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Multi-Horizon Financial and Housing Wealth Effects across the U.S. States

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Abstract
We examine multi-horizon wealth effects across U.S. states over the period of 1975:Q1 to 2012:Q2 by utilizing multi-horizon non-causality testing (Dufour et al., 2006) and multi-horizon causality measurement (Dufour and Taamouti, 2010). We find in both that housing wealth has a more statistically significant, persistent, and widespread impacts than financial wealth on state/aggregate levels. We also find that state-level housing/financial wealth effects show heterogenity accross the U.S. Moreover, except the result of multi-horizon causality measure for financial wealth, the evidence show thepresence of financial/housing wealth effects for consumption in longer horizons.State-level evidence suggests that state-level policies may specifically utilize the housing market to support consumption and growth.

Key words: Consumption, housing wealth effect, financial wealth effect, multi-step causality.
JEL Codes: C32, E21, E44.

1. Introduction

Evaluatingthe dynamics of the wealth effect has been of growing importance for the U.S. economy in the wake of therecent housing bubble and resulting negative growth effects, besides the inherent perceived risks associated with stock and housing markets. The literature reveals that income and wealth are the essential drivers of consumption, and fluctuations in the value of the wealth components, such as housing and financial wealth, result in some cyclical fluctuations in household consumption. Although there are some mixed results with respect to the selected sample, time period, and model specification to name a few., there has been a growing consensus that the housing wealth effect is generally greater than the financial wealth effect. However, variations in financial wealth effect are also important for the countries which are characterized by a market-based financial system and larger stock ownership such as in the case of the U.S. The wealth effect literature is already extensive. Most of the existing evidences on the wealth effect studies are based on a limited data set containing aggregate and micro (survey) data. This paper uses an expanded database with regional data to reinvestigate the wealth effects hypothesis in the U.S.In this respect, except for Case et al. (2005), no comprehensive-systemic analysis has been conducted by using data for the U.S. economy at the state-level.To the best of our knowledge, our study is the first empirical attempt to analyze multi-horizon wealth effects across U.S. states over the period of 1975:Q2 to 2012:Q2 by utilizing multi-period non-causality testing (Dufour et al., 2006) and causality measurement (Dufour and Taamouti, 2010).An analysis of the causality linkages between wealth and consumption across different prediction horizons and states provides a micro-level fresh perspective to the empirical literature.

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This article contributes to the wealth effect literature in fouraspects. First, we use a unique data set which allows us to document the presence of income, housing, and financial wealth effectsacrossU.S. states.In addition to the aggregate-level evidence, our study provides state-level evidence to therole of housing and financial wealth effectsin consumption by improving further on Case et al. (2005; 2013), which is the only study in the field.Second, our study is the first to classify US states with respect tothe relative importance of housing/financial wealth effects. This attempt may provide an interesting knowledge for federal and state-level policy-makers in the US. Third, we apply a new methodological approach,which enables us to compare the intensity of wealth effects at various time horizons in terms of predictability. This methodological improvement providescomparative evidences sensitive to the different model specifications. Fourth, based on our unique data set and application, we refine the scope of the wealth effect by comparatively analyzing aggregate and state-level income, housing, and financial wealth effects. Our main questions are addressedbelow.

The goal of this paper isto better understand thewealth effect-induced household consumption behaviors in US states: in particular, (i) whether state-level wealth effect dynamics in the U.S.differ from aggregate level dynamics?(ii) whether wealth effect upon consumption occur at different time horizons at the state level?(iii) which wealth effect component is more intense in the short-run and long-run? (iv) whether the results are robust to different model specifications? (v) whether the U.S. states can be classifiedwith respect towhich wealth effect is more dominant (housing or financial) based on some criteria such as short/long term persistency and magnitude of coefficient value of a wealth effect component?Eventually, by investigating these empirical questions, our study sheds more light on the field-classical research topic on which wealth effects matters most for the household consumption in U.S.

Causality measurement reveals that housing wealth constitutes the most crucial determinant of consumption growth changes from an economic viewpoint. Our evidence suggests that changes in housing wealth generate more intense, persistent and widespread impacts on consumption growth at the aggregate and state level when compared with financial wealth. Moreover, although we document the presence of both financial and housing wealth effects upon consumption at long horizons, the results show that there isheterogeneity in the wealth effect patterns accross U.S. states.

The remainder of the paper is organized as follows. The next section documents the literature review.Section 3 provides a discussion of our methodology. Data and empirical results are presented and discussed in Section 4. Finally, section 5 concludes the paper.

2. Literature Review

The life cycle (Modigliani and Brumberg 1954; Ando and Modigliani 1963)-permanent income (Friedman 1957) hypothesis is widely accepted as the proper application of the theory of the consumer to the problem of dividing consumption between present and future. According to the hypothesis, consumers form estimates of their ability to consume in the long run and then set current consumption to the appropriate fraction of the estimate. The estimate may be stated in the form of wealth, following Modigliani, in which case the fraction is the annuity value of wealth, or as permanent income, following Friedman, in which case the fraction should be very close to zero (Hall, 1972). Due to data constraints for pension and social security wealth, housing wealth studies have generally used financial and housing wealth data in their analyses (Browning and Crossley, 2001).

Althoughthe empirical literature presents some mixed evidence,common patterns of wealth effectsare documented in different samples.

First, in general, housing and financial wealth play a significant role in income, saving[1] and consumption behaviours and economic growth. Second, the business cycle of the economy is a determinant factor of the magnitude of the wealth effect. Namely, rising (declining) stock/housing market environment may increase (decrease) wealth effect components to different degreesas observed before/after global financial crisis periods. There may also beparalell relations betweem real estate and business cycles for those countries/regions where real estate and the general economy have strong linkages. Case (1992) argues that the real estate cycle amplified the business cycle significantly in the late 1980's in New England. The Global Financial Crisis was the latest example of this relation for the at least the US, UK and Ireland.Aoki et al. (2004) indicate that increasing optimism in consumers is likely to increase consumption of housing and non-housing goods. Nyakabawo et al. (2013) show that while the real house price generally leads real GDP per capita, both during expansions and recessions, significant feedback effects from the real GDP per capita onto the real house price. These findings also occur during the recent financial crisis and Great Recession.By exploring the asymmetric effect of housing and financial wealth on household consumption behaviour using panel data from 24 OECD countries, spanning the period 2000 to 2016 through a threshold empirical framework, Apergiss et al. (2019) finds that the impact of housing and stock market wealth has increased during the dot.com and housing bubble periods. Third, depending on the phase of the business cycle and the market, housing and financial wealth effects have some cyclical and non-asymmetrical features as well (i.e. Engelhardt, 1996; Case *et al*., 2005; Donihue and Avramenko, 2007; Sousa 2010;Chen et al., 2011).Fourth, the importance of housing and financial wealth is determined by various factors such as the level of mortgage market completeness and financial development, the ownership level/structure in housing/stock markets, market-specific policies (on i.e. protection of rights, transaction cost, information asymmetry etc.). However, it is generally difficult to make a generalization among countries from housing/wealth effect perspective, it seems that while financial wealth may become a primary wealth effect source in Anglo-Saxon and/or market-based economies, housing wealth effect may become a primary source in bank-based and some developing countries (i.e. Edison and Sløk 2001; Ludwig and Sløk, 2004; Paiella 2007; Albacete and Lindner, 2017).

