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

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Abstract: We investigate for the presence of multi-horizon wealth effects across U.S. states over the period of 1975:Q2 to 2012:Q2 by utilizing multi-horizon non-causality testing and multi-horizon causality measurement. At the state/aggregate level, we document that housing wealth has more statistically significant and persistent impact on private consumption than financial wealth. We also find that state-level housing/financial wealth effects are present at long time horizons and exhibit heterogeneity across the U.S. From a policy perspective, we suggest that state-level policies may specifically utilize the housing market to support consumption and growth.

Keywords: consumption; housing wealth effect; financial wealth effect; multi-step causality

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1. Introduction

Evaluating the dynamics of the wealth effect on the U.S. economy has been growing in importance in the wake of the recent housing bubble. 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 in the U.S. (i.e., see, [1–6]). However, variations in financial wealth effect are also important for the countries that are characterized by a market-based financial system and a larger stock ownership such as in the case of the U.S. The wealth effect literature is already extensive. Most of the existing evidence on the wealth effect studies is based on a limited data set involving aggregate and micro (survey) data. This paper uses an expanded dataset with regional data to reinvestigate the classic research problem of wealth effect, or the link between wealth and consumption [7] in the U.S. In this respect, except for [8], no comprehensive systemic analysis has been conducted using data for the U.S. economy at the state-level. There are state-level wealth effect studies for the U.S. (i.e., [5,6,8,9]), but, 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 [10] and causality measurement [11]. 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.

This article contributes to the wealth effect literature in four aspects. First, we use a unique data set that allows us to document the presence of income, housing, and financial wealth effects across U.S. states. In addition to the aggregate-level evidence, our study provides state-level evidence to the role of housing and financial wealth effects in consumption by improving further on [5,8]. Second, our study is the first to classify U.S. states with respect to the relative importance of housing/financial wealth effects. This attempt may provide an interesting knowledge for federal and state-level policymakers in the U.S. Third, we apply a new methodological approach that enables us to compare the intensity of wealth effects at various time horizons in terms of predictability. This methodological improvement provides comparative evidence 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 addressed below.

The goal of this paper is to better understand the wealth effect-induced household consumption behaviors in the U.S. 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 occurs 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, and (v) whether the U.S. states can be classified with respect to which 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 the most for the household consumption in the 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 is heterogeneity in the wealth effect patterns across 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-permanent income [12–14] 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 [12], in which case the fraction is the annuity value of wealth, or as permanent income, following [14], in which case the fraction should be very close to zero [15]. Due to data constraints for pension and social security wealth, housing wealth studies have generally used financial and housing wealth data in their analyses [16].

Although the empirical literature presents some mixed evidence, common patterns of wealth effects are documented in different samples. First, in general, housing and financial wealth play a significant role in income, saving, consumption behaviors and in economic growth. Second, the business cycle of the economy is a determinative factor of the magnitude of the wealth effect. Namely, a rising (declining) stock/housing market may increase (decrease) wealth effect components to different degrees as observed before/after global financial crisis periods. There may also be parallel relations between real estate and business cycles for those countries/regions where real estate and the general economy have strong linkages. Ref. [17] 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 at least the U.S., UK, and Ireland. Ref. [18] indicate that increasing optimism in consumers is likely to increase consumption of housing and non-housing goods. Ref. [19] show that while the real house price generally leads real GDP per capita, both during expansions and recessions, significant feedback effect from the real GDP per capita onto the real house price also exists. These findings also occur during the recent financial crisis and Great Recession. 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., [8,20–23]). 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, and market-specific policies (i.e., protection of rights, transaction cost, information asymmetry etc.). Although it is generally difficult to make a generalization among countries from a 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., [24–27]).

The variations in household consumption sensitivity to wealth effects depends on various factors such as liquidity conditions [28], utilities derived from the property right and the role of bequest [29], distributions of wealth among income groups, expected permanency of changes, measurement biases of wealth [30,31], housing/stock market features of the analyzed country/province, the policies, and behaviors and demographics of asset owners. However, ref. [32] discusses that standard measures of wealth may not adequately reflect newly emerging economic concerns such as sustainability.

