expected. Conversely persistence in total return is less robust across cities.

4.2 Direct Testing of the Dividend Pricing Hypothesis

There is a modest literature analyzing the predictive power of the capitalization rate on subsequent housing price appreciation. The general finding is that it moves inversely with future asset price returns, consistent with the dividend pricing hypothesis. However, the degree of the negative relation varies across studies and is always greater than the -1 predicted by theory, a result generally attributed to attenuation bias due to measurement error. Studies differ depending on the market geography, time periods and housing unit samples of the data set. This section demonstrates that the data used in this study (biannual data across 124 MSAs over 1985-2013) gives similar results in testing the dividend pricing hypothesis as the literature reviewed earlier.

Testing of the relation between asset price appreciation rate and the capitalization rate is conducted using Equation (8) below. $P_{m,t}$ is the average asset price in MSA m in year t, $CAP_{m,t}$ is the CAP rate in MSA m in year t. Also included are the MSA and time fixed effects. The dividend pricing hypothesis predicts that subsequent asset price appreciation varies inversely with the capitalization rate, if total return on housing is consistent with a no-arbitrage equilibrium.

$$\frac{P_{m,t+1} - P_{m,t}}{P_{m,t}} = \alpha + \beta * CAP_{m,t} + MSA + YEAR + \varepsilon_{m,t} \tag{8}$$

The estimate of β is expected to be -1 under the dividend pricing hypothesis, but measurement errors in both the capitalization rate estimate and the use of the actual rather than expected appreciation rate will attenuate the resulting estimate of β. As noted in the literature review, the expectation is that estimates of βare negative and significant but larger than -1 due to classical measurement error bias in the CAP rate.

Estimates of Equation (8) are shown in Table 8, using the annual average asset price appreciation rates of FHFA HPI and pooled-tenure hedonic capitalization rates from the AHS. The coefficient of the capitalization rate is statistically significant at the 1% significance level and negative in model (1)-(3) over the full sample period, ranging from -0.15 to -0.3. Subperiod tests are also conducted with year fixed effects and MSA fixed effects for 1985-1995, 1995-2005 and 2005-2013, as shown in model (4)-(6). The asset appreciation return predictability of the capitalization rate is statistically significant during 1995-2005 and 2005-2013, with the coefficient estimate of -0.7 and -0.4 respectively. Column (7) and (8) examine the predictive power of the CAP rate on the subsequent asset appreciation rate during the boom and bust periods around the financial crisis, i.e. 2005-2009 and 2009-2013 respectively. The estimate of the coefficient of CAP rate is equal to -1 at 1% confidence level during 2005-2009. This result given by the data constructed in this paper is consistent with but generally stronger than previous literature. Capitalization rates are inversely related with subsequent asset price appreciation rates, confirming the general prediction of the dividend pricing hypothesis. Although the point estimate is significantly different from -1, it is possible that the basic insights of the dividend pricing hypothesis would be valuable for examining consumption responses, as will be shown in next section.

The negative correlation between CAP rate and future asset appreciation rate found using data constructed in this paper is supported by Eisfeldt and Demers (2018), which examined the rental yields and capital gains of single family housing for 30 largest US cities over the same period. Eisfeldt and Demers (2018) found that rental yields increase with city house price tiers while house price appreciation rates fall with house price tiers. Their findings complements the results found in this paper. However, this paper goes beyond presenting the correlation of the two series of house returns and regressed CAP rates on asset appreciation rates to test the dividend pricing hypothesis.

5. Effect of shocks to total return to housing on consumption

The test here follows the empirical papers, reviewed in some detail below, that have examined the housing wealth effect on consumption. The difference here is that deviations from total return to housing rather than from asset price appreciation return are considered wealth shocks. The previous literature finds the housing wealth elasticity of consumption is in the range of 0.02 - 0.13 when housing wealth changes are measured by asset price appreciation rate alone.

Case, Quigley and Shiller (2005) test the effects on consumption using log differences in asset price appreciation and seeks to estimate the model in Equation (9),

$$\Delta C_{t,m} = \alpha + \beta_1 \Delta House_{t,m} + \beta_2 \Delta Stock_{t,m} + \beta_3 \Delta Inc_{t,m} + \epsilon_{t,m} \tag{9}$$

where $\Delta House_{t,m}$ is log change in housing wealth generated using Case-Shiller home value index, $\Delta Stock_{t,m}$ is log change in stock market wealth generated using data obtained from the Federal Reserve Flow of Funds (FOF) accounts, $\Delta Inc_{t,m}$ is change in personal income, and $\Delta C_{t,m}$ is the change in retail sales constructed by Moody's used as a proxy for consumption spending. The observations are in state-quarters over 1982-1999. They found the elasticity of consumption with respect to appreciation ranged from 0.03 to 0.06.

Case, Quigley and Shiller (2011) revisits their estimation from 2005, using an extended panel of observations on state-quarter level over 1978-2009. Their re-test used log differences in asset price appreciations with various error-correction consumption models, and found the elasticity of asset price on consumption ranges from 0.04 to 0.08. Their estimation model III (i.e. error-correction consumption models) is the basis for the specification in Equation (10),

$$\Delta C_{t,m} = \alpha + \beta_1 \Delta House_{t,m} + \beta_2 \Delta Stock_{t,m} + \beta_3 \Delta Inc_{t,m} + \gamma \Delta C_{t-1,m} + \delta(\frac{C}{Inc})_{t-1,m} + FEs + \epsilon_{t,m} \tag{10}$$

where a lagged log change in consumption $\Delta C_{t-1,m}$, a lagged log ratio of consumption to income $(\frac{C}{Inc})_{t-1,m}$, and fixed effects (state fixed effects, year fixed effects, or state specific time trends) are added to their original estimation models (Equation 9) in Case, Quigley and Shiller (2005).

Following the Case-Quigley-Shiller (CQS) empirical framework, this paper investigates the housing wealth effect using the state-level total returns to housing over 1985-2013. Due to data limitations, MSA-level consumption is not available, and state-level data is used instead. The state-level total return to housing is the sum of state-level capitalization rates and state-level asset price appreciation returns. Same as with the MSA level analysis discussed above, the capitalization rate component is generated using Phillips (1988) pooled-tenure hedonic estimation method from the AHS. State-level asset price appreciation returns are calculated as the annual appreciation rates of FHFA state-level HPI.

The baseline OLS estimation equation is shown in Equation (10)[4]. The overlapping years of the AHS and CQS 2005 dataset are 1985, 1987, 1989, 1991, 1993, 1995, 1997 and 1999. To be consistent, the following regressions are conducted using state-level biannual data. In each state m in year t, $\Delta House_{t,m}$ is the log change in housing wealth, measured using the total rate of return to housing. Other variables are directly employed from the CQS 2005 dataset. $\Delta C_{t,m}$ is the log change in consumption, and a panel of retail sales constructed by Moody's is used as a proxy.

[4] This regression model is the same as model III in Case et al. (2011), but uses the total return rate on housing to measure housing wealth change.

$\Delta Stock_{t,m}$ is the log change in stock market wealth. "Estimates of aggregate financial wealth were obtained annually from the Federal Reserve Flow of Funds (FOF) accounts and compared to the aggregate capitalization of the three major U.S. stock markets." (Case et al. 2005 page 7). $\Delta Inc_{t,m}$ is the log change in income. Also included in the equation are a lagged log change in consumption $\Delta C_{t-1,m}$, a lagged log ratio of consumption to income $(\frac{C}{Inc})_{t-1,m}$, state fixed effects, year fixed effects, state specific time trend and an error term $\epsilon_{t,m}$. The effect of changes in total housing return on consumption is expected to be statistically and economically significant. The effect of classical measurement error in the estimate of total return to housing should bias estimates of the effect of housing returns on consumption downward. However the measurement error bias in using only appreciation return rather than total return should produce even larger attenuation bias. This leads to the prediction that the elasticity of consumption with respect to total housing return will be larger than that due to asset price appreciation rate only.