However, despite some common joint features, the empirical literature reveals that in addition to sources of the wealth effect (Case et al., 2005), the variations in household consumption sensitivity to wealth effects depends on various factors such as liquidity conditions (Pissarides, 1978), utilities derived from the property right and the role of bequest (Poterba, 2000), distributions of wealth among income groups, expected permanency of changes, measurement biases of wealth (Dvornak and Kohler, 2003; Case et al., 2001), housing/stock market features of the analyzed country/province, the policies, and behaviors and demographics of asset owners. In

[1]Benjamin et al. (2004) argue that more than half of the decline in the saving rate from 9.1 percent in 1995 to 4.3% percent by 2001 in the US is attributable to increases in the real estate wealth during that period.Case et al. (2005) also indicate if unrealized capital gains in housing were included in both the income and savings of the household sector (as suggested by the Haig-Simons criteria), then the aggregate personal savings rates computed were much higher (Gale and Sabelhaus, 1999).

this respect, differences in marginal propensity to consume in both markets is generally explained by the well-documented differences in nature and risk characteristics of housing/stocks as the asset classes (see, Ludwig and Sløk, 2002, Apergis et al., 2014). For example, Kennickell and Starr-McCluer (1997) provide evidence that imperfect knowledge of households with respct to their financial wealth may result in them to react instantaneously to changes in wealth. Shefrin and Thaler (1988) discuss that psychology of framing may dictate that certain assets are more appropriate to use for current expenditures, while others are earmarked for long-term savings. Case et al. (2005) note that the emotional impact of accumulating stock market wealth may be quite different from that of real estate wealth. People are likely to be less aware of the short-run changes in real estate wealth since they do not receive regular updates on its value. Stock market wealth can be tracked daily in the newspaper. Tsai et al. (2012) argue that housing and stock markets respond rather differently to negative shocks when the stock market is more volatile, but price rigidity is found in the housing market. From the micro analysis perspective, the magnitude of the wealth effect is also related to demographic features. From the housing market perspective, Li and Yao (2007) discuss that house price appreciation increases the net worth and consumption of all homeowners, while it only improves the welfare of old homeowners.

Case et al. (2005) indicates that the importance of housing market wealth and financial wealth in affecting consumption is an empirical matter. For example, as the early study, using aggregate data in explaining US consumer expenditures over the period 1960-1977, Elliot (1980) finds that fluctuations in the net value of household holdings of consumer durables and real estate do not associate significantly in consumer spending and values of expenditure elasticity of stock price changes with mean values in the 0.030-0.055 range.Empirical work, such as Engelhardt (1996) and Skinner (1996), suggest at best a weak link between house price changes and nonhousing consumption. Carroll (2004) and Belsky and Prakken (2004) find similar housing and stock wealth elasticities in their estimations. Poterba (2000) discuss that house price fluctuations possibly trigger smaller consumption changes than stock market fluctuations do. The extent to which an unanticipated increase in house prices raises a household's real wealth depends on the time horizon over which the household plans to live in their current home. It is noted from the US Survey of Consumer Finances, in 1998 and 2001, that more than two-thirds of households are homeowners, while only half owned stock, bonds, and mutual funds concentrated in pension/retirement accounts, Benjamin et al. (2014) argue that if the marginal propensity to consume from real estate is higher than it is from financial wealth, then housing has a primary role in economic stabilization.Households use their housing and real estate with the higher marginal propensity to consume to smooth and stabilize consumption when other assets are performing poorly. So, when stock market prices decline, households use their real estate equity to increase consumption, thereby stabilizing economy. With the availability of home equity loans and low-cost tax-deductible refinancing, homeowners can access their housing to finance consumption.The recent empirical literature provides a large body of evidence on the larger and persistent source of housing wealth.Coskun et al. (2018) document thatthe housing wealth effect is more intense than the stock wealth effect for a panel of countries over the period from 1970 Q1 to 2015 Q4. They argue that housing is a powerful asset transmission channel irrespective of the size, financial structure, and geographic location of the analysed economies. Tracy et al. (1999) indicate that change in household net worth caused bya change in house prices is larger than the change from similarvariation in stock values for the vast majority of households. By estimating the consumption function for the U.S. economy with real estate and financial wealth for quarterly data for 1952:1–2001:4, Benjamin et al. (2004) find that an additional dollar of real estate wealth increases consumption by 8 cents, as compared with only 2 cents for financial wealth.Slacalek (2006) finds that the effect of housing wealth is somewhat smaller than that of financial wealth for most of the investigated countries, but not for the US and the UK. The housing wealth effect has risen substantially after 1988 as it has become easier to borrow against housing wealth.Carroll et al. (2006), consistent with several recent studies, find a housing wealth effect that is substantially larger than the stock wealth effect for the US. Sierminska and Takhtamanova (2007) find that overall wealth effect out of housing is stronger than the effect out of financial wealth for all the countries involving the US. Housing wealth effect is consistently stronger for the oldest group in Canada and the late middle-aged groups in Finland and Italy. Authors suggest that policymakers should keep an eye on housing market developments separately from financial markets. Bostic et al. (2009) research findings indicate relatively large housing wealth effects for the US. Among homeowners, the housing wealth elasticities are estimated in the range of .06 over the 1989-2001 period.

In general, analyses of the role of housing wealth in the determination of consumption spending have used one of three types of information: aggregate time-series data at the state or national level, micro-data from household-level surveys, and data based on refinance activity (Bostic et al., 2009). It seems that studies are mostly focused on aggregate and micro-level data, but state-level analysis is scarce in the empirical literature. By following Case et al (2001) and using a state-level panel for the Australian economy, Dvornak and Kohler (2003) find larger effects for financial wealth, but smaller effects for housing wealth. Using threshold regression to explore the asymmetric effects of housing price on consumption, Dong et al. (2017) investigated the linkage for 35 major Chinese cities. The authors argue that the housing market is indeed equally or even more important to the transmission channels from housing wealth to consumption in China. Based on China Family Panel Studies, Hui et al. (2018)find that urban housing price influences some nonessential expenditure items like education, medical, and transportation.Hui et al. (2018) in the paper that, heterogeneous responses offer meaningful implications for policy makers to transform housing wealth into consumption, along with bolstering economic development in China.

In parallel to studies for other countries, wealth effect studies based on state (and region, city) level data are also scarce for the US. Using aggregate data, Case (1992) find evidence of a significant consumption effect during the real estate price boom during late 1980's for New England. Case et al. (2005) estimate stock market wealth, housing market wealth and consumption for each U.S. state, quarterly, for the period 1982-1999. In Case et al. (2005) esstimates of aggregate financial wealth were obtained annually from the Federal Reserve Flow of Funds (FOF), estimates of housing market wealth were constructed from repeat sales price indexes, and Retail sales used asa proxy of consumer expenditure. Theyfind at best weak evidence of a stock market wealth effect and strong evidence that variations in housing market wealth have important effects upon consumption.Case et al. (2013) use similar data sources toCase et al. (2005) while theyestimate regression models in levels, first differences and in error-correction form over the period of 1975 through 2012Q2 for the US states.They documenta statistically significant and rather large effect of housing wealth upon household consumption; this effect is consistently larger than the effect of stock market wealth upon consumption.Among others, they argue that a decline of 35 percent in housing wealth would lower consumer spending by 3.5 percent in the US. The authors further indicate that changes in housing wealth and stock market wealth do not move closely with per capita income across states. The most dramatic cyclical pattern is in California and the patterns in Florida and Arizona are much like that in Texas. Apergis et al. (2015) examine the nature and causal direction of the relationship between house prices and economic growth proxied by per capita personal income for a panel of 351 US metropolitan statistical areas. The authors find a long-run relationship between local house prices and per capita personal income and also the existence of a bi-directional causality between real house prices and real per capita personal income over both long and short-horizons.Emirmahmutoglu et al. (2015) investigates the presence of causal linkages between asset prices and output per capita across the 50 US states and DC over the period 1975–2012 by implementinga bootstrap panel causality framework. Their findings indicate that, when controlling for cross-state dependency, heterogeneity and asset market interconnections, causality runs from asset prices (both housing and stock prices) to output, not only at the level of individual states, but also taking together all the agricultural and industrial states. By employing multistep a non-causality test (Dufour et al., 2006) and the causality measures (Dufour and Taamouti, 2010), Apergis et al. (2018) investigates the nature of the intertemporal relationship between household wealth and private consumption across the G7 countries. The authors document the absence of short-horizon causality and the presence of long-horizon causality across variables. The findings suggest that conventional Granger causality tests are incapable of capturing the true picture of the dynamic causality relationships between stock market and housing wealth and consumption. The results also document that the presence of both long horizon financial and housing wealth effects upon consumption supports the necessity for consumers in the G7 economies to use both financial and housing wealth to ease liquidity constraints.

Overall, not surprisingly, housing and financial wealth effects may exhibit heterogeneity accrossregions involving US states and cities if we account for the differences in ownership level in financial/housing assets, demographics, income-wealth level/distribution, consumption behaviours shaped by socio-econonomic/cultural structures, access to finance and credit constraints etc.