Differences of marginal propensity to consume in housing/stock markets are generally explained by the well-documented differences in nature and risk characteristics of housing/stock as the asset classes (see, [25,33]). For example, ref. [34] provide evidence that imperfect knowledge of households with respect to their financial wealth may result in them reacting instantaneously to changes in wealth. Ref. [35] discuss that the psychology of framing may dictate that certain assets are more appropriate to use for current expenditures, while others are earmarked for long-term savings. Ref. [8] 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 online. Ref. [36] 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, ref. [37] discuss that house price appreciation increases the net worth and consumption of all homeowners, while it only improves the welfare of older homeowners. Ref. [8] underline that the importance of housing market wealth and financial wealth in affecting consumption is an empirical matter. For example, in an earlier study, using aggregate data in explaining U.S. consumer expenditures over the period of 1960 to 1977, ref. [38] 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 change with mean values in the 0.030–0.055 range. Empirical work, such as [20,39], suggests at best a weak link between house price changes and nonhousing consumption. Refs. [40,41] find similar housing/stock wealth elasticities in their estimations. Ref. [29] discusses that house price fluctuations possibly trigger smaller consumption changes than do stock market fluctuations. 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 U.S. 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, ref. [1] argue that the level of marginal propensity to consume in real estate or financial wealth is a determinative factor in economic stabilization.

The recent empirical literature provides a large body of evidence on the larger and persistent source of housing wealth in general and for the U.S., in particular. For example, ref. [42] indicate that change in household net worth caused by a change in house prices is larger than the change from similar variation 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:Q1–2001:Q4, ref. [1] find that an additional dollar of real estate wealth increases consumption by 8 cents, as compared with only 2 cents for financial wealth. Ref. [2] 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 U.S. and the UK [43], consistent with several recent studies, find a housing wealth effect that is substantially larger than the stock wealth effect for the U.S. Ref. [3] find that overall wealth effect from housing is stronger than the effect from financial wealth for all countries involving the U.S. 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. Ref. [4] research findings indicate relatively large housing wealth effects for the U.S. Among homeowners, the housing wealth elasticities are estimated in the range of 0.06 over the 1989–2001 period. Ref. [43] suggest that it is not certain that the housing wealth effect is substantially larger than the financial wealth effect for the U.S., but monetary policies should follow housing markets separately from equity markets due to its significantly higher MPC from housing wealth. Ref. [9] find a strong association between consumption and housing wealth declines in the period after the real estate bubble burst in the U.S. Ref. [44] document that the housing wealth effect is more intense than the stock wealth effect for a panel of countries involving the U.S. 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 analyzed economies. By employing a multistep non-causality test [10] and causality measures [11,45] investigate 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.

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 [4]. It seems that studies are mostly focused on aggregate and micro-level data [46]. From a regional data perspective, by following [31] and using a state-level panel for the Australian economy, ref. [30] 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, ref. [47] investigate 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, ref. [48] find that urban housing price influences some nonessential expenditure items like education, medical, and transportation.

In parallel to studies for other countries, wealth effect studies based on state-level data (and region, city) are also scarce for the U.S. Using aggregate data, ref. [17] finds evidence of a significant consumption effect during the real estate price boom in the late 1980's for New England. Ref. [8] estimate stock market wealth, housing market wealth and consumption for each U.S. state, quarterly, for the period 1982–1999. They find at best weak evidence of a stock market wealth effect and strong housing wealth effect. Ref. [5] use similar data sources to [8] while they estimate regression models in levels, first differences and in error-correction form over the period of 1975 through 2012:Q2 for U.S. states. They document a statistically significant and rather large effect of housing wealth upon household consumption. Among others, they argue that a decline of 35% in housing wealth would lower consumer spending by 3.5% in the U.S. 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. Ref. [33] 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 U.S. 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. Ref. [49] investigate the presence of causal linkages between asset prices and output per capita across the 50 U.S. states and DC over the period 1975–2012:Q2 by implementing a bootstrap panel causality framework. Their findings indicate 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. Using geographically linked microdata, ref. [50] finds that a USD 1 increase in home values in the U.S. leads to a USD 0.047 increase in spending for homeowners, but a negligible response for renters. By analysing the 1978–2017 period for the city-level data of the U.S., time-varying estimates of [51] indicate that housing wealth effects were not particularly large in the 2000s. Ref. [6] provide evidence that the elasticities of consumption with respect to financial wealth and housing wealth vary considerably across U.S. states, with housing wealth effects being larger than financial wealth effects in 37 cases.

