Do *cay* and *cay*^{MS} predict stock and housing returns? Evidence from a nonparametric causality test[*]

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ABSTRACT

We use a nonparametric causality-in-quantiles test to compare the predictive ability of the consumption-wealth ratio (*cay*) and the Markov Switching version (*cay*^{MS}) for excess and real stock and housing returns and their volatility. Our results reveal strong evidence of nonlinearity and regime changes in the relationship between asset returns and *cay* or *cay*^{MS}, which corroborates the relevance of this econometric framework. Moreover, both *cay* or *cay*^{MS} are found to predict only excess stock returns over its entire conditional distribution, with the latter being a strong predictor only at certain quantiles. As for the housing market, these two consumption-wealth ratios only predict the volatility of real housing returns, with *cay*^{MS} outperforming *cay* over the majority of the conditional distribution.

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1. INTRODUCTION

The seminal contribution of Lettau and Ludvigson (2001) opened an important line of investigation that has been looking at the consumption-wealth ratio (*cay*) and the extent to which it captures the dynamics of the equity risk premium and the investors' expectations about future asset returns. Ever since, a large number of studies have confirmed this finding for not only equity markets, but also bond markets in developed and emerging countries (Sousa, 2010, 2015; Afonso and Sousa, 2011, Rapach and Zhou, 2013; Rocha Armada et al., 2015; Caporale and Sousa, 2016).[1]

As for housing returns, the literature primarily focuses on determining the macroeconomic drivers, such as business cycle fluctuations, income growth, industrial production or employment rate (Leung, 2004; Hwang and Quigley, 2006; Kallberg et al., 2014), and the wealth effects that it generates (Ludvigson and Steindel, 1999; Lettau and Ludvigson, 2004; Case et al., 2005, 2011).[2] Despite this, there is a lack of empirical work dealing with the specific question of predictability of housing risk premium. This is somewhat surprising in the light of: (i) the strong the linkages between the housing sector, the financial system and real economic activity, as exposed by the financial turmoil of 2007-2009, (ii) the transmission of asset market volatility during periods of financial stress (Blenman, 2004); and (iii) the fact that housing is the most important asset in households' portfolios, providing both utility and collateral services (Banks *et al.* 2004). In this context, some recent works try to pave the way for further analysis on the issue of predicting housing returns. For instance, Caporale *et al.* (forthcoming) shows that the predictability of housing risk premium depends on whether investors perceive financial and housing assets as being substitutes or complements. While, Caporale and Sousa (2016) also validate empirically the predictive power of *cay* for both equity and housing risk premia in a set of emerging countries.

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[1] Besides time series-based predictive regressions, panel frameworks have also been used in Caporale and Sousa (2016) and Caporale et al. (forthcoming), who analyse the panel correlation between stock returns and a series of country characteristics, such as: (i) the risk-free rate; (ii) the income level; (iii) the real GDP growth rate; (iv) the leverage ratio; (v) the country's size; (vi) the inflation rate; and (vii) the level of financial development. Similarly, Rangvid et al. (2014), Jordan et al. (2014) and Rocha Armada et al. (2015) estimate pooled regressions where the dependent variable is the adjusted R-square of the individual forecasting regressions and the explanatory variables are the country characteristics described above. This empirical exercise provides further evidence on the differences in asset return predictability that were previously uncovered in the forecasting regressions estimated at the country level.

[2] Other studies in the empirical finance literature include features of the housing market dynamics into asset pricing models of equity risk premium (Kallberg et al., 2002; Lustig and van Nieuwerburgh, 2005; Yogo, 2006; Piazzesi et al., 2007; Leung et al., 2006; Leung, 2007; Sousa, 2010; Pakos, 2011; Quijano, 2012; Ren et al., 2014).

More recently, Bianchi *et al.* (2015) provide evidence of infrequent shifts, or breaks, in the mean of *cay*. One may interpret this as a troubling feature of stock returns (for example, the presence of asset price bubbles) or as reflecting irregular changes in the moments of the distribution. As a result, the authors introduce a Markov-switching version of the consumption-wealth ratio i.e., cay^{MS}, and show that it has superior forecasting power for quarterly excess stock market returns compared to the conventional *cay*.

It should be also noted that, as is standard practice in the literature of asset returns predictability (Rapach and Zhou, 2013), the existing studies by Lettau and Ludvigson (2001), Bianchi *et al.,* (2015), Caporale and Sousa (2016) and Caporale *et al.* (forthcoming) rely on linear predictive regression frameworks.

Against this backdrop, the objective of our paper is to compare the predictive ability of *cay* and cay^{MS} not only for excess and real stock and housing returns of the US, but also their volatility. We accomplish this goal by using a nonparametric causality-in-quantiles test that has been recently developed by Balcilar *et al.* (2015).

This test studies higher order causality over the entire conditional distribution and is inherently based on a nonlinear dependence structure between the variables. It essentially combines the causality-in-quantile test of Jeong *et al*. (2012) and the higher-moment k^{th}-order nonparametric causality of Nishiyama *et al*. (2011).

Its main novelties are as follows. First, it is robust to mis-specification errors, as it detects the underlying dependence structure between the examined dependent variables (i.e. excess and real stock and housing returns) vis-à-vis the regressors (i.e. *cay* and cay^{MS}). This could prove to be particularly important, as it is well-known that financial markets data tend to display nonlinear dynamics. Second, it tests for causality that may exist at the tails of the joint distribution of the variables. Therefore, it assesses causality not only in the mean asset return (i.e. the first moment), but also in the volatility of the asset return (i.e. higher moments). Consequently, we are able to investigate causality-in-variance (thereby, volatility spillovers), as sometimes one does not uncover causality in the conditional mean, but higher order interdependencies emerge.