Table 9 presents the estimation results under four specifications: (1) housing wealth shocks are measured as the total return to housing, (2) asset price appreciation rate from FHFA only, (3) capitalization rate from the AHS only, and (4) total return to housing together with its asset appreciation component. When the housing wealth shock is measured as the total return to housing, as in model (1), the marginal propensity to consume from a \$1 change in total housing return is about 11 cents, compared to 9 cents for appreciation return only as shown in model (2). When testing the effect of capitalization rates only (model 3), the coefficient is larger than that of total housing return or asset appreciation return. This may be due to an association between high capitalization rates and local labor market conditions, for example declining local employment should generate a housing market with replacement cost higher than housing price.

Model (4) is the encompassing test that includes the total return to housing and its asset appreciation component. The coefficient estimate of the total housing return is positive and significant, while the coefficient of asset appreciation return component is non-significant. This is consistent with the theory, which says both of the two components of total return to housing have equally important effects on consumption. The encompassing test in column 4 shows that in the presence of total return, appreciation return has the "wrong" sign and is non-significant. Total return dominates appreciation rates in determining consumption effects.

Case, Quigley and Shiller (2005, 2011) measured the housing wealth shock as the change of housing value using repeat sales estimates of asset price change. This index is an alternative measure of asset price appreciation return, and an alternative total housing return is generated using this CQS repeat-sale asset price appreciation rate and capitalization rate from the AHS. Table 10 demonstrates the test results using these measures. The marginal propensity to consume out of real housing capital gains in owner-occupied housing is about 0.06 (not statistically significant). This result is consistent with Case, Quigley and Shiller (2005, 2011) in which the marginal propensity to consume out of housing wealth shock is in the range of 0.03-0.13. In contrast, the results from model (2) based on total return to housing calculated using the CQS appreciation rate is about 0.08 and is statistically significant. When both the asset appreciation return and total return are included to form an encompassing test, as in model (3), the coefficient of the appreciation rate is non-significant, again confirming the important effect of the capitalization rate component of total return on consumption.

Note that, the effect of a housing wealth shock is systematically larger than that of the stock market wealth shock, which is about 0.03 but not statistically significant. Benjamin, Chinloy and Jud (2004), Bostic, Gabriel and Painter (2009) and Quigley and Shiller (2005, 2011) found non-significant or even slightly negative coefficients on stock market wealth change. Tests in paper provide consistent results with the literature.

6. Conclusions

According to the substantial literature reviewed above, the total return to housing is properly measured by the sum of its rental and appreciation returns. This paper discusses specific properties of the relation among the two components of the total return to housing using the estimates of these rates across US MSAs. Empirical estimates, including Im-Pesaran-Shin panel unit root test and augmented Dickey-Fuller regressions, demonstrate that differences in asset price appreciation are systematically associated with location and that there is persistence in returns. These results suggested that differences in appreciation rates are predictable and therefore are not shocks.

The innovation in this paper is that shocks to total housing return, as well as its division between capitalization and asset appreciation rates, are constructed and related to household consumption. capitalization rates are generated following the Phillips (1988) method by conducting pooled-tenure hedonic estimating of the AHS self-reported asset and rental prices. And a panel data set of total return to housing across 124 US MSAs over 1985-2013 is constructed by combining the FHFA HPI appreciation rate and capitalization rate.

Then the relation between total return and its capitalization rate and appreciation rate components and consumption is estimated. Empirical tests following the Case-Quigley-Shiller framework estimate the housing wealth effect on consumption, using different measures. The principle finding is that the effect of a housing wealth shock on consumption is much larger when it is measured as an innovation in the total return to housing, implying that the capitalization rate component of return is important. The empirical tests demonstrate that the marginal propensity to consume from a $1 change in total housing wealth is about 11-18 cents. When both total return and either appreciation or capitalization rates are included in the model, total return estimates are both statistically and economically significant while estimated coefficients of either appreciation or capitalization rates are non-significant. This result of the encompassing test provides strong evidence that shocks to total return to housing are important to consumption rather than either of the separate components of that return. Consumption effects of shocks to total return to housing are systematically larger than those of stock market wealth change on consumption, which are non-significant and about 0.03 in this data.

These estimates suggest the possibility of a sizable effect of fluctuations in the total return to housing. However, just as a financial asset shock on household consumption should be based on unanticipated variation in total return to the household portfolio, the effect of housing investment shocks is properly based on changes in total return rather than on either of its components.

To estimate and explain the independent roles of financial wealth and housing wealth shocks on consumption, the literature has been focusing on the dual purpose of housing, which is to serve as both an instrument for saving and as a consumption good. What is being neglected is that housing returns differ from stock market returns in one crucial aspect. The household owning the housing investment lives in the local labor and housing market where the return is experienced. Accordingly, there are likely to be omitted variables reflecting local economic conditions that cause actual housing returns to differ from expectations. These omitted variables could also influence other aspects of the economic welfare of the household. Changes in consumption could result from these omitted variables and could account for the finding that shocks to housing return are more consequential for consumption than shocks to stock market returns. Cities with rising housing costs could also be experiencing local amenity changes that influence household consumption choice and well-being. However, the return from the stock market investment is not associated with changes in local economic or amenity conditions. This difference could account for the smaller effect of stock market returns on consumption.

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Tables and Figures

Table 1: Summary of Statistics of Asset Appreciation Rate, CAP Rate and Total Return to Housing

	Appreciation Rates		CAP Rates		Total Return	
Year	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
1985	4.89%	0.0559	7.67%	0.0189	12.34%	0.0560
1987	5.97%	0.0725	7.46%	0.0207	13.18%	0.0712
1989	5.42%	0.0657	7.47%	0.0199	12.70%	0.0611
1991	2.36%	0.0301	7.96%	0.0220	10.40%	0.0407
1993	2.64%	0.0319	8.12%	0.0187	10.81%	0.0403
1995	2.94%	0.0286	7.97%	0.0187	11.07%	0.0354
1997	3.21%	0.0212	8.35%	0.0198	11.50%	0.0273
1999	4.89%	0.0315	8.06%	0.0203	12.78%	0.0322
2001	7.32%	0.0338	7.59%	0.0222	14.81%	0.0335
2003	6.63%	0.0405	6.86%	0.0215	13.62%	0.0376
2005	12.06%	0.0854	6.68%	0.0252	18.43%	0.0748
2007	0.51%	0.0474	6.44%	0.0244	6.95%	0.0601
2009	-6.36%	0.0635	7.29%	0.0234	0.83%	0.0714
2011	-3.66%	0.0262	7.98%	0.0220	4.33%	0.0326
2013	4.19%	0.0554	9.00%	0.0276	12.79%	0.0571
1985-2013	4.29%	0.0630	7.55%	0.0226	11.10%	0.0658
1985-1995	4.00%	0.0526	7.67%	0.0201	11.74%	0.0531
1997-2005	6.89%	0.0546	7.47%	0.0226	14.23%	0.0503
2007-2013	-2.19%	0.0624	7.47%	0.0259	6.22%	0.0718

Note: The total return on housing for each MSA is calculated as the sum of capitalization rate from AHS and asset appreciation rate from FHFA. Bi-annual asset appreciation rate is generated using average quarter-level FHFA HPI within each year. capitalization rates are generated using pooled-tenure hedonic estimation. Reported in the table above are the mean and standard deviation of the total housing return for each year and its two components, when MSAs are pooled in each year or in each time period.