3. Methodology

The traditional concept of Wiener-Granger (1956,1969) causality is defined in terms of incremental predictability one period-ahead. It is by now a commonplace observation that this conceptdoes not take into account the possibility that the predictive ability of a variable for another may vary over different time periods into the future. Lütkepohl (1993) and Dufour and Renault (1998), argue that even if there is no causality between two variables one period-ahead, causal links may be present at subsequent time periods. In a multivariate framework, a set of auxiliary variables, say Z, can induce an indirect influence of X on Y at higher prediction horizons than one. Dufour and Renault (1998) are the first to present a theoretical multivariate framework, referred as long (or short) horizon non-causality, which allows one to disentangle potentially different Granger causality relations over different forecast horizons. The authors provide definitions and a set of conditions which ensure the equivalence between standard Wiener - Granger type one-step ahead non-causality and non-causality at any forecast period. Their multivariate frameworkdefines conditions on non-causality between two variables of interest at a forecast horizon greater than one in terms of multi-linear zero restrictions on the VAR model parameter coefficients.

Testing such hypotheses using likelihood ratio or Lagrange multiplier tests is problematic due to the difficulty of estimating parametric models which encompass the multi-linear coefficient zero restrictions. The use of a Wald test is a feasible alternative to this problem. However, a regularity condition states that the asymptotic distribution of a standard Wald test is valid only when the matrix of the first partial derivatives of the VAR coefficient restrictions is of full rank. Lütkepohl and Burda (1997) argue that the matrix of the first partial derivatives of Dufour and Renault's (1998) VAR coefficient restrictions may be of reduced rank because these restrictions have a multilinear form. Therefore, the Wald statistic may fail to be asymptotically distributed as chi square under the null, and as a consequence, the use of the asymptotic chi square critical values may lead to misleading inference. Lütkepohl and Müller (1994) and Lütkepohl and Burda (1997) propose modified Wald statistics to test the noncausality hypothesis at a specific horizon *h*. These tests are shown to have a valid asymptotic distribution under the null hypothesis even when these highly nonlinear zero coefficient restrictions violate the regularity condition of a usual Wald test. However, the proposed tests yield a poor finite sample performance. An alternative test procedure is proposed by Dufour et al (2006). Their methodology requires the estimation of parametric mean regressions denoted as '(p,h)- autoregressions'. Inference is conducted by testing simple zero coefficient restrictions on the parameters of the '(p,h)-autoregressions' via an asymptotic chi-square Wald test. The authors also introduce a parametric Monte Carlo procedure to calculate *p*-values, to ensure enhanced finite sample properties.

3.1. Testing for Granger Non-Causality at Time Horizon h (Dufour et al., 2006)

Testing for multi-horizon non-causality(see,Dufour et al., 2006) involves estimating the conditional vector autoregressive model of order p (VAR(p)),

$$V_t = \mu + \sum_{k=1}^{p} \theta_k V_{t-k} + u_t, \quad t = 1,2,...,T, \qquad (1)$$

where $V_t = (v_{1t}, v_{2t}, ..., v_{mt})$is an $m\times 1$random vector, μ is an $m\times 1$ vector of intercepts, and u_t is the vector of uncorrelated residuals with $E(u_t u_t') = \Omega$. The model in equation (1) can be rewritten for the time period $t+h$:

$$V_{t+h} = \mu^{(h)} + \sum_{k=1}^{p} \theta_k^{(h)} V_{t+1-k} + \sum_{\tau=0}^{h-1} \psi_\tau u_{t+h-\tau}, \quad t = 0,1,...,T-h, \ (2)$$

where ψ_τ is the matrix of impulse responsecoefficients.Estimators for the parameter coefficients of model (2), which is denoted by the authors as "(p,h)-autoregression", are presented in Dufour and Renault (1998) and Dufour et al. (2006). Suppose we want to test the null hypothesis that the variable v_{jt} does not Granger cause variable v_{it} at time horizon h. The null hypothesis is defined in terms of specific zero coefficient restrictions on the parameters of model (2):

$$H_0^{(h)} : \theta_{ijk}^{(h)} = 0, \quad k = 1,2,..., p, \ (3)$$

where $\theta_k^{(h)} = \left[\theta_{ijk}^{(h)}\right], \quad i, j = 1,..., m.$

The authors propose an asymptotic chi-square Wald test statistic to test the null hypothesis in (3). Evidence from Monte Carlo simulations indicates that inference based on the asymptotic chi-square critical values may be misleading due to size distortions. Therefore, they introduce a simulation method to calculate the *p*-value of the Wald test which ensures enhanced finite sample properties of the test procedure.The simulated *p*-values of the Wald test results are calculated using the method described at page 351 of Dufour et al. (2006).

3.2. Measuring Granger Non-Causality at Time Horizon h (Dufour and Taamouti, 2010)

While testing for Granger non-causality at multiple time horizons may yield interesting insights, this approach by construction cannot help the researcher to conclude whether a statistically significant causal effect at a specific time horizon may lead to enhanced forecastability of the series or not. Quantifying the degree of multi-horizon conditional mean codependence between the data would give a richer and more comprehensive picture than just documenting the presence of a causality relation.Dufour and Taamouti (2010) propose measures for Granger multi-horizonnon-causality which quantify the strength of a causality relation between two random variables at a specific time horizon *h*. Their method is an adaptation of Geweke's (1982;1984a,b) framework for the assesment of one-period ahead conditional mean dependence between multivariate series, but generalized for multi-horizon causality measurement. Dufour and Taamouti (2010) quantify the intensity of causality from *Y* to *X* at horizon *h* by means of the mean-square based causality measure

$$C_L\left(Y \underset{h}{\rightarrow} X \middle| I\right) = \ln\left[\frac{\det\left\{\Sigma\left[X_{t+h} \middle| I_{X,t}\right]\right\}}{\det\left\{\Sigma\left[X_{t+h} \middle| I_{XY,t}\right]\right\}}\right] \tag{4}$$

where $\Sigma\left[X_{t+h} \middle| I_t\right]$is the covariance matrix of the prediction error $u\left[X_{t+h} \middle| I_t\right] = X_{t+h} - P\left[X_{t+h} \middle| I_t\right]$, with $P\left[X_{t+h} \middle| I_t\right]$denoting the best linear forecast of X_{t+h}.The causality measure (5) is applied for multivariate ARMA –type processes in the context of infinite vector autoregressive models (VAR(∞)) or infinite vector autoregressive moving average models (VARMA(∞)). Estimation of expression (5) involves the following steps:

Assume that we want to measure the intensity of causality from v_{1t} to v_{2t}at forecast period *h*. Let the stationary and invertible process V_t be partitioned into $V_t = \left(v_{1t}, v_{2t}, v_{qt}\right)$, where v_{1t}, v_{2t} are two $T \times 1$vectors and $v_{qt}$is a $T \times (m-2)$matrix with auxiliary variables. The process $V_t$can be approximated by a VAR(*p*) model (see equation (1)), while the variance-covariance matrix of the forecast error of v_{2t+h} is estimated as:

$$\hat{\Sigma}_h = \sum_{z=0}^{h-1} R\hat{\psi}_z\hat{\Sigma}\hat{\psi}_z'R', \tag{5}$$

where $R = (0, 1, 0,..,0)$ is a $1 \times m$ vector,$\hat{\psi}_z = \hat{\theta}_1^{(z)}$, $\hat{\theta}_1^{(z+1)} = \hat{\theta}_2^{(z)} + \hat{\theta}_1^{(z)}\hat{\theta}_1$, $\hat{\theta}_1^{(1)} = \hat{\theta}_1$, $\theta_1^{(0)} = I_m$, for $z \geq 1$, $\hat{\theta}_k = \left[\hat{\theta}_{1k}, \hat{\theta}_{2k}, ..., \hat{\theta}_{kk}\right]$is the matrix of the least-squares estimators of the coefficients θ_k ,and $\hat{\Sigma} = \hat{u}_t\hat{u}_t'/(T-p)$ with $\hat{u}_t$denoting the estimated residuals from model (1). Subsequently, consider the marginal process $V_t^* = \left(v_{2t}, v_{qt}\right)$.Let$V_t^*$evolve as a VAR(*p*) process, while the variance-covariance matrices of the forecast errors of v_{2t+h} are estimated as:

$$\hat{\Sigma}_h^* = \sum_{z=0}^{h-1} R^*\psi_z^*\hat{\Sigma}^*\psi_z^{*\prime}R^{*\prime}, \tag{6}$$

where the quantities $\hat{\psi}_z^*, \hat{\Sigma}^*$ are estimated similarly with those of equation (5),and $R^* = (1, 0,...,0)$ is a $1 \times (m-1)$ vector.