Our analysis relies on quarterly data for the US over the period of 1952:Q1-2014:Q3 for stock returns, and 1953:Q2-2014:Q3 for housing returns. We find evidence of nonlinearity and regime changes between asset returns and *cay* or cay^{MS}, which supports the use of the nonparametric causality-in-quantiles test. Moreover, while the linear Granger causality tests provide overwhelming evidence of the predictability for both excess and real stock returns, with cay^{MS} outperforming *cay*, the causality-in-quantiles approach shows that

these two predictors are only relevant for excess stock returns. Furthermore, while the entire conditional distribution of excess stock returns can be forecasted by both *cay* and cay^{MS}, the latter is only a strong predictor at certain quantiles. In what concerns the predictability for excess housing returns and their variance, as well as real housing returns, neither *cay* nor cay^{MS} appear to display a large predictive ability. However, *cay* outperforms cay^{MS} in forecasting the variance of real housing returns over the majority of the quantiles of the conditional distribution.

To the best of our knowledge, this is the first paper that uses a nonparametric causality-in-quantiles framework to investigate the forecasting power of *cay* and cay^{MS} for excess and real stock and housing returns, as well as their volatility. Yet, our study is related to the works of Ludvigson and Ng (2007) and Bekiros and Gupta (2015). While the former analyses finds in favour of predictive ability for *cay,* for both excess returns and their volatility using a linear predictive regression framework, the latter investigates the predictability of real stock returns and its volatility emanating from *cay* and cay^{MS} using the kth-order nonparametric causality test of Nishiyama *et al*. (2011). Note, the causality-in-quantiles test that we employ in this paper is more general than the Nishiyama *et al*. (2011) test used by Bekiros and Gupta (2015), since our approach allows us to study the entire conditional distribution of returns and volatility. In addition, unlike Ludvigson and Ng (2007) and Bekiros and Gupta (2015), we also analyse housing returns and volatility over and above stock returns and volatility. Note that, unlike the conditional mean-based approach of Bekiros and Gupta (2015), we are able to study the various phases of the asset markets, since we can analyze the existence or non-existence of predictability over the entire conditional distribution of asset returns and volatility. Note that, lower quantiles refer to the bear market, with the median associated with normal mode, and higher quantiles capturing bullish regimes for asset returns. Similarly, various quantiles of the conditional distribution of the volatility captures the current state of the riskiness in the market, i.e., whether it is low (lower quantiles), normal (median) or high (upper quantiles). Thus, our approach can be considered time-varying, with predictability captured at various phases of the evolution of housing and the stock market.

The rest of the paper is organized as follows: Section 2 describes the econometric framework of quantile and higher-moment nonparametric causality. Section 3 presents the data and discusses the empirical results. Finally, Section 4 concludes.

2. NONPARAMETRIC QUANTILE CAUSALITY TESTING

In this section, we present a novel methodology for the detection on nonlinear causality via a hybrid approach developed by Balcilar *et al.* (2016) and based on the frameworks of Nishiyama *et al.* (2011) and Jeong *et al.* (2012). This approach is robust to extreme values in the data and captures general nonlinear dynamic dependencies.

We start by denoting asset returns (i.e. excess or real stock and housing returns) by y_t and the predictor variable (in our case, *cay* or *cay^{MS}*) as x_t.

Let $Y_{t-1} \equiv (y_{t-1},...,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},...,x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t | Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t | Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) | Z_{t-1}\} = \theta$ with probability one. Consequently, the (non)causality in the θ-th quantile hypotheses to be tested are:

$$H_0 : \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})| Z_{t-1}\} = \theta\} = 1, \tag{1}$$

$$H_1 : \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})| Z_{t-1}\} = \theta\} < 1. \tag{2}$$

Jeong *et al.* (2012) employ the distance measure $J = \{\varepsilon_t E(\varepsilon_t | Z_{t-1}) f_z(Z_{t-1})\}$, where ε_t is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null hypothesis in (1), which can only be true if and only if $E[1\{y_t \leq Q_\theta(Y_{t-1}) | Z_{t-1}\}] = \theta$ or, equivalently, $1\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong *et al.* (2012) show that the feasible kernel-based sample analogue of J has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s \neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s. \tag{3}$$

where $K(\cdot)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated as follows:

$$\hat{\varepsilon}_t = 1\{y_t \leq Q_\theta(Y_{t-1})\} - \theta. \tag{4}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θth conditional quantile of y_t given Y_{t-1}, and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}_{y_t|Y_{t-1}}^{-1}(\theta | Y_{t-1}), \tag{5}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left((Y_{t-1}-Y_{s-1})/h\right)1(y_s \le y_t)}{\sum_{s=p+1,s\neq t}^{T} L\left((Y_{t-1}-Y_{s-1})/h\right)}, \qquad (6)$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

In an extension of Jeong *et al.* (2012)'s framework, we develop a test for the *second* moment. In particular, we want to test the volatility causality between *cay* (or *cay^{MS}*) and asset returns. Adopting the approach in Nishiyama *et al.* (2011), higher order quantile causality can be specified as:

$$H_0: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})\mid Z_{t-1}\} = \theta\} = 1 \qquad \text{for } k=1,2,...,K \qquad (7)$$

$$H_1: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})\mid Z_{t-1}\} = \theta\} < 1 \qquad \text{for } k=1,2,...,K \qquad (8)$$

Integrating the entire framework, we define that x_t *Granger causes* y_t *in quantile* θ *up to the kth moment* using Eq. (7) to construct the test statistic of Eq. (6) for each k. The causality-in-variance test can be calculated by replacing y_t in Eqs. (3) and (4) with y_t^2. However, it can be shown that it is not easy to combine the different statistics for each $k=1,2,...,K$ into one statistic for the joint null in Eq. (11), because the statistics are mutually correlated (Nishiyama *et al.*, 2011).To efficiently address this issue, we include a sequential-testing method as described Nishiyama *et al.* (2011). First, we test for the nonparametric Granger causality in the *first* moment (*i.e.* $k=1$). Nevertheless, failure to reject the null for $k=1$ does not automatically leads to no-causality in the *second* moment. Thus, we can still construct the tests for $k=2$.