Table 2: Im-Pesaran-Shin Panel Unit Root Tests for House Price Appreciation Rates $ln(\Delta HPI_{i,t,k})$

Model	(1)	(2)	(3)	(4)
Lag structure for ADF	0	1	2	3
Panel 1: k=1				
W-t-bar Statistic	-59.3945***	-38.9251***	-23.7725***	-16.4677***
Panel 2: k=4				
W-t-bar Statistic	-11.9916***	-16.5166***	-18.8972***	-21.1358***
Panel 3: k=8				
W-t-bar Statistic	-2.8350***	-9.2230***	-16.2535***	-20.4970***
Panel 4: k=20				
W-t-bar Statistic	2.5816	-2.7317***	-12.3374***	-20.2740***

Note: Reported are Im-Pesaran-Shin panel unit root tests statistics when a time trend is included and cross-sectional means are subtracted, with 1-4 lag structures for ADF regressions. House price appreciation rate is the percentage change of purchase-only FHFA HPI over k quarters for k=1,4,8,20 respectively. Sample covers 124 US. MSAs over 1975 q1 - 2019 q1. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 3: Im-Pesaran-Shin panel Unit Root Tests for Cumulative House Price Appreciation $\Delta HPI_{i,t,k}$				
Model	(1)	(2)	(3)	(4)
Lag structure for ADF	0	1	2	3
Panel 1: k=1				
W-t-bar Statistic	-31.1584***	-15.3616***	-10.9766***	-12.4307***
Panel 2: k=4				
W-t-bar Statistic	-1.2779	-21.4242***	-24.6332***	-24.5429***
Panel 3: k=8				
W-t-bar Statistic	4.6374	-27.4763***	-31.3656***	-30.9181***
Panel 4: k=20				
W-t-bar Statistic	11.7374	-19.7042***	-26.4161***	-31.9860***

Note: Reported are Im-Pesaran-Shin panel unit root tests statistics when a time trend is included and cross-sectional means are subtracted, with 0-3 lag structures for ADF regressions. House price cumulative appreciation is the cumulative change of purchase-only FHFA HPI over k quarters for k=1,4,8,20 respectively. Sample covers 124 US. MSAs over 1975 q1 - 2019 q1. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 4. Panel Regressions of Cumulative Change in log(HPI) on Lagged Term with MSA and Time Fixed Effects

Model	(1)	(2)	(3)	(4)
k=	1	4	8	20
Lagged log(HPI)	0.5356***	0.6207***	0.3519***	-0.3544***
	[0.0338]	[0.0139]	[0.0159]	[0.0247]
Constant	0.0244***	0.0894***	0.2776***	0.6068***
	[0.0008]	[0.0023]	[0.0062]	[0.0322]
Number of obs	20,086	19,336	18,336	15,336
Pesaran's test of cross sectional independence	-2.601	26.359	36.786	20.249
Wooldridge test for autocorrelation	315.006	629.167	1,049.655	15,980.053
F-test on MSA fixed effect	746.72	13,722.02	170,000.00	4,300,000.0

Note: Reported are the regression results of cumulative changes in log value of HPI on its lagged terms. Sample covers 124 MSAs over 1975-2019 on quarter frequency. Cumulative appreciations rate of MSA-level HPI are calculated as quarterly change, annual change, bi-annual change and 5-year change (k=1,4,8,20). Lagged log HPI changes in each model corresponding to the value of k. The row of Wooldridge test for autocorrelation in panel data presents the F-statistics under null hypothesis of no first-order autocorrelation. F-statistics shown in the last row is the result of a F test on the set of MSA dummy variables. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 5. Summary of Statistics of the MSA Dummy Coefficient Estimates Using Equation (5)

Model	(1) k=1		(2) k=4		(3) k=8		(4) k=20	
mean	0.121%		0.500%		1.698%		8.072%	
std dev	0.11%		0.41%		1.57%		9.43%	
largest	San Jose, CA	0.458%	San Francisco, CA	1.555%	San Francisco, CA	5.976%	San Francisco, CA	34.470%
	San Francisco, CA	0.456%	San Jose, CA	1.482%	San Jose, CA	5.680%	San Jose, CA	31.356%
	Seattle, WA	0.365%	Nassau County, NY	1.353%	Nassau County, NY	5.503%	Nassau County, NY	31.232%
	Boston, MA	0.363%	Seattle, WA	1.330%	New York, NY	4.711%	Urban Honolulu, HI	28.049%
	Los Angeles, CA	0.354%	Urban Honolulu, HI	1.293%	Boston, MA	4.574%	Los Angeles, CA	27.151%
	Urban Honolulu, HI	0.339%	New York, NY	1.292%	Los Angeles, CA	4.472%	New York, NY	26.747%
	Santa Rosa, CA	0.331%	Boston, MA	1.275%	Salinas, CA	4.410%	Santa Rosa, CA	25.664%
	San Diego, CA	0.318%	Los Angeles, CA	1.221%	Santa Rosa, CA	4.239%	Salinas, CA	25.512%
	New York, NY	0.307%	Santa Rosa, CA	1.159%	Seattle, WA	4.154%	Santa Maria, CA	24.839%
	Oxnard, CA	0.300%	Salinas, CA	1.126%	Miami, FL	3.889%	San Diego, CA	23.813%
smallest	Mobile, AL	-0.024%	Fort Wayne, IN	-0.039%	Oklahoma City, OK	-0.396%	Memphis, TN	-2.960%
	Canton, OH	-0.033%	Corpus Christi, TX	-0.051%	Beaumont, TX	-0.405%	McAllen, TX	-3.070%
	Davenport, IA	-0.035%	Tulsa, OK	-0.063%	Wichita, KS	-0.488%	Jackson, MS	-3.151%
	Augusta, GA	-0.040%	Cleveland, OH	-0.064%	Tulsa, OK	-0.507%	Rochester, NY	-3.579%
	Wichita, KS	-0.044%	Peoria, IL	-0.066%	Toledo, OH	-0.584%	Oklahoma City, OK	-4.201%
	Peoria, IL	-0.045%	Oklahoma City, OK	-0.086%	Corpus Christi, TX	-0.632%	Fort Wayne, IN	-4.569%
	Shreveport, LA	-0.049%	Shreveport, LA	-0.123%	Rockford, IL	-0.704%	Tulsa, OK	-4.945%
	Toledo, OH	-0.061%	Rockford, IL	-0.206%	Montgomery, AL	-0.821%	Rockford, IL	-4.952%
	Montgomery, AL	-0.082%	El Paso, TX	-0.209%	Jackson, MS	-0.849%	Wichita, KS	-5.224%
	Rockford, IL	-0.088%	Montgomery, AL	-0.229%	El Paso, TX	-0.884%	Montgomery, AL	-6.049%

Table 6. Panel Regressions of HPI Appreciation Rates on Lagged log(HPI) with MSA and Time Fixed Effects

Model	(1)	(2)	(3)	(4)
k=	1	4	8	20
Lagged HPI	-0.0087***	-0.0636***	-0.2009***	-0.8330***
	[0.0009]	[0.0044]	[0.0122]	[0.0444]
Constant	0.0484***	0.3455***	0.9636***	3.7454***
	[0.0026]	[0.0125]	[0.0349]	[0.1284]
Number of obs	20,211	19,836	19,336	17,836
Pesaran's test of cross sectional independence	10.30	24.05	25.20	21.83
Wooldridge test for autocorrelation	76.96	740.59	1,726.52	19,083.76
F-test on MSA fixed effect	75,451	1,000,000	9,800,000	61,000,000

Note: Reported are the regression results of HPI appreciation rates on lagged log HPI. Sample covers 124 MSAs over 1975-2019 on quarter frequency. Appreciation rates of MSA-level HPI are calculated as quarterly rate, annual rate, bi-annual rate and 5-year rate of HPI appreciations (k=1,4,8,20). Lagged log HPI in each model is defined corresponding to the value of k. The row of Wooldridge test for autocorrelation in panel data presents the F-statistics under null hypothesis of no first-order autocorrelation. F-statistics shown in the last row is the result of a F test on the set of MSA dummy variables. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 7: Im-Pesaran-Shin Panel Unit Root Tests for Total Housing Return

Model	(1)	(2)
Lag structure for ADF	0	1
W-t-bar Statistic	-11.6347***	-12.8261***