Then, the expression in (4) is estimated as

$$\hat{C}_L\left(v_{1t} \underset{h}{\rightarrow} v_{2t} \middle| I\right) = \ln\left[\frac{\det\left\{\hat{\Sigma}^*_h\right\}}{\det\left\{\hat{\Sigma}_h\right\}}\right] \tag{7}$$

The causality measure at horizon *h* indicates how strong is the causal relationship between the two time series at the specific forecast period. Therefore, a large value of the causality measure is interpreted as an indication that the variable v_{1t} induces a severe effect on the conditional mean of variable v_{2t} at horizon *h*. On the other hand, non-causality from v_{1t} to v_{2t} at horizon *h* is equivalenttoazero causality measure.

The causality measure estimator in (7) is shown to be consistent and asymptotically normal by Dufour and Taamouti (2010). Estimation of the asymptotic variance of the measure involves difficult calculations since it requires the analytical differentiation of the causality measure with respect to θ_k. To circumvent this problem, the authors introduce a residual-based bootstrap procedure to construct confidence intervals. In this paper, the bootstrap method of Dufour and Taamouti (2010) is usedto compute the 95% confidence intervals for each*h*-horizon causality measure. The order*p*of the autoregressive specifications used for testing and measuring multi-horizon causality is set arbitrarily to be four quarters.

4. Data and Empirical results

4.1. Data

We use state-level per capita owner-occupied real housing wealth, per capita real financial wealth and per capita real household consumption, as imputed in Case et al. (2005, 2013). This is virtually the only data set that has both the financial wealth and housing wealth disaggregated to the state-level (including District of Columbia); the imputation covers a significant period of time, from 1975:Q1 to 2012:Q2. We aggregate all these variables across the 50 states and District of Columbia to obtain the corresponding values for overall United States. One issue with this dataset is that per capita consumption is approximated at the state level by total retail sales. Further, note that Case et al. (2005, 2013) restricted the growth rate in household financial wealth solely to the growth rate in households' holdings of mutual funds due to data availability. Various unit root tests are implemented in order to test whether the variables are non-stationary at both the aggregate and the state level. Our findings indicate that all variables are nonstationary.[2] Therefore, we calculated the logarithmic first differences of the data to ensure that the series are stationary. Throughout the empirical analysis that follows, the testing and measurement procedures are applied to the differenced data.

[2]The results are available upon request from the authors.

4.2. Test Results

4.2.1.Multi-HorizonNon-Causality Measure Test Results and Implications

Tables 1 to 3 report the results when we implement the multi-horizon non-causality test of Dufour et al. (2006) described in section 3.1 to investigate for multi-horizon wealth effects on private consumption growth for 51 States of US. Each table exhibits the simulated p-value of the Wald test statistic over the range one to eight quarters ahead. Following Dufour et al. (2006), we used 1000 replications foreach simulation to calculate the p-value.

We observe in Table 1 that in 37 States housing wealth growth Granger cause consumption growth at multiple forecast horizons at levels of statistical significance 1%, 5% and 10%.In some states housing wealth effects occur one or two quarters-ahead (Florida, Idaho, Illinois, Kansas, Maine, Montana, New York, Wisconsin).In some other states we documentthe presence of long horizon causalitiesexclusively (Alaska, Arizona, Arkansas, Connecticut, Delaware, Indiana, Maryland, Michigan, Nebraska, North Dakota, Rhode Island, South Dakota, Texas). Causality from housing wealth to consumption is also found at both short and long horizons (California, Colorado, Iowa, Massachusetts, Minnesota, Mississippi, Missouri, New Hampshire, New Jersey, Ohio, Oklahoma, Oregon, Pennsylvania, Tennessee, Vermont, Virginia).On aggregate in the US we find highly significant housing wealth effects upon consumption one, two, four, five, six, and eight quarters-ahead.

Table 2 demonstrates thepresence of statistical significant income effects upon consumption at different time horizons in 21 states at levels 1%, 5% and 10%. We document cases of causality from income growth to consumption growth at short horizons (Alaska, Florida, Kansas, Maine, North Carolina, Virginia), at long horizons (Arizona, Connecticut, District of Columbia, Illinois, Iowa, Kentucky, Louisiana, North Dakota, Ohio, Washington), and at both short and long horizons (Delaware, Hawaii, Maryland, Oklahoma, South Dakota, Texas). On aggregate in the US we find that income does not cause consumption over any time horizon.

We see in Table 3 thatthe null hypothesis of non-causality from stock holdings growth to consumption growth is rejected at multiple time horizons in 43 states at levels 1%, 5% and 10%.This evidence suggests a significant state-level financial wealth effects according to non-causality measure. Causal effectsfrom stock holdings toconsumption occur up to two quarters-ahead (Arizona, California, Colorado, Connecticut, Delaware, District of Columbia, Hawaii, Maine, Massachusetts, Michigan, Ohio, Virginia), several distant quarterly periods-ahead(Alabama, Arkansas, Idaho, Illinois, Mississippi, Montana, New Hampshire, Oklahoma, South Carolina, Texas, Vermont, West Virginia, Wyoming), over the range between one and eight quarters (Florida, Georgia, Indiana, Minnesota, Missouri, Nevada, New Jersey, New Mexico, New York, North Carolina, Oregon, Pennsylvania, Rhode Island, Tennessee, Utah, Washington, Wisconsin). On aggregate in US, causality is statistically significant one quarter-ahead at level 5% and eight quarters-ahead at level 10%.

The evidence of aggregate/state level non-causality test results of housing/financial wealth effects are comparatively summarized below.As far as it concerns the aggregate results of non-causality test, while causality from stock holdings growth to consumption growth is statistically significant in (1; 8) quarters-ahead with corresponding simulated p-values(0.019; 0.086), causality from housing wealth growth to consumption growth is statistically significant at (1; 2; 4; 5; 6; 8) quarters-ahead with corresponding p-values(0.014; 0.032; 0.005; 0.005; 0.010; 0.006). At the state-level,we document that in four states there arestatistically significant housing wealth effects upon consumptionat all eight quarterly-periods-ahead, namely Alaska, Minnesota, Missisipi, Pennsylvania.These states are classified as the states which exhibit the most persistent housing wealth effects upon consumptiondue to the fact that we find the higher number of statistical significant causalities. Furthermore, among these states, we observe atPennsylvania and Minnesota the most persistent long-term housing wealth effects,which are well above the aggregate level averages atthe corresponding time horizons. A different state classification in terms of the intensity of housing wealth effects would be also possible based on themagnitude of the p-values.So, the test results ofTable 1 suggest that causality from housing wealth growth to consumption growth seems statistically important and also relatively higher in the following states (where the largest p-value and its corresponding quarterly prediction periodare in the parenthesis): Arizona (0.071; 7), Colarado (0.077; 6), Delaware (0.090; 5), Idaho (0.079; 2), Illionis (0.074; 2), Iowa (0.081; 1), Maine (0.091; 2), Maryland (0.081; 8), Massachusetts (0.087; 6), Missouri (0.084; 8), New Hampshire (0.099; 6), Ohio (0.081; 1), Pennsylvania (0.091;6), South Dakota (0.096; 4), and Virginia (0.080; 5). At the same time, financial wealth effectsupon consumption occurat most 5 quarters-ahead in Minnesota and Utah. We observe at Table 3, that the most profound financial wealth effect upon consumption is foundin the following states (where the largestsimulated p-value and its corresponding quarterly prediction period are in the parenthesis): Alabama (0.083; 8), District of Columbia (0.063; 1), Georgia (0.093; 2), Illinois (0.095; 7), Michigan (0.054; 1), Minnesota (0.085; 2), Nevada (0.094; 8), New Hampshire (0.066; 8), New Mexico (0.061; 7), Ohio (0.093; 1), Oklahoma (0.080; 8), Pennsylvania (0.075; 8), Utah (0.089; 6), Vermont (0.070; 8), Washington (0.081; 8), Wisconsin (0.074; 8).