The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$ in Eq. (6) and (9) respectively. In our study, the lag order of one is determined using the Schwarz Information Criterion (SIC) under a VAR comprising of excess or real returns on stock and housing prices and *cay* or *cay^{MS}* respectively. The bandwidth value is selected using the least squares cross-validation method. Lastly, for $K(\cdot)$ and $L(\cdot)$ we employ Gaussian-type kernels.

3.   DATA ANALYSIS AND EMPIRICAL RESULTS

3.1.   DATA

Our quarterly dataset comprises excess and real stock and housing returns, *cay* and *cay^MS*. The data on *cay* and *cay^MS* span over the period 1952:Q1-2014:Q3 and are obtained from Sydney C. Ludvigson's website: http://www.econ.nyu.edu/user/ludvigsons/. As we want to compare the predictive ability of both measures, we standardize them by dividing the actual series by the corresponding standard deviations. Note that the start and end dates are driven by data availability of *cay* and *cay^MS* at the time of writing this paper.

Excess stock market returns are computed as the excess returns of a market index (*exsr*) over the risk-free asset return, which is common in the relevant literature. Specifically we calculate the continuously compounded log return of the Center for Research in Security Prices (CRSP) index (including dividends) minus the 3-month Treasury bill rate. We also compute the volatility of excess stock market returns (*exsv*) using the squared values of *exsr*.

Real stock returns (*rsr*) are computed as the difference between the nominal stock returns and consumer price index (CPI – All Urban Consumers, with base year 1982-1984) inflation. The volatility of real stock returns (*rsv*) is then computed as the squared values of *rsr*. Data on the value-adjusted CSRP index, the risk free rate and CPI inflation are obtained from Amit Goyal's website: http://www.hec.unil.ch/agoyal/. Note that, as pointed out by Lettau and Ludvigson (2001), the CRSP Index (which includes the NYSE, AMEX, and NASDAQ) is believed to provide a better proxy for nonhuman components of total asset wealth because it is a much broader measure than S&P index. We decided to use Amit Goyal's website, since the CRSP returns data is freely available for download from there (and does not require subscription), and in addition, data from this website have been widely used in the stock market forecasting literature due to its reliability (see Raoach and Zhou (2013) for a detailed discussion in this regard).

Nominal and real house prices (obtained by deflating the nominal house price with the Consumer Price Index (CPI)) come from Shiller (2015), which is available at Robert J. Shiller's website: http://www.econ.yale.edu/~shiller/data.htm. Data are available at the monthly frequency since January 1953, which we convert into quarterly frequency by taking three-month averages.[3] We calculate the difference between continuously compounded log nominal housing returns and the risk-free rate to derive excess housing returns (*exhr*) since

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[3] To the best of our knowledge, this is the longest available (monthly) house price data for the US economy. Other house price data at monthly or quarterly frequencies can be obtained from Freddie Mac and the Federal Housing Finance Agency (FHFA) since 1975, and from the Lincoln Institute of Land Policy since 1960.

1953:Q2. The volatility of excess housing returns (*exhv*) is measured as the squared values of *exhr*. Real housing returns (*rhr*) and their volatility (*rhv*) are computed in the same way as their stock market counterparts. Note that, we decided to look at both excess returns and real returns of the stock and housing markets, since both these variables have been studies in their respective predictive literature discussed above. Adjusting the nominal return to compensate for inflation, allows an investor to determine how much of the nominal return is actually real return, with the real return capturing the purchasing power of an asset over time. While, excess returns are investment returns from an asset that exceed the riskless rate on a security generally perceived to be risk-free, i.e., it is a measure of value added by an asset.

3.2. EMPIRICAL RESULTS

In Table 1, we start by presenting the summary statistics of excess and real stock and housing returns, *cay* and cay^{MS}. As can be seen, all variables display excess kurtosis and, barring *exhr* and cay^{MS}, are skewed to the left. Normality is strongly rejected for all the returns, but we cannot reject normality for cay^{MS} and rejected only at the 10% level for *cay*. This non-normality of asset returns provides a preliminary motivation to look into causality based on the entire conditional distribution, rather than just on the conditional mean. Not surprisingly, stock market returns are more volatile than housing market returns.

Table 1. Summary statistics.

	exsr	*rsr*	*exhr*	*rhr*	*cay*	cay^{MS}
Mean	0.0181	0.0206	-0.0015	0.0011	1.59E-11	-0.0021
Median	0.0277	0.0282	-0.0021	0.0013	0.000125	-0.0025
Maximum	0.2145	0.2109	0.0531	0.0478	0.043397	0.0291
Minimum	-0.2723	-0.2848	-0.0538	-0.0482	-0.047730	-0.0401
Standard deviation	0.0797	0.0802	0.0148	0.0135	0.019354	0.0121
Skewness	-0.5816	-0.5586	0.1964	-0.3651	-0.205892	0.0424
Kurtosis	3.9044	3.8772	4.5536	4.7524	2.437870	2.8493
Jarque-Bera test	22.7032	21.1029	26.3227	36.9440	5.078114	0.3125
Probability	0.0000	0.0000	0.0000	0.0000	0.078941	0.8553
Observations	251 (1952:Q1-2014:Q3)	251 (1952:Q1-2014:Q3)	246 (1953:Q2-2014:Q3)	246 (1953:Q2-2014:Q3)	251 (1952:Q1-2014:Q3)	251 (1952:Q1-2014:Q3)

Though our objective is to analyse the causality-in-quantiles running from *cay* and cay^{MS} to asset returns and their volatilities, for the sake of completeness and comparability, we also conduct the standard linear Granger causality test based on VAR(1) models.