Note: Reported are Im-Pesaran-Shin panel unit root tests statistics when a time trend is included and cross-sectional means are subtracted, with 0-1 lag structures for ADF regressions. MSA-level total return on housing is the sum of capitalization rate from the AHS and asset appreciation rate from the FHFA HPI. Sample covers 124 U.S. MSAs over 1985-2013. The average number of periods is 14.91 years. Null hypothesis is that all panels contain unit roots. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Table 8: Tests of Predictive Power of CAP Rate on Subsequent Asset Appreciation Rate								
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CAP rate	-0.264	-0.300	-0.149	0.033	-0.660	-0.386	-0.978	-0.023
	[0.084]***	[0.051]***	[0.067]***	[0.141]	[0.137]***	[0.166]***	[0.382]***	[0.261]
Constant	0.050	0.071	0.054	0.059	0.140	0.126	0.054	0.054
	[0.007]***	[0.007]***	[0.008]***	[0.013]***	[0.012]***	[0.017]***	[0.026]**	[0.037]
R2	0.03	0.43	0.45	0.18	0.52	0.57	0.57	0.57
N	1,849	1,849	1,849	733	744	620	372	372
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Time Period	1985 - 2013	1985 - 2013	1985 - 2013	1985 - 1995	1995 - 2005	2005 - 2013	2005 - 2009	2009 - 2013
* p<0.1; ** p<0.05; *** p<0.01								

Note: This table reports the test results of panel regressions of MSA-level asset appreciation returns against CAP rates, for 124 MSAs over 1985-2013 and each decade (or so). MSA-level asset appreciation returns are calculated using FHFA MSA-level HPI, by averaging quarterly data over a year. CAP rates are generated using pooled-tenure hedonic estimation of AHS data.

Table 9: Error Correction Models of Consumption Effects w.r.t. Housing Return Shocks Using FHFA and AHS Data

Model	(1)	(2)	(3)	(4)
Total return to housing	0.112**			0.249**
	[0.041]			[0.109]
Asset appreciation return (FHFA)		0.086**		-0.154
		[0.041]		[0.105]
CAP rate (AHS)			0.206**	
			[0.092]	
Stock market wealth shock	0.035	0.037	0.035	0.033
	[0.027]	[0.027]	[0.024]	[0.027]
Income change	0.409***	0.448***	0.586***	0.406***
	[0.141]	[0.143]	[0.140]	[0.140]
Lagged consumption change	-0.179	-0.174	-0.035	-0.15
	[0.114]	[0.112]	[0.128]	[0.111]
Lagged ratio of consumption to income	-0.034	-0.034	-0.136	-0.06
	[0.133]	[0.133]	[0.144]	[0.129]
Constant	0.000	0.006	-0.011	-0.01
	[0.008]	[0.007]	[0.009]	[0.010]
R2	0.55	0.54	0.53	0.55
N	278	278	278	278

* p<0.1; ** p<0.05; *** p<0.01

Note: This table reports the panel regression results of the Error correction consumption models in equation (9). Variables are generated as the first difference of inflation-adjusted values in per capita terms. Sample covers biannual observations over 1985-1999 on state level. Measures of housing wealth shock are, respectively, the total return to housing generated in this study, asset appreciation return from FHFA, capitalization rates from the AHS, and total return to housing together with its asset appreciation components. All other variables are from the Case-Quigley-Shiller 2005 dataset. All models include year fixed effects and state fixed effects. Standard errors in all models are clustered by state.

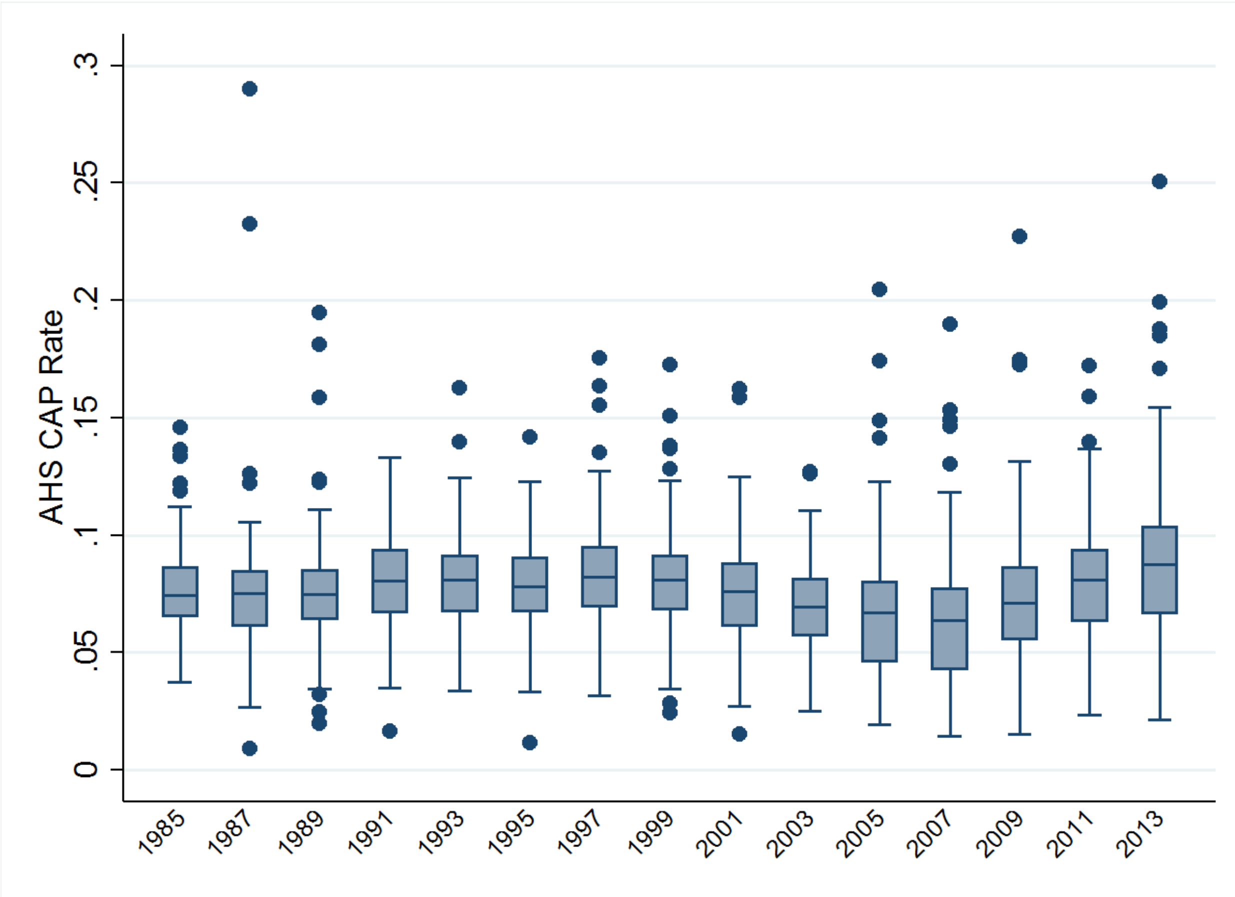
Table 10. Error Correction Models of Consumption Effects w.r.t. Asset Appreciation and Total Housing Return Using Case-Quigley-Shiller 2005 Data

Model	(1)	(2)	(3)
Asset appreciation rate (CQS)	0.063		-0.164
	[0.044]		[0.099]
Total return to housing		0.078*	0.235**
		[0.046]	[0.104]
Stock market wealth shock	0.038	0.037	0.035
	[0.025]	[0.025]	[0.025]
Income change	0.494***	0.458***	0.456***
	[0.136]	[0.134]	[0.134]
Lagged consumption change	-0.133	-0.138	-0.108
	[0.123]	[0.123]	[0.121]
Lagged ratio of consumption to income	-0.069	-0.071	-0.097
	[0.141]	[0.140]	[0.136]
Constant	0.005	0	-0.01
	[0.007]	[0.007]	[0.009]
R2	0.53	0.54	0.54
N	278	278	278

* p<0.1; ** p<0.05; *** p<0.01

Note: This table reports the panel regression results of the Error correction consumption models in equation (9). Variables are generated as the log first difference of inflation-adjusted values in per capita terms. Sample covers biannual observations over 1985-1999 on state level. Asset appreciation return is the change of real housing value from the Case-Quigley-Shiller 2005 dataset. Total housing return is the sum of CQS appreciation rate and capitalization rate from the AHS. All other variables are from the Case-Quigley-Shiller 2005 dataset. All models include year fixed effects and state fixed effects. Standard errors in all models are clustered by state.