Finally, multi-horizon non-causality test results indicatethat short, long, and simoultaneusly short/long horizon causality from housing (financial) wealth to consumption isfound in 9 (12), 11 (12), and 17 (19)states respectively, suggesting the presence of both short and long housing/financial wealth effects upon consumption in the majority of states (Table 1 and 3).

Overall, multi-horizon non-causality test of Dufour et al. (2006)test results suggest that (i) housing and financial wealth effects are equally importantin the short and long runat the state-level, (ii) at the aggregate level,financial wealthappears to have stronger short/long termimpact on consumption, but housing wealth induces more persistent short/long run effects, (iii) wealth effects occur across different time horizons fordifferent states, but our evidence indicates the presence of simoultaneously short and long horizon housing and financial wealth effects in the majority of the states, (iv) Minnesota and Pennsylvaniaare the two states where housing/ financial wealth growth have the strongest and most persistent impact on private consumption growth.

[INSERT TABLES 1 TO 3 HERE]

4.2.2.Multi-Horizon Causality Measure Test Resultsand Implications

Tables 4 to 6 report the results when we implement the multi-horizon causality measure of Dufour and Taamouti (2010) described in section 3.2 to quantify the intensity of wealth effects on private consumption growth at different prediction periods for 51 States of the US. Each table exhibits the causality measure described in equation (7) over the range one to eight quarters ahead. The bootstrap 95% confidence interval for each measure is calculated by using 5000 bootstrap samples. We report only the statistically different from zero causality measures based on the bootstrap confidence interval.

The results of Table 4 show that causality measures on housing wealth effects are statistically significant at different forecast periods in 30 states. Our results indicate that causality measures are statistically different from zero up totwo quarters-ahead (Florida, Kentucky, Michigan, Minnesota, North Carolina, Tennessee, Washington, Wisconsin), over the range from 5 quarters to 8 quarters ahead (Arizona, Delaware, Louisiana, Rhode Island, Texas), and over the range from 1 quarter-ahead to 8 quarters-ahead (Alabama, Arkansas, California, Colorado, Illinois, Kansas, Kentucky, Maryland, Massachusetts, Mississippi, Missouri, Montana, Nebraska, New Hampshire, New Jersey, Ohio, Pennsylvania, Virginia). The majority of the measure estimates are relatively large since they range from 0.010 to 0.14. These findings indicate the presence of strong housing wealth effects. The intensity of these linkages diminishes as h increases, especially after the fifth quarter.We document that in the US the causality measures running from housing wealth to consumption are relatively large and statistically different from zero at all horizons.

In Table 5 we see that the estimates of measures of Granger causality-in-mean from income growth to consumption are not statistically equal to zeroat short horizons (Alaska, California, Florida, Kentucky, New York, North Carolina, Texas, Virginia, West Virginia), at long horizons (Arizona, North Dakota), and at both short and long horizons (Delaware, Georgia, Hawaii, Kansas, Maryland, Massachusetts, Montana, Rhode Island, South Dakota). We document only significant short horizon causality from income to consumption in US. The income wealth effects appear to be weaker than housing wealth effects in terms of the causality measure size. Still, the impact of income growth to consumption is relatively large up to four quarters ahead approximately (the estimates at h = 4 range from 0.018 to 0.077).

In the case of causality measurement from stock holdings to consumption (Table 6), we document a very small number of statistically significant causality measures. In particular, changes in stock holdings growth induce a strong effect on the conditional mean of consumption in 9 states up to two quarters-ahead approximately. The magnitude of the stock effect on consumption is relatively large since the estimates of the measures vary from 0.030 to 0.128. Our results also indicate that stock holdings do not anticipate changes in consumption on aggregate in the US.

Overall, atthe aggregate level causality measurementfrom housing wealth growth to consumption is statistically important for all quarters with themeasure values ranging from 0.094 to 0.018. On the other hand, financial wealth has virtually no aggregate-level effect upon private consumption.At the state-level,causality measurement shows that strong housing wealth effectsupon consumption are presentat all 8 quarterly periods-ahead in Arkansas, Colorado, Kansas, Massachusetts, Nebraska, Ohio, and Virginia. We also documentthat housingwealth has a strong impact on private consumptionat six prediction periods in California and seven prediction periods in Mississippi. In paralell to the discussion of 4.1, we may classify these states as the ones which exhibit the most persistent housing wealth effects upon consumptionin terms of predictive intensity. Moreover, Massachusetts, Virginia and Nebraska are the states that share the largest and most persistent long-term causality measure estimates, which are generally above the aggregate level averages in relevant time horizons. Interestingly, comparing state-level non-causality test results and causality measurement results collectively for the relationship between housing wealthgrowth and consumption growth (Tables 1 and 4), we find that Mississippi is the state which displays the mostpersistent short and long horizon housing wealth effects upon consumption. As far as it concernsthe magnitude of the housing wealth effects upon consumption,the resultsofTable 4show thatthe causality measures for the direction from housing wealth growth to consumption growth seem statistically meaningful and also relatively higherin the following states (where the largestcausality measure value and its corresponding quarterly prediction period are in the parenthesis): California (0.085; 1), Colarado (0.095; 1), Illinois (0.104; 1), Kansas (0.095; 1), Massachusetts (0.101; 1), Mississippi (0.109; 1), Montana (0.013; 2), New Hampshire (0.115; 1), New Jersey (0.146; 1), Virginia (0.093; 1), and Wisconsin (0.140; 1).The results of both methods collectively suggest (Table 1 and Table 4) that housing wealth has a big impact on consumption in Colarado, Illinois, Massachusetts, New Hampshire, and Virginia. These states may be classified as the states which experience the most intensehousing wealth effects upon consumption.

At the state level,intense financial wealth effects upon consumption existup totwo quarters-ahead in eight states and up to three quarters-ahead only in Maryland (Table 6). The estimates of thecausality measures for the direction from stock holdings growth to consumption growthreveal that the most profound financial wealth effects upon consumption can be found in the following states (the largest causality measure value and its corresponding quarterly prediction period are in the parenthesis): Arizona (0.069; 1), Missouri (0.065; 1), Oregon (0.0128-0.117; 1-2) and Pennsylvania (0.085;1).Comparing the results of Table 2 and Table 6, we document that Pennsylvania is the state which enjoys the strongest financial wealth influence on consumption for different time horizons.

On the other hand, multi-horizon causality measurement highlightsthat strong short, long, and simoultaneusly short and long horizon causalities from housing wealth to consumption are present in 9, 6, and 16 states respectively. This finding suggeststhat the majority of states experienceintense housingwealth effects upon consumption at both short and long horizons (Table 4). However, we find evidence ofonly short horizon financial wealth effects upon consumption (Table 6).

[INSERT TABLES 4 TO 6 HERE]

To sum up, the results from the application of the multi-horizon causality measure of Dufour and Taamouti (2010) suggest that (i) at the aggregate level, although housing wealth induceseconomically significant effects on consumption for all time horizons, financial wealth has no economically significant effect on consumption, (ii)at the state level, housing appears to be a clearly dominant and persistent wealth effect componentat multiple time horizons, (iii) housing wealth effects upon consumption exist across different time horizons and different states,but financial wealth influences consumption only at short-time horizons. Moreover, (i)

Colarado, Illinois, Massachusetts, New Hampshire, Virginia experience the most intense housing wealth effects upon consumption while Mississippi presents the most persistent influences of housing wealth on consumption, (ii) no housing wealth effects are documented inHawaii, Utah and Wyoming, (iii) Pennsylvania is state which experiences the strongest financial wealth effectsat different time horizons.

From the methodological perspective, one interesting result is that causality measurement does not always confirm the findingsof causality testing. For instance, test results of Table 3 indicate the presence of highly statistically significant causalities from stock holdings to consumption at long horizons in several states. On the other hand, the estimates of the measures are statistically equal to zero at these prediction horizons for all states. Hence, the output of causality measurement shows that long horizon financial wealth effects are economically weak, which in turn implies that there is no gain in predictive power at these horizons. Similar contradictory results are also found in the cases of housing and income wealth effects upon consumption in some states at specific time horizons, but to a lesser degree. These findings highlight the importance of testing implementation in conjunction with measurement in order to distinguish among the statistically important and economically important causal linkages.