The results are reported in Table 2. The null hypothesis that *cay* and cay^{MS} do not Granger-cause stock returns (*exsr* and *rsr*) are overwhelmingly rejected at the 1%

significance level, with cay^{MS} being a stronger predictor than cay - a result that is consistent with Bianchi *et al.* (2015). However, there is no evidence of predictability originating from cay or cay^{MS} for housing returns (*exhr* and *rhr*). The lack of predictability of cay is in line with Caporale *et al.* (forthcoming). Moreover, it is relevant to highlight that, as we show below based on the tests of nonlinearity and structural breaks, the linear models for the predictability analysis are mis-specified and, hence, the results from the standard Granger causality test cannot be deemed robust.

Table 2. Linear Granger causality test.

Null hypothesis	$\chi^2(1)$ test statistic	*p*-value
cay does not Granger cause *exsr*	9.9107***	0.0016
cay^{MS} does not Granger cause *exsr*	14.9947***	0.0001
cay does not Granger cause *rsr*	12.0734***	0.0005
cay^{MS} does not Granger cause *rsr*	15.8214***	0.0001
cay does not Granger cause *exhr*	0.2259	0.6346
cay^{MS} does not Granger cause *exhr*	0.8740	0.3498
cay does not Granger cause *rhr*	0.4094	0.5223
cay^{MS} does not Granger cause *rhr*	0.3117	0.5767

Note: *exsr*, *rsr*, *exhr* and *rhr* stand for excess stock returns, real stock returns, excess housing returns and real housing returns, respectively. *** indicates rejection of the null hypothesis at the 1% significance level.

To further motivate the use of the nonparametric quantile-in-causality approach, we investigate two features of the relationship between asset returns and the two predictors, namely, nonlinearity and structural breaks. To assess the existence of nonlinearity, we apply the Brock *et al.* (BDS, 1996) test on the residuals of an AR(1) model for excess and real returns, and the excess or real returns equation in the VAR(1) model involving cay or cay^{MS}. The *p*-values of the BDS test are reported in Table 3 and, in general, they reject the null hypothesis of no serial dependence. These results provide strong evidence of nonlinearity in not only excess and real stock and housing returns, but also in their relationship with cay or cay^{MS}. Consequently, the evidence of predictability for the stock market and the lack of it in the case of the housing market emanating from the linear Granger causality test cannot be relied upon.

<div align="center">**Table** 3. Brock *et al.* (1996) BDS test.</div>

	Dimension				
	2	3	4	5	6
AR(1): exsr	0.0103	0.0003	0.0000	0.0000	0.0000
AR(1): rsr	0.0138	0.0004	0.0000	0.0000	0.0000
AR(1): exhr	0.0039	0.0000	0.0000	0.0000	0.0000
AR(1): rhr	0.0021	0.0000	0.0000	0.0000	0.0000
VAR(1): [exsr,cay]	0.0099	0.0004	0.0000	0.0000	0.0000
AR(1): [exsr, cay^{MS}]	0.0693	0.0156	0.0014	0.0008	0.0002
VAR(1): [rsr, cay]	0.0142	0.0005	0.0000	0.0000	0.0000
VAR(1): [rsr, cay^{MS}]	0.0606	0.0093	0.0012	0.0007	0.0002
VAR(1): [exhr, cay]	0.0058	0.0000	0.0000	0.0000	0.0000
VAR(1): [exhr, cay^{MS}]	0.0045	0.0000	0.0000	0.0000	0.0000
VAR(1): [rhr, cay]	0.0014	0.0000	0.0000	0.0000	0.0000
VAR(1): [rhr, cay^{MS}]	0.0014	0.0000	0.0000	0.0000	0.0000

Note: See notes to Table 2. *p*-value of the BDS test statistic, with the test applied to the residuals recovered from the AR(1) models of *exsr*, *rsr*, *exhr* and *rhr*, and the residuals from the *exsr*, *rsr*, *exhr* and *rhr* equations of the VAR(1) model comprising these returns and *cay* or *cay^{MS}*.

Next, we turn to the Bai and Perron's (2003) tests of multiple structural breaks, applied again to the AR(1) model for asset returns, and the asset return equations from a VAR(1) model involving *cay* or *cay^{MS}*. The results are summarized in Table 4 and corroborate the existence of structural breaks. Therefore, the Granger causality tests based on a linear framework are, again, likely to suffer from mis-specification.

<div align="center">**Table 4**. Bai and Perron (2003)'s test of multiple structural breaks.</div>