Figure 1. Distribution of MSA-level AHS CAP Rates 1985-2013



Note: This figure shows the by-year distribution of MSA-level capitalization rates generated based on Phillips (1988) pooled-tenure hedonic estimation method using AHS PUF 1985-2013.

Figure 2. AHS CAP Rates in the 10 Biggest US MSAs over 1985-2013

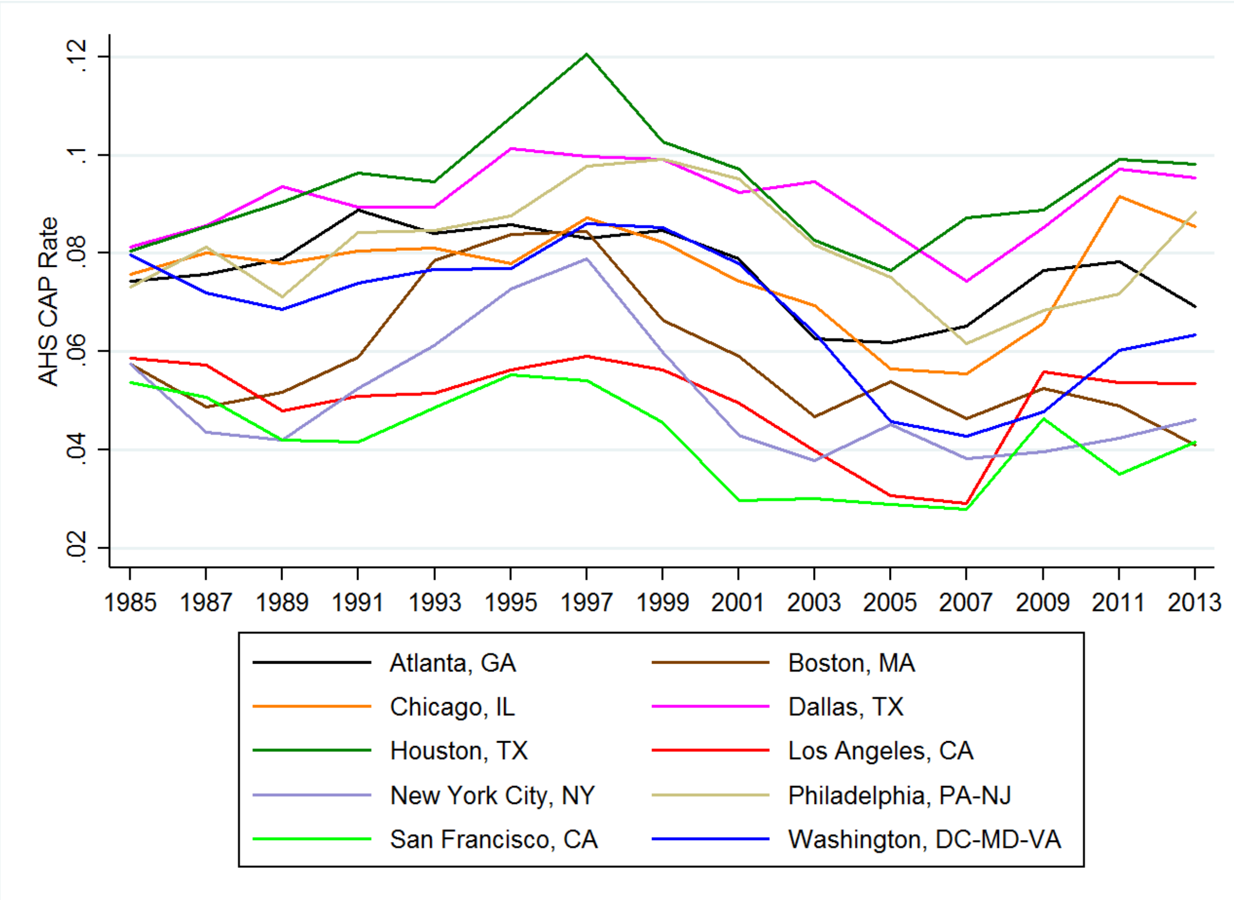
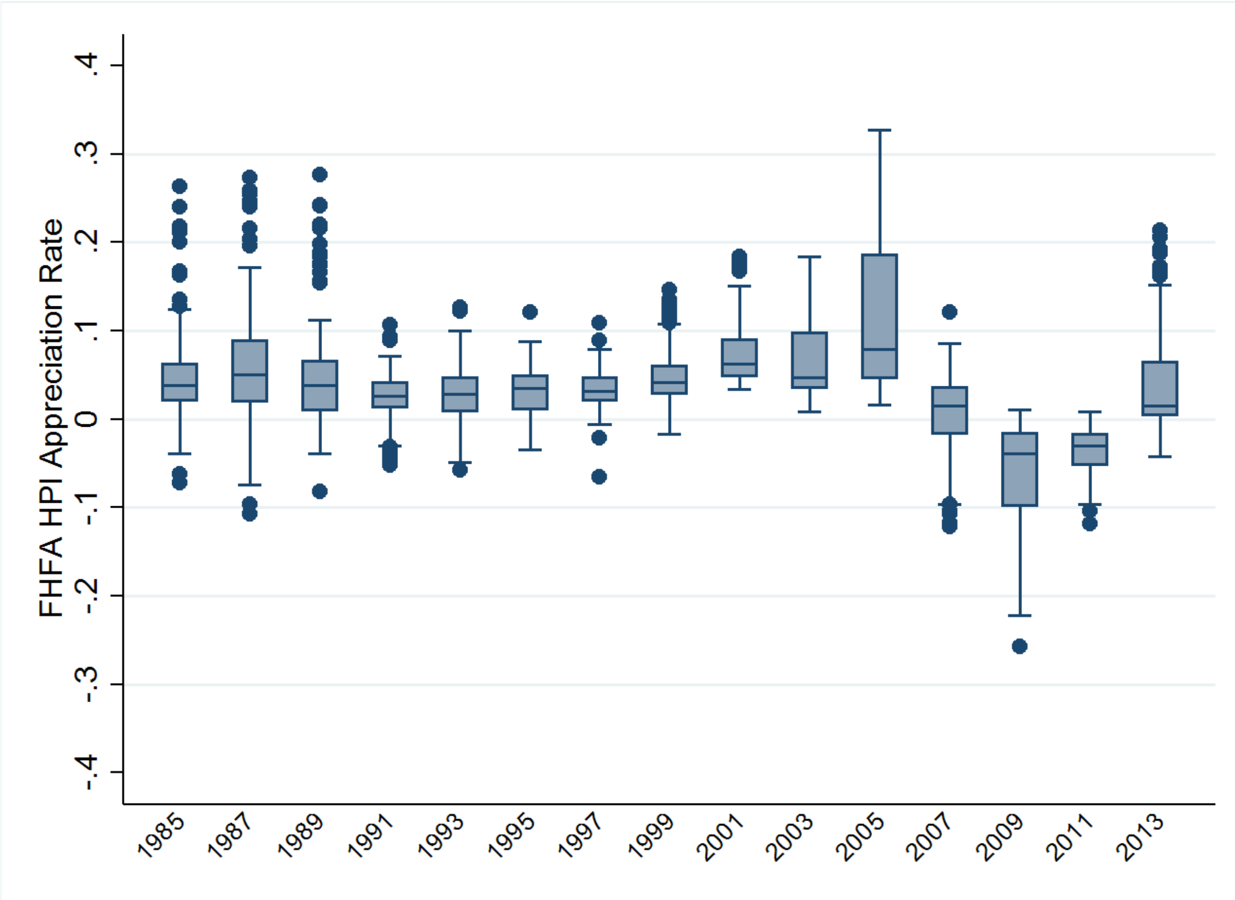


Figure 4. Distribution of MSA-level FHFA HPI Appreciation Rates 1985-2013



Note: This figure shows the by-year distribution of MSA-level FHFA HPI Appreciation rates over 1985-2013.