5. Conclusions

The housing and financial wealth effectson consumption have been widely analyzed for the US economy due tohousing and stock market-centered policies since mid-1990s. Stock and housing market boom-bust episodes during almost the entire 2000's have also highlighted the importance of a better understandingof the foundations of wealth effects. While the magnitude, and drivers of wealth effects have been broadly analyzed for the US economy atthe aggregate level, questions remain about the intertemporal co-behavioral patterns between housing/financial wealth and consumption growth at the state-level. This paper provides newevidence that sheds more light on the dynamics of housing and financial wealth effects in US states.

The major findings of our investigation can be summarized as follows. First, based on the multi-horizon non-causality test of Dufour et al. (2006), our empirical results suggest that(i) housing (financial) wealth growth Granger cause consumption growthin 37 (43) States implying that both effects are simoultaneously importantat the state-level, (ii) at the aggregate level, although financial wealth induces stronger short/long run effects upon consumption, changes in housing wealth trigger more persistent effects both in the short and long run, (iii) housing and financial wealth effects occur at both short and long time horizons in the majority of states, (iv) we find in Minnesota and Pennsylvania the strongest and persistent housing/financial wealth effects upon consumption.Second, the application of the multi-horizon causality measure of Dufour and Taamouti (2010) at the state-level indicates thatcausality measurement from housing (financial) wealth growth to consumption growth is statistically significant at different forecast periods in 31 (9) states. Dufour and Taamouti (2010) test results also suggest that (i) while financial wealth has no statistically significant effect, housing wealth has statistically significant effects upon consumption in all time horizons at the aggregate level, (ii) housing is a clearly dominant and persistent wealth effect component at the state level across different time horizons, (iii) while housing wealth effects occur at both short and long time horizons accross many states,financial wealth effects are found only at short-time horizons. Third, the states which exhibit the most intense housing wealth effectsareColarado, Illinois, Massachusetts, New Hampshire, and Virginia in terms of the magnitude of the coefficient value and Mississippi in terms of short/long horizon persistency.Again, no housing wealth effects are documented in Hawaii, Utah and Wyoming whilePennsylvania is the State where the strongest multi-horizon financial wealth effects occur.It is also important to note that we document significant wealth effects across different prediction horizons at the remaining States.

Our results lead to various implications. Housing/financial wealth effectsshow heterogeneity accross U.S. States depending on the scope of the data (state vs. aggregate) and employed methodology. Furthermore, while non-causality testing suggests that financial wealth is as important as housing wealth, causality measurement clearly indicates that housing wealth has more statistically significant, persistent, and widespread impacts than financial wealth on state/aggregate level.Our evidence of stronger housing wealth effectsat the state-level confirms the results of Case et al. (2005; 2013), which is the only available housing wealth effect state-based analysis for the US.Our evidence is in line with the findings of Benjamin et al. (2004), Slacalek (2006), Carroll et al. (2006), Sierminska and Takhtamanova (2007), Bostic et al. (2009), among others, in aggregate level. The significant role of the housing market as the state level wealth effect channel may be related to its relatively more uniform increase in valueacross regions compared to the quite unequal geographical distribution of stock market wealth across households in the US (see, Case et al., 2005). This evidence has important implicationsfor monetary policies aiming to develop a strategy combining asset prices, consumption, and price stability (see, Gertler et al., 1998).Moreover, our classification attempt suggests that federal and state level economic policies may define specific targets for the consumption, saving, and economic growth depending on the wealth effect strength of the relavant state. For example, while housing economy may not be a priority in Hawai, Utah and Wyoming, both housing/financial ownership may be specifically supported in Pennsylvania. Moreover, the evidence of the presence of housing wealth effects upon consumption at long horizonsis in line with the result of Apergis et al. (2018), suggesting that housing markets are positively sensitive to long-run state-level policy-making.

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Table 1: Causality from housing wealth growth to consumption growth at different time horizons

Time horizonh	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Alabama	0.193	0.696	0.453	0.268	0.091	0.203	0.574	0.509
Alaska	0.485	0.412	0.234	0.022**	0.009***	0.004***	0.010**	0.061*
Arizona	0.207	0.215	0.900	0.206	0.128	0.007***	0.071*	0.034**
Arkansas	0.375	0.722	0.884	0.665	0.582	0.798	0.035**	0.017**
California	0.003***	0.027**	0.583	0.001***	0.001***	0.006***	0.603	0.033**
Colorado	0.006***	0.398	0.693	0.102	0.056*	0.077*	0.414	0.393
Connecticut	0.566	0.959	0.970	0.296	0.432	0.339	0.190	0.025**
Delaware	0.361	0.488	0.681	0.133	0.090*	0.131	0.038**	0.007***
District Of Columbia	0.636	0.826	0.633	0.307	0.731	0.317	0.508	0.206
Florida	0.046**	0.329	0.515	0.334	0.500	0.585	0.241	0.179
Georgia	0.941	0.825	0.914	0.713	0.796	0.780	0.724	0.221
Hawaii	0.991	0.959	0.389	0.420	0.881	0.799	0.712	0.671
Idaho	0.144	0.079*	0.142	0.397	0.226	0.437	0.465	0.775
Illinois	0.024**	0.074*	0.392	0.085	0.284	0.700	0.602	0.519
Indiana	0.157	0.307	0.367	0.008***	0.044**	0.126	0.132	0.016**
Iowa	0.081*	0.276	0.304	0.150	0.556	0.756	0.938	0.001***
Kansas	0.067*	0.422	0.826	0.170	0.280	0.276	0.879	0.670
Kentucky	0.162	0.935	0.818	0.348	0.498	0.248	0.192	0.100
Louisiana	0.618	0.550	0.893	0.852	0.661	0.528	0.192	0.303
Maine	0.087*	0.091*	0.597	0.581	0.966	0.917	0.658	0.188
Maryland	0.214	0.834	0.871	0.491	0.442	0.306	0.418	0.081*
Massachusetts	0.027**	0.122	0.790	0.128	0.112	0.087*	0.145	0.016**
Michigan	0.184	0.848	0.970	0.355	0.069	0.229	0.339	0.003***
Minnesota	0.047**	0.565	0.709	0.117	0.035**	0.042**	0.023**	0.029**
Mississippi	0.065*	0.165	0.199	0.025**	0.021**	0.003***	0.017**	0.535
Missouri	0.011**	0.148	0.305	0.404	0.225	0.076*	0.204	0.084*
Montana	0.009***	0.058*	0.398	0.575	0.404	0.738	0.886	0.818
Nebraska	0.111	0.597	0.539	0.520	0.793	0.148	0.484	0.041**
Nevada	0.366	0.393	0.677	0.365	0.766	0.286	0.377	0.359
New Hampshire	0.015**	0.949	0.792	0.605	0.483	0.099*	0.508	0.059*
New Jersey	0.007***	0.169	0.275	0.009***	0.001***	0.957	0.811	0.263
New Mexico	0.438	0.847	0.694	0.268	0.177	0.335	0.258	0.166
New York	0.018**	0.005***	0.528	0.441	0.757	0.772	0.437	0.732
North Carolina	0.154	0.427	0.323	0.139	0.174	0.136	0.188	0.125
North Dakota	0.796	0.677	0.853	0.465	0.768	0.250	0.205	0.094*
Ohio	0.082*	0.660	0.861	0.233	0.107	0.194	0.374	0.029**
Oklahoma	0.023**	0.022**	0.668	0.416	0.151	0.100	0.060*	0.019**
Oregon	0.011**	0.065*	0.191	0.169	0.092*	0.190	0.219	0.328
Pennsylvania	0.113	0.501	0.695	0.053*	0.088*	0.091*	0.062*	0.050*
Rhode Island	0.154	0.329	0.016**	0.020**	0.006***	0.983	0.759	0.147
South Carolina	0.700	0.764	0.967	0.591	0.252	0.285	0.486	0.692
South Dakota	0.068*	0.037**	0.111	0.096*	0.218	0.275	0.493	0.635
Tennessee	0.043**	0.388	0.859	0.230	0.017**	0.055*	0.103	0.036**
Texas	0.344	0.540	0.984	0.788	0.603	0.035**	0.005***	0.009***
Utah	0.349	0.699	0.752	0.499	0.426	0.282	0.353	0.254
Vermont	0.115	0.164	0.004***	0.185	0.380	0.443	0.015**	0.146
Virginia	0.005***	0.013**	0.335	0.069*	0.080*	0.472	0.537	0.204
Washington	0.236	0.917	0.999	0.248	0.191	0.145	0.215	0.121
West Virginia	0.839	0.588	0.626	0.300	0.432	0.201	0.351	0.328
Wisconsin	0.002***	0.002***	0.892	0.274	0.132	0.186	0.229	0.129
Wyoming	0.858	0.664	0.283	0.219	0.288	0.370	0.602	0.530
United States	0.014**	0.032**	0.870	0.005***	0.005***	0.010**	0.206	0.006***

Note: the table reports the simulated p-values of Dufour et al. (2006) test procedure on non-causality from housing wealth growth to consumption growth for forecast horizons (h) 1 – 8 quarters ahead. The sample covers a period from 1975:Q2 to 2012:Q2, a total of 149 observations.