| Models	Break Dates
AR(1): exsr	1995:Q1, 2000:Q2, 2003:Q2, 2009:Q2
AR(1): rsr	1995:Q1, 2000:Q2, 2003:Q2, 2006:Q2, 2009:Q2
AR(1): exhr	1966:Q2, 2009:Q2
AR(1): rhr	1966:Q3, 2007:Q1, 2011:Q2
VAR(1): [exsr, cay]	1997:Q2, 2000:Q2, 2003:Q2, 2006:Q2, 2009:Q2
VAR(1): [exsr, cay^{MS}]	1997:Q2, 2000:Q2, 2003:Q2, 2006:Q2, 2009:Q2
VAR(1): [rsr, cay]	1997:Q2, 2000:Q2, 2003:Q2, 2006:Q2, 2009:Q2
VAR(1): [rsr, cay^{MS}]	1997:Q2, 2000:Q2, 2003:Q2, 2006:Q2, 2009:Q2
VAR(1): [exhr, cay]	1968:Q3, 1979:Q3, 1989:Q4, 1993:Q2, 2002:Q2, 2005:Q4, 2009:Q2
VAR(1): [exhr, cay^{MS}]	1968:Q4, 1976:Q4, 1979:Q4, 1983:Q1, 2002:Q2, 2005:Q4, 2009:Q2
VAR(1): [rhr, cay]	1972:Q4, 1980:Q1, 1983:Q1, 1989:Q4, 1993:Q2, 2001:Q2, 2005:Q4, 2008:Q4, 2011:Q4
VAR(1): [rhr, cay^{MS}]	1966:Q3, 1989:Q4, 1993:Q2, 2001:Q3, 2005:Q4, 2008:Q4, 2011:Q4

Note: See notes to Table 2. Break dates are based on the Bai and Perron (2003) test of multiple structural breaks applied to the AR(1) models of *exsr*, *rsr*, *exhr* and *rhr*, and the the *exsr*, *rsr*, *exhr* and *rhr* equations of the VAR(1) model comprising of these returns and *cay* or *cay^{MS}*.

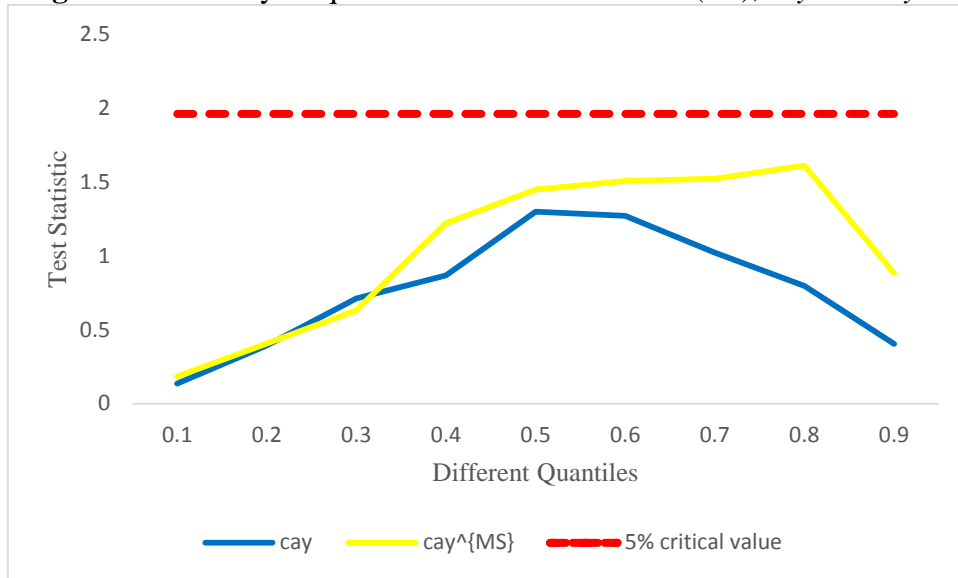**Figure 1.** Causality-in-quantiles: Excess stock returns (*exsr*), *cay* and cay^{MS}.
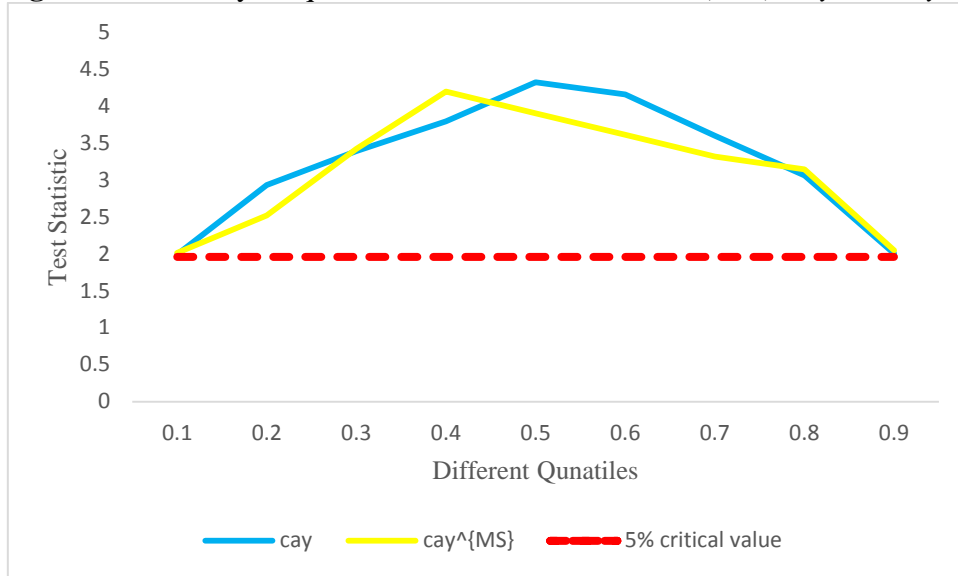
Note: cay^{MS} stands for cay^{MS}.