Overall, not surprisingly, housing and financial wealth effects may exhibit heterogeneity across regions involving U.S. states/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 [52,53] causality is defined in terms of incremental predictability one period-ahead. It is by now a commonplace observation that this concept does not take into account the possibility that the predictive ability of a variable for another may vary over different time periods into the future. Refs. [54,55], 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. Ref. [55] 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 framework defines 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 that 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. Ref. [56] argue that the matrix of the first partial derivatives of [55] 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. Refs. [56,57] 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 [10]. 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

Testing for multi-horizon non-causality (see [10]) involves estimating the conditional vector autoregressive model of order p (VAR(p)),

$$V_t = \mu + \sum_{k=1}^{p} \theta_k V_{t-k} + \mu_t,\ \ t = 1, 2, \ldots,\ T, \tag{1}$$

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

$$V_{t+h} =\ \mu^{(h)} + \sum_{k=1}^{p} \theta^{(h)} V_{t+1-k} + \sum_{\tau-1}^{h-1} \Psi_t u_{t+h-\tau},\ \ t = 0, 1,\ \ldots, T-h, \tag{2}$$

where Ψ_t is the matrix of impulse response coefficients. Estimators for the parameter coefficients of model (2), which is denoted by the authors as "(p,h)-autoregression", are presented in [10,55]. 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):

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

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

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 [10].

3.2. Measuring Granger Non-Causality at Time Horizon h

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. 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. Ref. [11] propose measures for Granger multi-horizon non-causality that quantify the strength of a causality relation between two random variables at a specific time horizon h. Their method is an adaptation of [58–60] framework for the assessment of one-period ahead conditional mean dependence between multivariate series, but generalized for multi-horizon causality measurement.

Ref. [11] quantify the intensity of causality from Y to X at horizon h by means of the mean-square based causality measure:

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

where $\sum[X_{t+h}|I_t]$ is the covariance matrix of the prediction error $u[X_{t+h}|I_t] = X_{t+h} - P[X_{t+h}|I_t]$, with $P[X_{t+h}|I_t]$ 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 $V_t = (v_{1t}, v_{2t},\ v_{qt})$, 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:

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

where $R = (0,1,0,\ldots,0)$ is a $1 \times m$ vector, $\hat{\Psi}_z = \hat{\theta}_1^{(z)}\ \hat{\theta}_1^{(z+1)} = \hat{\theta}_2^{(z)} + \hat{\theta}_1^{(z)}\hat{\theta}_1$, $\hat{\theta}_1^{(1)} = \hat{\theta}_1$, $\hat{\theta}_1^{(0)} = I_m$ for $z \geq 1$, $\hat{\theta}_k = [\hat{\theta}_{1k}, \hat{\theta}_{2k}, \ldots, \hat{\theta}_{kk}]$ 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 $V_t^* = (v_{2t}, v_{qt})$. 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:

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

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

Then, the expression in (4) is estimated as

$$\hat{C}_l(v_{1t} \to v_{2th}|I) = \ ln\left[\frac{\det\{\ \hat{\Sigma}^*_h\}}{\det\{\ \hat{\Sigma}_h\}}\right].. \tag{7}$$

The causality measure at horizon h indicates how strong the causal relationship is 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 equivalent to a zero-causality measure.