Table 2: Causality from income growth to consumption growth at different time horizons

Time horizon h	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Alabama	0.284	0.338	0.285	0.301	0.314	0.281	0.619	0.754
Alaska	0.052*	0.023**	0.189	0.849	0.739	0.296	0.198	0.309
Arizona	0.561	0.393	0.795	0.697	0.898	0.660	0.083*	0.042**
Arkansas	0.800	0.385	0.740	0.706	0.439	0.787	0.681	0.548
California	0.223	0.125	0.336	0.645	0.813	0.674	0.377	0.112
Colorado	0.189	0.225	0.971	0.476	0.504	0.141	0.569	0.158
Connecticut	0.783	0.593	0.500	0.727	0.608	0.566	0.575	0.029**
Delaware	0.022**	0.012**	0.039**	0.092*	0.686	0.441	0.266	0.190
District Of Columbia	0.914	0.979	0.997	0.354	0.068*	0.027**	0.008***	0.036**
Florida	0.461	0.003***	0.463	0.513	0.849	0.591	0.731	0.865
Georgia	0.185	0.200	0.295	0.298	0.361	0.219	0.432	0.416
Hawaii	0.218	0.063*	0.025**	0.294	0.827	0.882	0.574	0.557
Idaho	0.576	0.379	0.386	0.418	0.892	0.999	0.991	0.955
Illinois	0.468	0.398	0.398	0.358	0.117	0.329	0.043**	0.137
Indiana	0.760	0.906	0.709	0.365	0.249	0.136	0.233	0.234
Iowa	0.953	0.628	0.270	0.036**	0.018**	0.134	0.166	0.294
Kansas	0.041**	0.062*	0.420	0.289	0.302	0.344	0.178	0.179
Kentucky	0.279	0.654	0.481	0.204	0.718	0.778	0.780	0.086*
Louisiana	0.835	0.939	0.791	0.030**	0.129	0.074*	0.050*	0.406
Maine	0.068*	0.088*	0.176	0.296	0.515	0.389	0.309	0.326
Maryland	0.050*	0.034**	0.038**	0.028**	0.106	0.155	0.502	0.325
Massachusetts	0.598	0.407	0.530	0.645	0.803	0.995	0.538	0.146
Michigan	0.336	0.502	0.340	0.157	0.543	0.447	0.751	0.392
Minnesota	0.404	0.411	0.283	0.657	0.997	0.896	0.816	0.707
Mississippi	0.668	0.589	0.761	0.814	0.803	0.751	0.109	0.235
Missouri	0.655	0.570	0.683	0.451	0.350	0.364	0.241	0.371
Montana	0.322	0.388	0.311	0.252	0.212	0.293	0.535	0.766
Nebraska	0.912	0.956	0.969	0.959	0.967	0.999	0.448	0.632
Nevada	0.754	0.406	0.490	0.539	0.877	0.612	0.552	0.636
New Hampshire	0.420	0.257	0.256	0.336	0.846	0.500	0.476	0.841
New Jersey	0.361	0.410	0.457	0.346	0.676	0.257	0.155	0.323
New Mexico	0.840	0.546	0.623	0.179	0.199	0.277	0.155	0.574
New York	0.414	0.379	0.999	0.661	0.193	0.169	0.145	0.439
North Carolina	0.071*	0.275	0.443	0.457	0.680	0.497	0.636	0.695
North Dakota	0.197	0.177	0.900	0.938	1.000	0.420	0.075*	0.229
Ohio	0.485	0.456	0.605	0.832	0.559	0.882	0.355	0.035**
Oklahoma	0.199	0.032**	0.063*	0.072*	0.008***	0.629	0.025**	0.001***
Oregon	0.910	0.236	0.763	0.930	0.669	0.651	0.426	0.240
Pennsylvania	0.671	0.389	0.812	0.685	0.982	0.946	0.749	0.275
Rhode Island	0.603	0.644	0.754	0.810	0.869	0.943	0.915	0.543
South Carolina	0.291	0.533	0.463	0.583	0.998	0.995	0.757	0.450
South Dakota	0.221	0.098*	0.402	0.531	0.814	0.409	0.118	0.001***
Tennessee	0.921	0.962	0.965	0.869	0.816	0.813	0.740	0.481
Texas	0.253	0.085*	0.574	0.462	0.447	0.618	0.274	0.045**
Utah	0.626	0.313	0.540	0.186	0.334	0.702	0.326	0.528
Vermont	0.333	0.277	0.159	0.232	0.738	0.896	0.649	0.656
Virginia	0.131	0.062*	0.225	0.609	0.960	0.927	0.455	0.433
Washington	0.400	0.470	0.193	0.290	0.389	0.511	0.017**	0.044**
West Virginia	0.154	0.506	0.559	0.650	0.849	0.451	0.122	0.458
Wisconsin	0.806	0.642	0.619	0.452	0.390	0.556	0.711	0.539
Wyoming	0.976	0.937	0.975	0.939	0.786	0.379	0.351	0.409
United States	0.540	0.187	0.902	0.829	0.854	0.485	0.570	0.262

Note: See notes of Table 1.

Table 3: Causality from stock holdings growth to consumption growth at different time horizons