Figure 2. Causality-in-quantiles: Volatility of excess stock returns (*exsv*), *cay* and cay^{MS}.
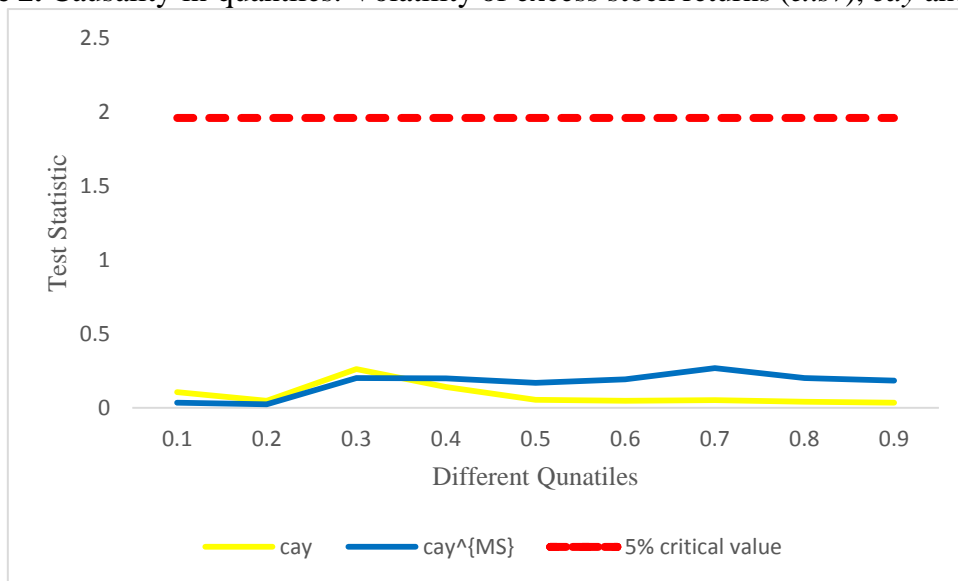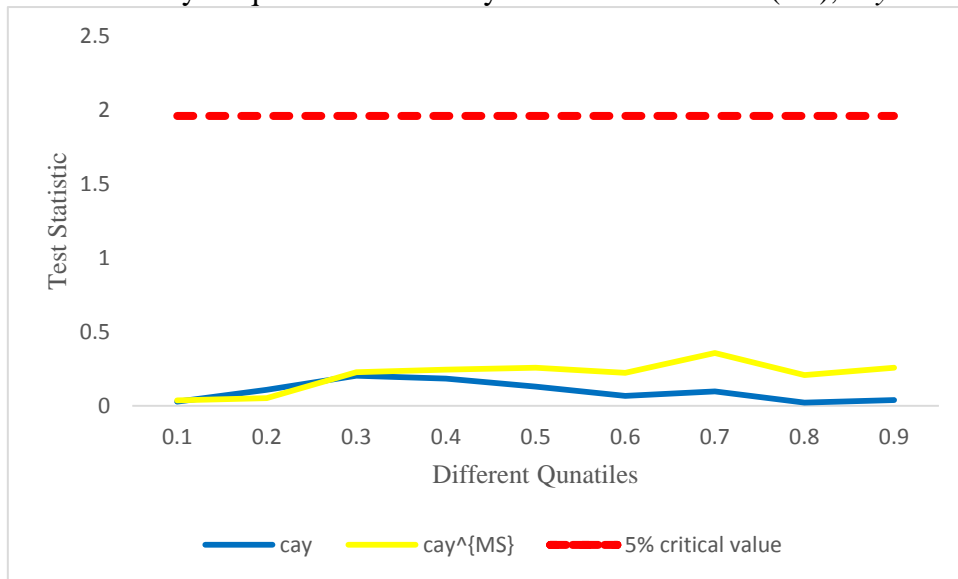

Note: See note to Figure 1.

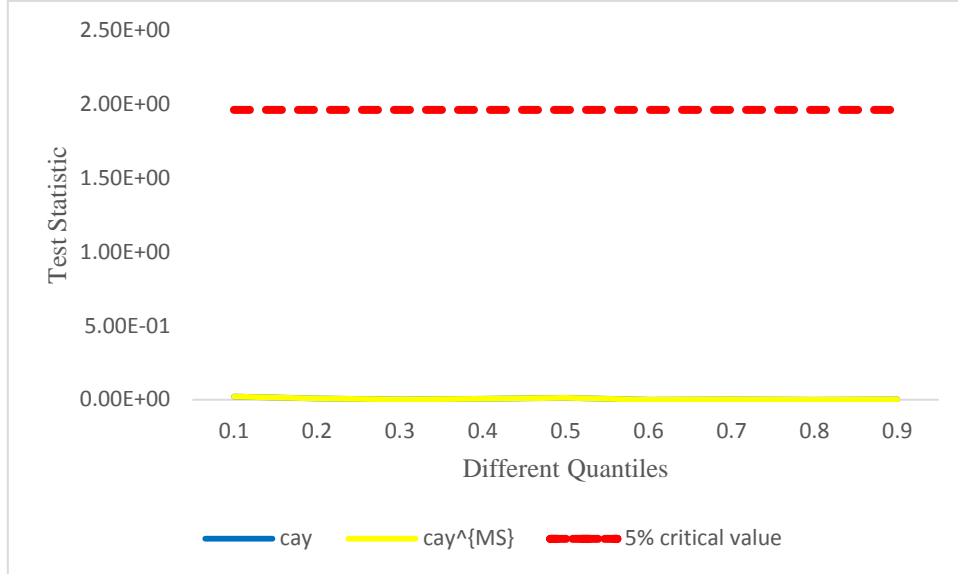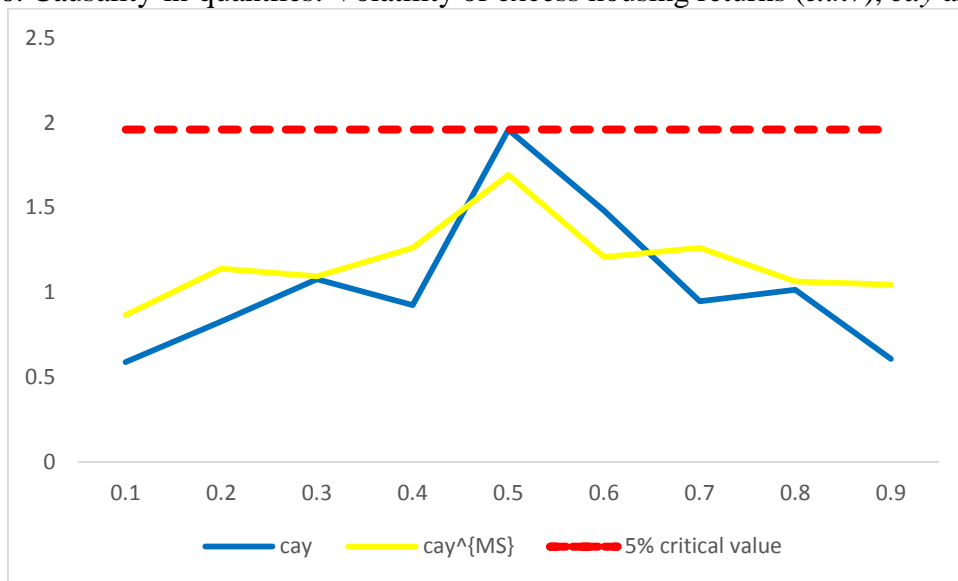**Figure 3.** Causality-in-quantiles: Real stock returns (*rsr*), *cay* and *cay^{MS}*.