The causality measure estimator in (7) is shown to be consistent and asymptotically normal by [11]. 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 [11] is used to 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 [5,8]. This is virtually the only data set that has both the financial wealth and housing wealth disaggregated to the state-level (including the District of Columbia (DC)); the imputation covers a significant period of time, from 1975:Q2 to 2012:Q2. We aggregate all these variables across the 50 states and for DC 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 [5,8] 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 to test whether the variables are non-stationary at both the aggregate and the state level. Our findings indicate that all variables are nonstationary (the results are available upon request from the authors). 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.

4.2. Test Results

4.2.1. Multi-Horizon Non-Causality Measure Test Results and Implications

Tables 1–3 report the results when we implement the multi-horizon non-causality test of [10] described in Section 3.1 to investigate for multi-horizon wealth effects on private consumption growth for 50 U.S. States and DC. Each table exhibits the simulated p-value of the Wald test statistic over the range one to eight quarters ahead. Following [10], we used 1000 replications for each simulation to calculate the p-value.

We observe in Table 1 that in 37 states housing wealth growth Granger causes on consumption growth at multiple forecast horizons at levels of statistical significance 1%, 5%, and 10%. In some states, housing wealth effect occurs one or two quarters ahead (Florida, Idaho, Illinois, Kansas, Maine, Montana, New York, and Wisconsin). In some other states, we document the presence of long horizon causalities exclusively (Alaska, Arizona, Arkansas, Connecticut, Delaware, Indiana, Maryland, Michigan, Nebraska, North Dakota, Rhode Island, South Dakota, and 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, and Virginia). On the aggregate level in the U.S., we find highly significant housing wealth effects upon consumption in one, two, four, five, six, and eight quarters ahead.

Table 2 demonstrates the presence of statistical significance of 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, and Virginia), at long horizons (Arizona, Connecticut, District of Columbia, Illinois, Iowa, Kentucky, Louisiana, North Dakota, Ohio, and Washington), and at both short and long horizons (Delaware, Hawaii, Maryland, Oklahoma, South Dakota, and Texas). On the aggregate level in the U.S., we find that income does not cause consumption over any time horizon.

We see in Table 3 that the 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 effect according to non-causality measure. Causal effects from stock holdings to consumption occur up to two quarters ahead (Arizona, California, Colorado, Connecticut, Delaware, District of Columbia, Hawaii, Maine, Massachusetts, Michigan, Ohio, and Virginia), several distant quarterly periods-ahead (Alabama, Arkansas, Idaho, Illinois, Mississippi, Montana, New Hampshire, Oklahoma, South Carolina, Texas, Vermont, West Virginia, and Wyoming), and over the range between one and eight quarters ahead (Florida, Georgia, Indiana, Minnesota, Missouri, Nevada, New Jersey, New Mexico, New York, North Carolina, Oregon, Pennsylvania, Rhode Island, Tennessee, Utah, Washington, and Wisconsin). On the aggregate level, causality is statistically significant in one quarter-ahead at level 5% and eight quarters ahead at level 10%.

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

Time Horizon h	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 [10] 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. ***, ** and * refers to a 1%, 5% and 10% significance, respectively.

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: The table reports the simulated *p*-values of [10] 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. ***, ** and * refers to a 1%, 5% and 10% significance, respectively.

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: The table reports the simulated p-values of [10] 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. ***, ** and * refers to a 1%, 5% and 10% significance, respectively.

The evidence of aggregate/state-level non-causality test results of housing/financial wealth effects are comparatively summarized in 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 at (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 Alaska, Minnesota, Mississippi, and Pennsylvania there are statistically significant housing wealth effects on consumption in all eight quarterly-periods-ahead. These states are classified as the states that exhibit the most persistent housing wealth effects upon consumption. Furthermore, among these states, we observe that the most persistent long-term housing wealth effect takes place in Pennsylvania, and Minnesota, which are well above the aggregate level averages at the corresponding time horizons. A different state classification in terms of the intensity of housing wealth effects would be also possible based on the magnitude of the p-values. So, the test results of Table 1 suggest that higher housing wealth effect on consumption occurs in the following states (where the largest p-value and its corresponding quarterly prediction period are in the parenthesis): Arizona (0.071; 7), Colorado (0.077; 6), Delaware (0.090; 5), Idaho (0.079; 2), Illinois (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 effects upon consumption occur at most 5 quarters ahead in Minnesota and Utah. We observe in Table 3 that the most profound financial wealth effect upon consumption is found in the following states (where the largest simulated 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 indicate that at short, long, and simultaneous short-/long-horizon causality from housing (financial) wealth to consumption are found in 9 (12), 11 (12), and 17 (19) states, respectively, suggesting the presence of short-/long-horizon housing/financial wealth effects upon consumption in the majority of states (Tables 1 and 3).