Time horizon h	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Alabama	0.172	0.158	0.905	0.916	0.842	0.032**	0.075*	0.083*
Alaska	0.555	0.463	0.833	0.769	0.836	0.268	0.030**	0.395
Arizona	0.037**	0.131	0.752	0.295	0.150	0.458	0.151	0.162
Arkansas	0.440	0.498	0.597	0.492	0.656	0.590	0.034**	0.017**
California	0.041**	0.024**	0.564	0.188	0.122	0.202	0.127	0.166
Colorado	0.019**	0.248	0.951	0.898	0.267	0.256	0.157	0.125
Connecticut	0.039**	0.288	0.918	0.836	0.425	0.571	0.445	0.400
Delaware	0.006***	0.024**	0.933	0.703	0.784	0.776	0.371	0.369
District Of Columbia	0.063*	0.337	0.887	0.422	0.110	0.388	0.471	0.422
Florida	0.022**	0.002***	0.915	0.998	0.030**	0.286	0.122	0.294
Georgia	0.030**	0.093*	0.625	0.758	0.998	0.317	0.045**	0.003***
Hawaii	0.021**	0.014**	0.755	0.511	0.277	0.376	0.176	0.229
Idaho	0.392	0.625	0.403	0.381	0.303	0.253	0.089*	0.117
Illinois	0.257	0.195	0.447	0.716	0.763	0.885	0.095*	0.002***
Indiana	0.039**	0.063*	0.715	0.452	0.501	0.130	0.139	0.066*
Iowa	0.213	0.279	0.964	0.871	0.311	0.314	0.202	0.184
Kansas	0.391	0.778	0.997	0.932	0.723	0.856	0.526	0.387
Kentucky	0.332	0.166	0.898	0.302	0.956	0.635	0.156	0.120
Louisiana	0.277	0.440	0.831	0.437	0.695	0.238	0.252	0.566
Maine	0.018**	0.032**	0.978	0.960	0.996	0.782	0.146	0.133
Maryland	0.108	0.250	0.717	0.788	0.478	0.317	0.101	0.281
Massachusetts	0.002***	0.103	0.692	0.124	0.128	0.582	0.559	0.492
Michigan	0.054*	0.261	0.816	0.754	0.372	0.633	0.219	0.191
Minnesota	0.029**	0.085*	0.756	0.725	0.081*	0.025**	0.009***	0.047**
Mississippi	0.506	0.473	0.751	0.902	0.997	0.338	0.001***	0.002***
Missouri	0.023**	0.237	0.468	0.499	0.199	0.091*	0.155	0.381
Montana	0.103	0.109	0.658	0.316	0.046**	0.402	0.481	0.137
Nebraska	0.185	0.617	0.720	0.731	0.569	0.197	0.226	0.227
Nevada	0.043**	0.071*	0.447	0.728	0.893	0.140	0.142	0.094*
New Hampshire	0.239	0.518	0.661	0.634	0.530	0.232	0.023**	0.066*
New Jersey	0.049**	0.255	0.679	0.046**	0.053*	0.173	0.206	0.121
New Mexico	0.065*	0.429	0.999	0.956	0.906	0.423	0.061*	0.042**
New York	0.003***	0.039**	0.812	0.346	0.097*	0.141	0.299	0.249
North Carolina	0.023**	0.037**	0.722	0.742	0.902	0.138	0.226	0.025**
North Dakota	0.200	0.290	0.780	0.700	0.463	0.300	0.134	0.127
Ohio	0.093*	0.336	0.741	0.515	0.317	0.686	0.340	0.250
Oklahoma	0.853	0.729	0.761	0.756	0.617	0.442	0.050*	0.080*
Oregon	0.004***	0.024**	0.887	0.831	1.000	0.278	0.037**	0.034**
Pennsylvania	0.002***	0.066*	0.942	0.434	0.094*	0.219	0.222	0.075*
Rhode Island	0.120	0.071*	0.935	0.226	0.216	0.322	0.066*	0.519
South Carolina	0.176	0.363	0.969	0.791	0.857	0.017**	0.009***	0.036**
South Dakota	0.273	0.339	0.238	0.179	0.149	0.278	0.292	0.172
Tennessee	0.160	0.065*	0.575	0.423	0.445	0.386	0.225	0.028**
Texas	0.133	0.458	0.965	0.945	0.903	0.478	0.011**	0.027**
Utah	0.020**	0.040**	0.856	0.790	0.826	0.089*	0.014**	0.072*
Vermont	0.546	0.340	0.474	0.471	0.517	0.461	0.066*	0.070*
Virginia	0.038**	0.111	0.503	0.326	0.410	0.394	0.214	0.272
Washington	0.015**	0.259	0.934	0.782	0.549	0.382	0.019**	0.081*
West Virginia	0.442	0.151	0.844	0.757	0.729	0.901	0.046**	0.038**
Wisconsin	0.043**	0.107	0.979	0.608	0.780	0.179	0.182	0.074*
Wyoming	0.426	0.373	0.138	0.837	0.652	0.420	0.361	0.001***
United States	0.019**	0.141	0.925	0.756	0.260	0.699	0.137	0.086*

Note: See notes of Table 1.

Table 4: Causality measurement from housing wealth growth to consumption growth at different time horizons

Time horizonh	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Alabama	0.061						0.010	0.010
Alaska								
Arizona					0.036	0.030	0.022	0.019
Arkansas	0.056	0.039	0.024	0.025	0.021	0.021	0.020	0.020
California	0.085	0.063			0.044	0.033	0.022	0.021
Colorado	0.095	0.034	0.028	0.027	0.035	0.026	0.020	0.018
Connecticut								
Delaware					0.030	0.021	0.020	0.017
District Of Columbia								
Florida	0.066							
Georgia								
Hawaii								
Idaho								
Illinois	0.104				0.065	0.036	0.035	0.036
Indiana								
Iowa								
Kansas	0.095	0.042	0.033	0.040	0.030	0.023	0.018	0.019
Kentucky	0.046			0.017	0.014		0.006	0.006
Louisiana						0.011	0.011	0.010
Maine								
Maryland	0.050	0.038	0.018					
Massachusetts	0.101	0.055	0.030	0.044	0.046	0.040	0.039	0.039
Michigan	0.039							
Minnesota	0.065							
Mississippi	0.109	0.073		0.019	0.020	0.014	0.013	0.014
Missouri	0.110				0.062			
Montana	0.110	0.113			0.030		0.019	0.019
Nebraska	0.088	0.048	0.046	0.045	0.035	0.033	0.032	0.031
Nevada								
New Hampshire	0.115				0.023	0.028	0.028	0.026
New Jersey	0.146				0.042			
New Mexico								
New York								
North Carolina	0.048	0.029						
North Dakota								
Ohio	0.072	0.036	0.024	0.026	0.031	0.020	0.016	0.012
Oklahoma								
Oregon								
Pennsylvania	0.076				0.051	0.041	0.039	0.038
Rhode Island					0.057	0.055	0.055	0.049
South Carolina								
South Dakota								
Tennessee	0.060	0.047						
Texas					0.029	0.025	0.023	0.023
Utah								
Vermont								
Virginia	0.093	0.079	0.060	0.071	0.065	0.055	0.043	0.041
Washington	0.034							
West Virginia								
Wisconsin	0.140	0.135						
Wyoming								
United States	0.094	0.059	0.027	0.031	0.033	0.025	0.018	0.018

Note: the table presents the causality measure from housing wealth growth to consumption growth for forecast horizons (h) 1 – 8 quarters ahead. We only report the statistical significant causality measures based on the 95% bootstrap confidence interval. The sample covers a period from 1975:Q2 to 2012:Q2, a total of 149 observations.

Table 5: Causality measurement from income growth to consumption growth at different time horizons

Time horizon h	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Alabama								
Alaska	0.059							
Arizona					0.014	0.013	0.011	0.010
Arkansas								
California		0.049						
Colorado								
Connecticut								
Delaware	0.087	0.082	0.079	0.074				
District Of Columbia								
Florida		0.054						
Georgia	0.053	0.051	0.042	0.046				0.018
Hawaii	0.052	0.051	0.039					
Idaho								
Illinois								
Indiana								
Iowa								
Kansas	0.070	0.075	0.046	0.022	0.019	0.014	0.012	0.012
Kentucky	0.038							
Louisiana								
Maine								
Maryland	0.049	0.048	0.042	0.038	0.034	0.032	0.027	0.023
Massachusetts		0.029	0.021	0.018				0.012
Michigan								
Minnesota								
Mississippi								
Missouri								
Montana	0.089	0.093	0.085	0.077	0.025	0.020	0.018	0.018
Nebraska								
Nevada								
New Hampshire								
New Jersey								
New Mexico								
New York	0.033	0.033						
North Carolina	0.064	0.060						
North Dakota								0.009
Ohio								
Oklahoma								
Oregon								
Pennsylvania								
Rhode Island			0.026	0.028		0.016	0.017	0.012
South Carolina								
South Dakota	0.038	0.046	0.041	0.035	0.030	0.027	0.025	0.022
Tennessee								
Texas	0.067	0.068						
Utah								
Vermont								
Virginia	0.049	0.052	0.053					
Washington								
West Virginia	0.041							
Wisconsin								
Wyoming								
United States		0.047						

Note: See notes of Table 4.

Table 6: Causality measurement from stock holdings growth to consumption growth at different time horizons

Time horizon h	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Alabama								
Alaska								
Arizona	0.069	0.058						
Arkansas								
California								
Colorado								
Connecticut								
Delaware								
District Of Columbia								
Florida								
Georgia								
Hawaii								
Idaho								
Illinois								
Indiana								
Iowa	0.044	0.035						
Kansas								
Kentucky								
Louisiana								
Maine	0.079	0.079						
Maryland	0.107	0.101	0.030					
Massachusetts								
Michigan								
Minnesota								
Mississippi	0.033	0.031						
Missouri	0.065	0.033						
Montana								
Nebraska								
Nevada								
New Hampshire								
New Jersey								
New Mexico								
New York								
North Carolina								
North Dakota								
Ohio	0.057	0.042						
Oklahoma								
Oregon	0.128	0.117						
Pennsylvania	0.085	0.059						
Rhode Island								
South Carolina								
South Dakota								
Tennessee								
Texas								
Utah								
Vermont								
Virginia								
Washington								
West Virginia								
Wisconsin								
Wyoming								
United States								

Note: See notes of Table 4.