Figure 5. FHFA HPI Appreciation Rates over 1985-2013 in the Top 10 MSAs

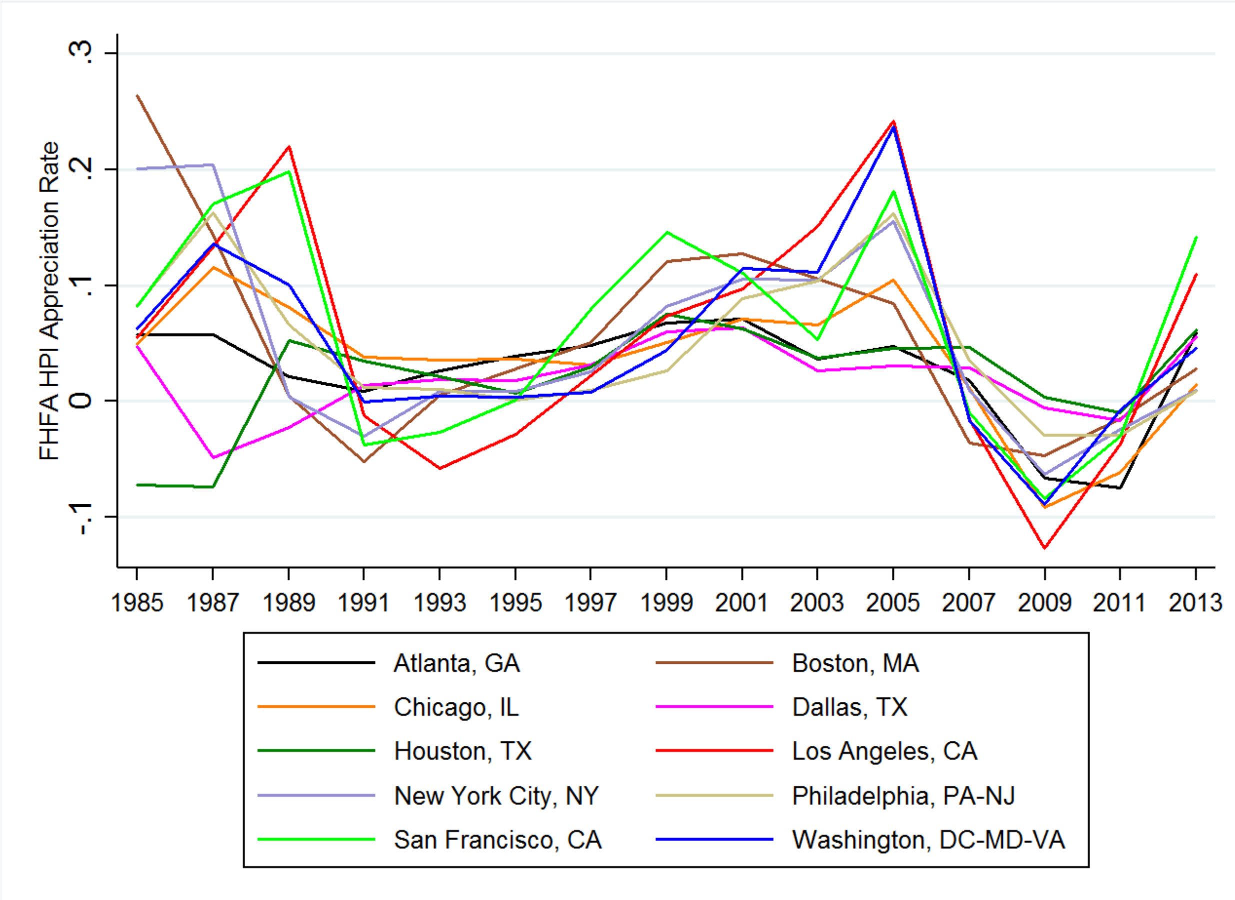


Figure 6: Mean and Standard Deviation of Total Housing Return and Components across MSAs

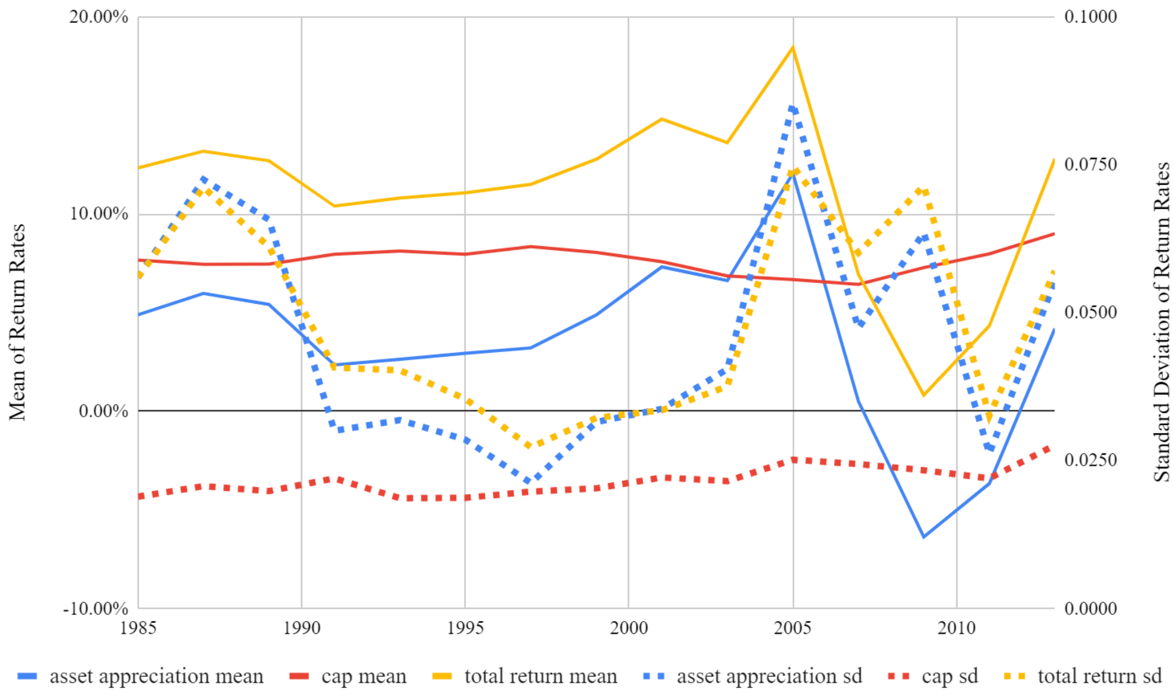


Figure 7. Scatter Plot of AHS CAP Rates and Subsequent FHFA HPI Appreciation Rates in Selected Years