Overall, the multi-horizon non-causality test results of Dufour et al. (2006) [10] suggest that (i) housing/financial wealth effects are equally important in the short-/long-run at the state level; (ii) at the aggregate level, financial wealth appears to have stronger short-/long-term impact on consumption, but housing wealth induces more persistent short-/long-run effects; (iii) wealth effects occur across different time horizons for different states, but our evidence indicates the presence of simultaneous short-/long-horizon housing/financial wealth effects in the majority of the states; (iv) Minnesota and Pennsylvania are the two states where housing/financial wealth growth have the strongest and the most persistent impact on private consumption growth.

4.2.2. Multi-Horizon Causality Measure Test Results and Implications

Tables 4–6 report the results when we implement the multi-horizon causality measure of [11] described in Section 3.2 to quantify the intensity of wealth effects on private consumption growth at different prediction periods for 50 U.S. states and DC. 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.

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

Time Horizon h	**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.

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 to two quarters ahead (Florida, Kentucky, Michigan, Minnesota, North Carolina, Tennessee, Washington, Wisconsin), over the range from five quarters to eight quarters ahead (Arizona, Delaware, Louisiana, Rhode Island, and Texas), and over the range from one to eight quarters ahead (Alabama, Arkansas, California, Colorado, Illinois, Kansas, Kentucky, Maryland, Massachusetts, Mississippi, Missouri, Montana, Nebraska, New Hampshire, New Jersey, Ohio, Pennsylvania, and 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. Therefore, we document that in the U.S. 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 zero at short horizons (Alaska, California, Florida, Kentucky, New York, North Carolina, Texas, Virginia, and West Virginia), at long horizons (Arizona and North Dakota), and at both short and long horizons (Delaware, Georgia, Hawaii, Kansas, Maryland, Massachusetts, Montana, Rhode Island, and South Dakota). We document only significant short horizon causality from income to consumption. 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 growth 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 nine 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 an aggregate level.

Overall, at the aggregate level causality measurement from housing wealth growth to consumption is statistically important for all quarters with the measure 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 effects on consumption are present at all 8 quarterly periods-ahead in Arkansas, Colorado, Kansas, Massachusetts, Nebraska, Ohio, and Virginia. We also document that housing wealth is a strong impact on private consumption at six prediction periods in California and seven prediction periods in Mississippi. We may classify these states as the ones which exhibit the most persistent housing wealth effects on consumption in terms of predictive intensity. Moreover, Massachusetts, Virginia, and Nebraska have the largest and the most persistent long-term causality measure estimates that are generally above the aggregate level averages in relevant time horizons. Interestingly, comparing state-level non-causality test results and causality measurement results (Tables 1 and 4), we find that Mississippi has the most persistent short-/long-horizon housing wealth effects upon consumption. Moreover, Table 4 shows that the causality measures for the direction from housing wealth growth to consumption growth seem statistically meaningful and also relatively higher in the following states (where the largest causality measure value and its corresponding quarterly prediction period are in parenthesis): California (0.085; 1), Colorado (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 (Tables 1 and 4) that housing wealth has a big impact on consumption in Colorado, Illinois, Massachusetts, New Hampshire, and Virginia. These states may be classified as the states which experience the most intense housing wealth effects upon consumption.