Figure 4. Causality-in-quantiles: Volatility of real stock returns (*rsv*), *cay* and *cay^{MS}*.

Note: See note to Figure 1.

Figure 5. Causality-in-quantiles: Excess housing returns (*exhr*), *cay* and *cay*^{MS}.

Note: See Note to Figure 1.

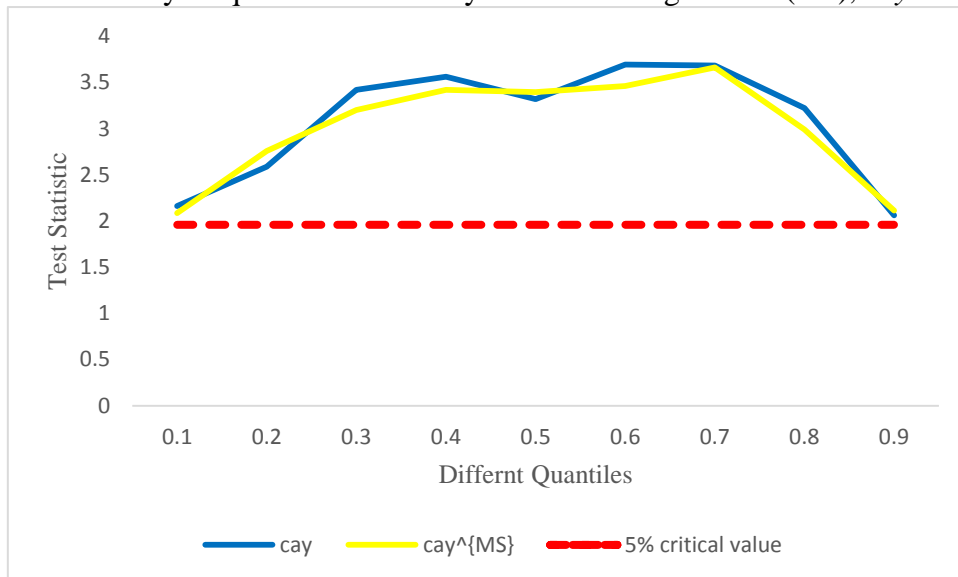**Figure 6**. Causality-in-quantiles: Volatility of excess housing returns (*exhv*), *cay* and *cay*^{MS}.

Note: See note to Figure 1.

Figure 7. Causality-in-quantiles: Real housing returns (*rhr*), *cay* and *cay*[MS].
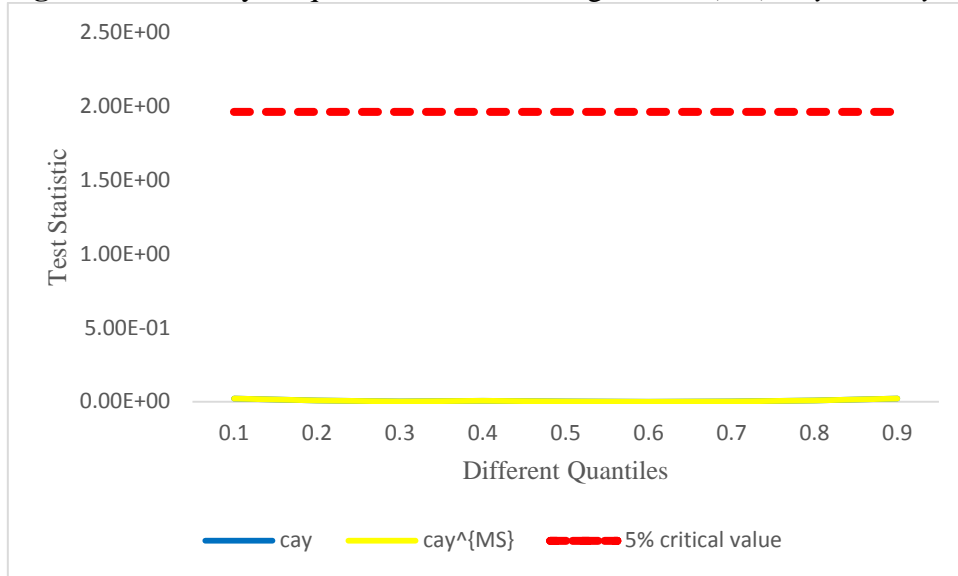
Note: See note to Figure 1.

Figure 8. Causality-in-quantiles: Volatility of real housing returns (*rhv*), *cay* and *cay*[MS].