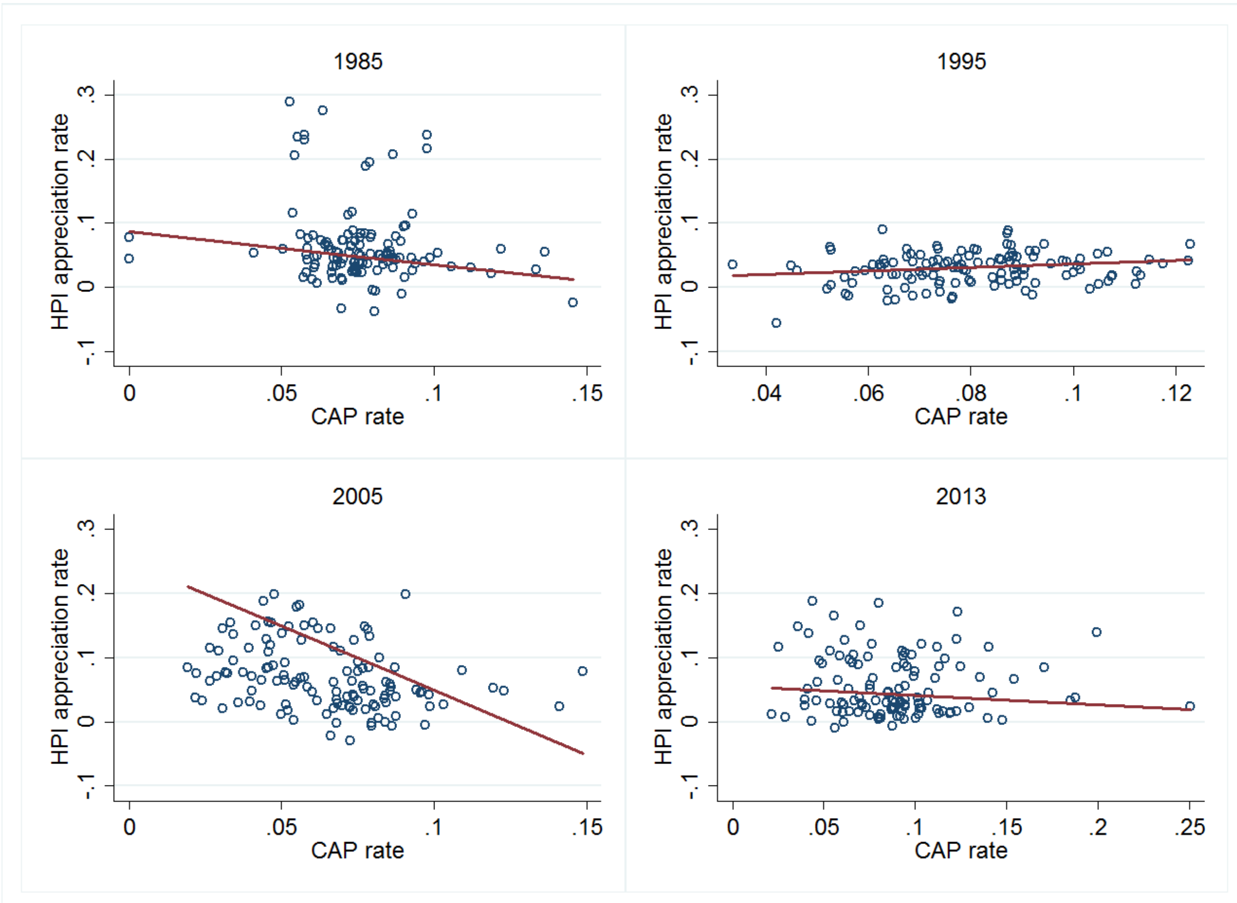
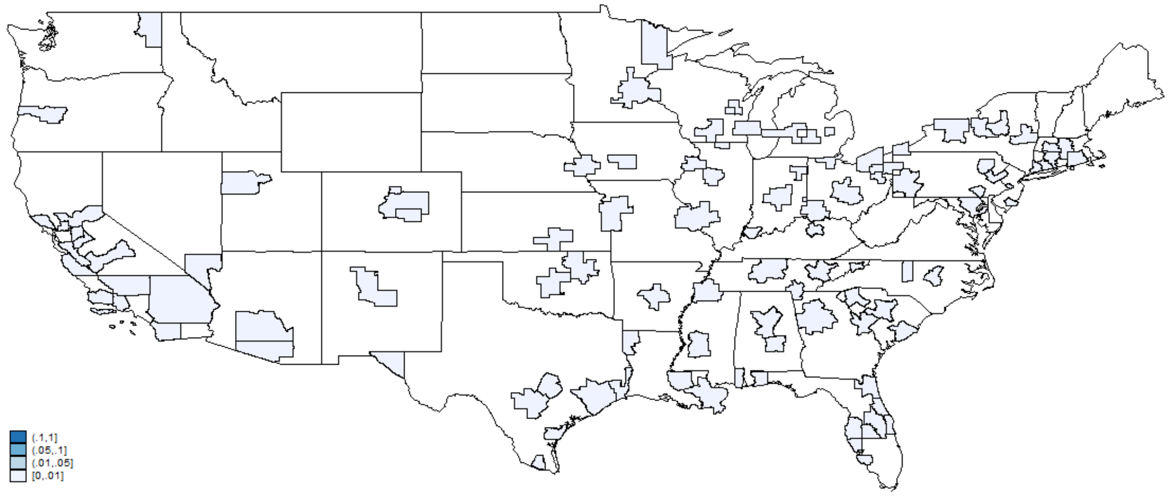
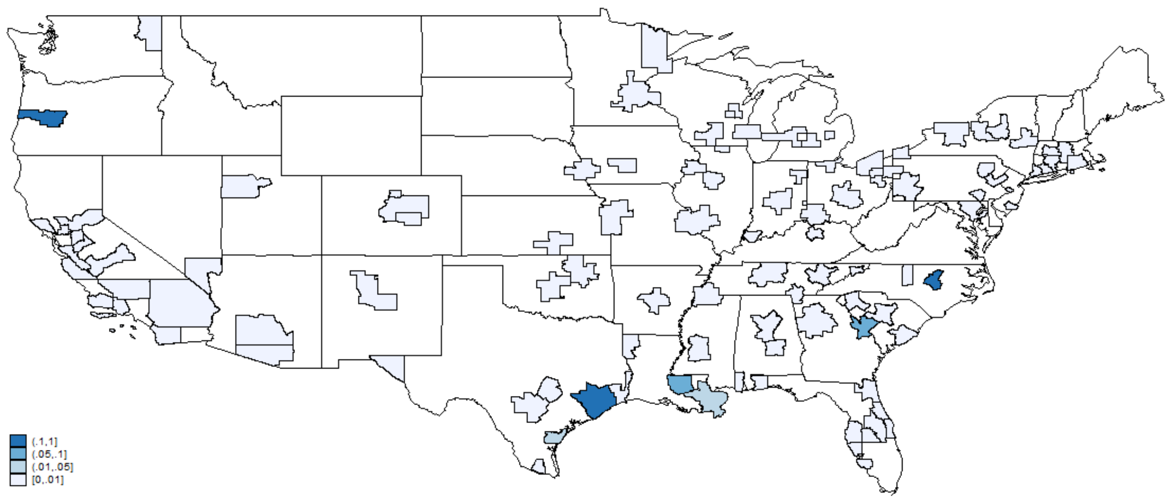


Figure 8. MacKinnon approximate p-values of ADF tests on FHFA HPI quarterly appreciation rates