At the state level, intense financial wealth effects upon consumption exist up to two quarters ahead in eight states and up to three quarters ahead only in Maryland (Table 6). The estimates of the causality measures for the direction from stock holdings growth to consumption growth reveal 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 Tables 2 and 6, we document that Pennsylvania is the state that enjoys the strongest financial wealth influence on consumption for different time horizons.

On the other hand, multi-horizon causality measurement results highlight that short, long, and simultaneously short-/long-horizon causalities from housing wealth to consumption are present in 9, 6, and 16 states, respectively. This finding suggests that the majority of states experience intense housing wealth effects upon consumption at both short and long time horizons (Table 4). However, we find evidence of only short horizon for financial wealth effect (Table 6).

To sum up, the results from the application of the multi-horizon causality measure of [11] suggest that (i) at the aggregate level, although housing wealth induces economically 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 component at multiple time horizons, and (iii) housing wealth effect upon consumption exists across different time horizons and in different states, but financial wealth influences consumption only at short-time horizons. Moreover, (i) Colorado, Illinois, Massachusetts, New Hampshire, and Virginia experience the most intense housing wealth effects upon consumption while Mississippi presents the most persistent influences of housing wealth effect, (ii) no housing wealth effects are documented in Hawaii, Utah and Wyoming, and (iii) Pennsylvania has the strongest financial wealth effects at different time horizons. (We also conducted the analyses with 99% confidence intervals and our main results, which are available upon request from the authors, do not change).

From the methodological perspective, one interesting result is that causality measurement does not always confirm the findings of causality testing. For instance, test results of Table 3 indicate the presence of statistically highly 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 the measurement to distinguish among the statistically important and economically important causal linkages.

5. Conclusions

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

The major findings of our investigation can be summarized as follows. First, based on the multi-horizon non-causality test of [10], our empirical results suggest that (i) housing (financial) wealth growth Granger cause consumption growth in 37 (43) States implying that both effects are simultaneously important at 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, and (iv) we find in Minnesota and Pennsylvania the strongest and most persistent housing/financial wealth effects upon consumption. Second, the application of the multi-horizon causality measure of [11] at the state level indicates that the causality measure from housing (financial) wealth growth to consumption growth is statistically significant at different forecast periods in 31 (9) states. Ref. [11] test results also suggest that (i) while financial wealth has no statistically significant effect, housing wealth has statistically significant effects upon consumption at all time horizons at the aggregate level; (ii) housing is the dominant and the most persistent wealth effect component at the state level across different time horizons; and (iii) while housing wealth effects occur at both short and long time horizons across many states, financial wealth effects are found only at short-time horizons. Third, we document the most intense housing wealth effects occur in Colorado, Illinois, Massachusetts, New Hampshire, and Virginia in terms of the magnitude of the causality measure estimate. Again, no housing wealth effects are documented in Hawaii, Utah and Wyoming, and Pennsylvania has the strongest multi-horizon financial wealth effect. It is also important to note that we document significant wealth effects across different prediction horizons in the remaining states.

Our results lead to various implications. Housing/financial wealth effects show heterogeneity across 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 on consumption growth than financial wealth at both the state and the aggregate level. Our evidence of stronger state-level housing wealth effect confirms the results of [5,6,8]. Our evidence is in line with the findings of [1–4,43], among others, at the aggregate level. The dominance of the housing market in generating wealth effects upon consumption at the state level may be attributed to the relatively more uniform increase in housing value across regions compared to the quite unequal geographical distribution of stock market wealth across households in the U.S. (see, [8]). This evidence has important implications for monetary policies aiming to develop a strategy combining asset prices, consumption, and price stability (see [61]). Moreover, our findings suggest that federal/state level economic policies may define specific targets for consumption, saving, and economic growth depending on the magnitude of the wealth effect of the relevant state. For example, while housing economy may not be a priority in Hawaii, Utah, and Wyoming, both housing/financial ownership may be specifically supported in Pennsylvania. Moreover, the evidence on the presence of housing wealth effects upon consumption at long horizons is in line with the result of [45], suggesting that housing markets are positively sensitive to long-run state-level policymaking.

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