0 lag



1 lag



2 lags

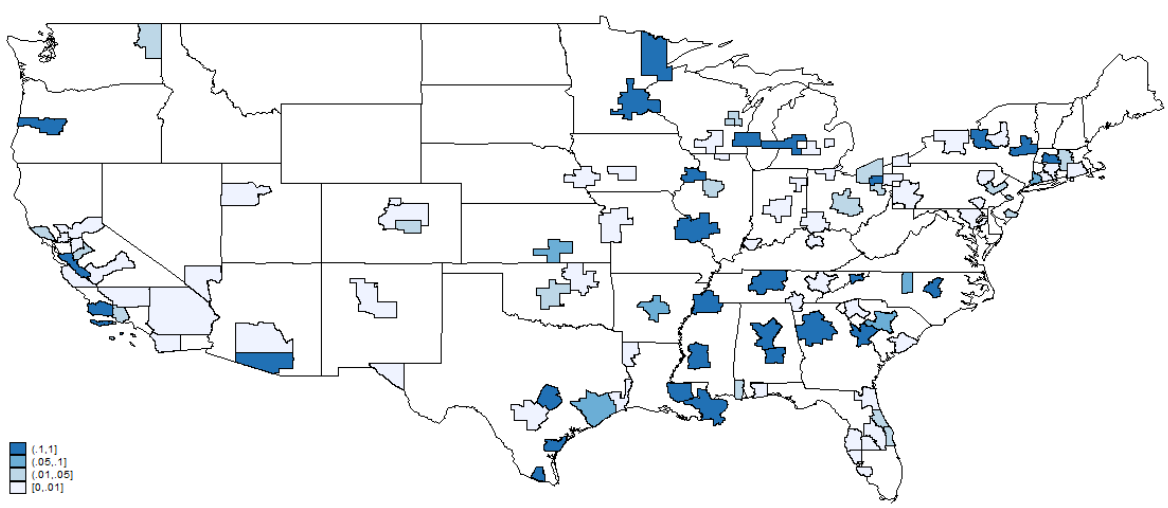
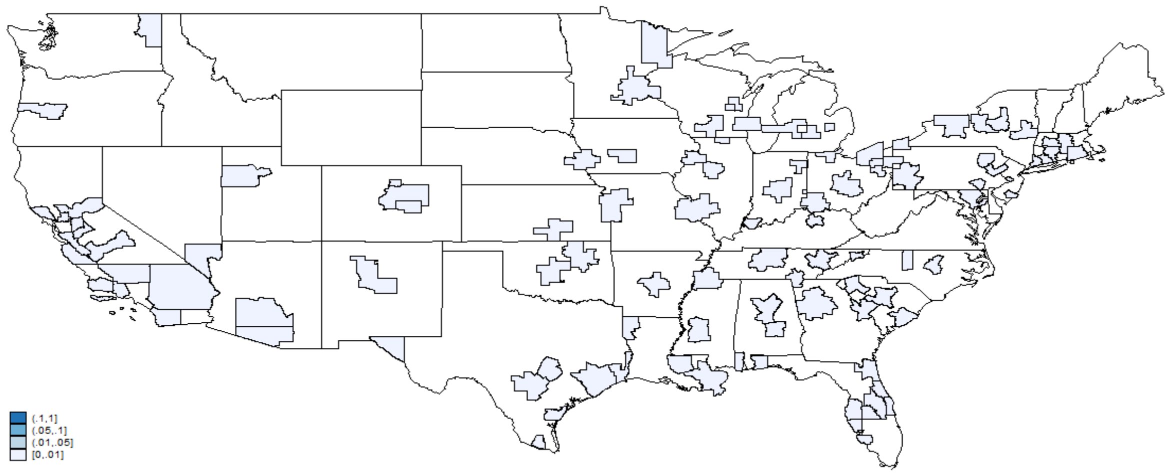
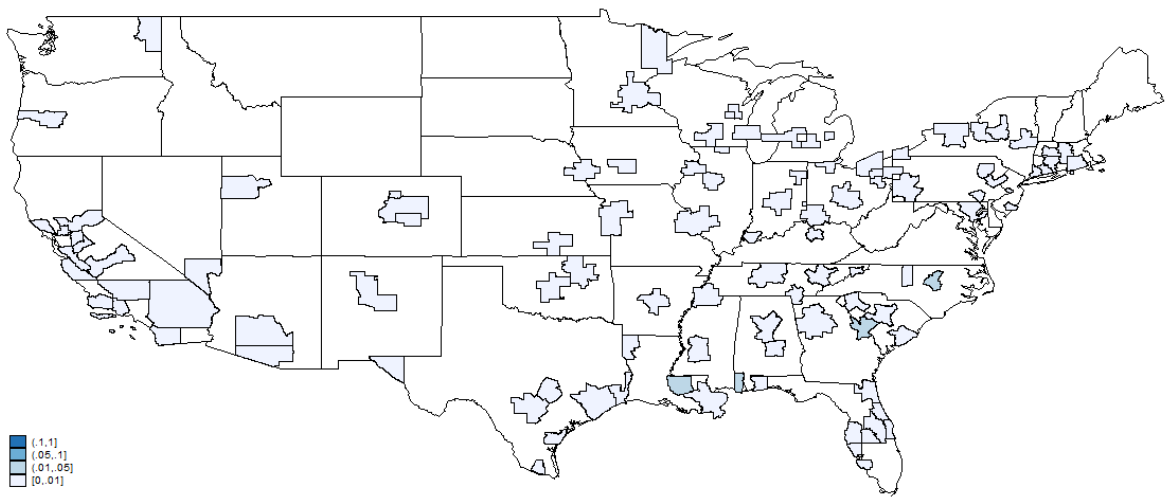


Figure 9. MacKinnon approximate p-values of ADF tests on cumulative HPI appreciations

0 lag



1 lag



2 lags

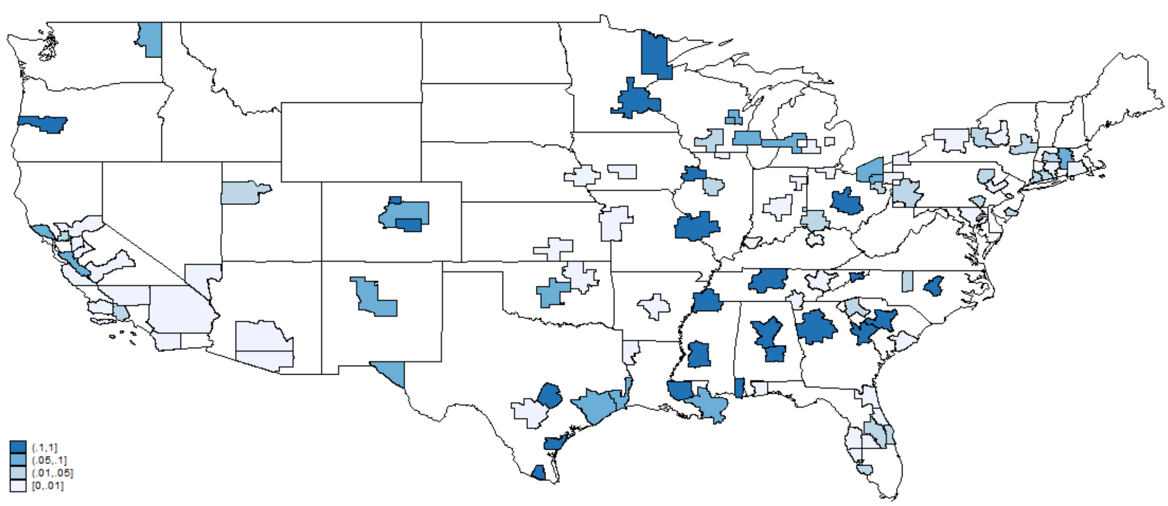
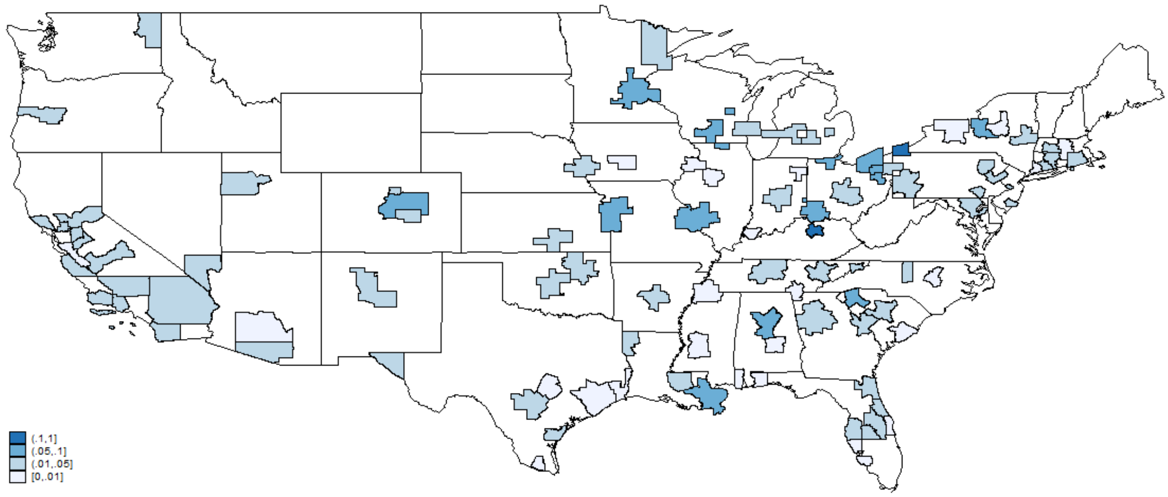


Figure 10. MacKinnon approximate p-values of ADF tests on total housing return rates

0 lag



1 lag