Note: See note to Figure 1.

In this context, we now turn our attention to the nonparametric causality-in-quantiles test, i.e. a framework that, by design, is robust to the above mentioned econometric problems. Figures 1 to 4 display the results from the causality-in-quantiles test for excess (*exsr*) and real stock returns (*rsr*) and their volatilities (*exsv* and *rsv*), while Figures 5 to 8 report the same evidence for excess (*exhr*) and real housing returns and associated volatilities. We find that *cay* and *cay*[MS] fail to predict *rsr* and *rsv* over their conditional distributions, a result that is in line with the work of Bekiros and Gupta (2015). Moreover, *cay* and *cay*[MS] predict *exsr*, but

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not *exsv* over the entire conditional distribution. However, it is important to note that cay^{MS} performs better than *cay* at certain quantile of the distribution of *exsr*, such as 0.10, 0.30, 0.40, 0.80 and 0.90. In other words, cay^{MS} is a stronger predictor than cay at the lowr or upper ends of the quantiles, i.e., when the market is bearish or bullish, not so when the market is performing in its normal mode, i.e., around the median. So unlike the misspecified linear model and results of Bianchi *et al.,* (2015), it is not necessarily true that cay^{MS} is always the stronger predictor of excess stock returns than *cay*, but the predictability is contingent on the state of the market. Our results also highlight the importance of taking a nonparametric route, since now we no longer observe any evidence of predictability from either *cay* or cay^{MS} for real stock returns as observed with the linear Granger causality tests, which in any event we show to be misspecified and hence, unreliable. The fact that *cay* and cay^{MS} tend to predict excess stock returns rather than real returns tend to suggest the role played by these two consumption-wealth ratios in determining investment in equities relative to a risk-free asset (like the Treasury bill rate), but not so much in determining the purchasing power of equities.

In what concerns excess housing returns (*exhr*) and its volatility (*exhv*), there is no evidence of predictability emanating from *cay* or cay^{MS}. Additionally, while *cay* and cay^{MS} still fail to predict *rhr* (real housing returns), these two variables tend to forecast the volatility of real housing returns (*rhv*) over the entire conditional distribution.[4] So while, like the linear model, the nonparametric model fail to detect causality for excess and real housing returns, we now do observe the benefits of using the higher-order nonparametric causality-in-quantiles test in the sense that it picks up predictability for the volatility of the purchasing power of housing as an asset, with cay^{MS} being a stronger predictor from quantiles above 0.3,

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[4] Since the house price data of Shiller (2015) does not include housing rents, we recomputed returns on housing including rents, with the data on house price as well as rents obtained from the Lincoln Institute of Land Policy and the Organisation for Economic Co-operation and Development (OECD). The data based on the Lincoln Institute of Land Policy started in 1960:Q1 till 2014:Q3, while the data set from the OECD covered the period of 1970:Q1-2013:Q4. The results based on the first data set from the Lincoln Institute of Land Policy showed no evidence of predictability for *exhr*, *exhv*, *rhr* and *rhv* originating from *cay* or cay^{MS} using the causality-in-quantiles test. For the OECD database, again there was no evidence of predictability from either *cay* or cay^{MS} for *exhr*, *exhv* and *rhr*, but we observed that *cay* and cay^{MS} caused *rhv* over the quantiles 0.45 to 0.60, and 0.50 to 0.60 respectively, i.e., around the median of the conditional distribution. In other words, evidence of predictability for *rhv* based on the OECD housing returns that include rent, was found to be weaker than that obtained using the house price of Shiller (2015). We decided to use the Shiller (2015) data as it gives us a longer sample relative to the two other data sets, and from an estimation point of view involving quantiles and nonparametric estimation, this is highly desirable to prevent the overparametrization problems and insignificant estimates associated with nonparametric causality-in-quantiles test using smaller-sized samples (Balcilar et al., 2016). Besides, our results with the OECD data for compared to the Shiller (2015) data are qualitatively similar, but weaker, given that the only effect on the housing market from the two consumption-wealth ratios are on the real housing returns volatility. Complete details of these results have been provided in the Appendix of the paper.

i.e., primarily from just below the median to the upper end of the conditional distribution of the real housing returns volatility.

Summing up, while the linear Granger causality tests provide evidence of predictability for both *exsr* and *rsr*, with *cay*^{MS} outperforming *cay*, the causality-in-quantiles approach shows that the two predictors are only relevant for *exsr*. In addition, while the entire conditional distribution of *exsr* can be predicted by both *cay* and *cay*^{MS}, the latter is only a strong predictor at certain quantiles. As for housing returns, there is evidence of predictability over the entire conditional distribution of *rhv*, with *cay*^{MS} performing better than *cay* in the majority of the quantiles of the distribution.

4. CONCLUSION

This paper compares the predictive ability of *cay* and the Markov-switching cay (*cay*^{MS} introduced by Bianchi *et al.* (2015)) for stock and housing returns in the US over the period 1953Q2-2014Q3, as well as their volatility, using a nonparametric causality-in-quantiles test developed by Balcilar *et al.* (2016).

We find strong evidence of nonlinearity and regime changes in the relationship between stock and housing returns and *cay* or *cay*^{MS}, which gives support to the use of nonparametric causality-in-quantiles test.

Our results also indicate that the two predictors are mainly relevant for excess stock returns but not for real stock returns. Furthermore, the entire conditional distribution of excess stock returns can be predicted by both *cay* and *cay*^{MS}, with the latter being a strong predictor at lower and higher quantiles, i.e., when the equity market is in bearish and bullish modes.

With regard to housing returns, we only find evidence of predictability emanating from *cay* or *cay*^{MS} in the case of the conditional distribution of the variance of real housing returns. In this case, *cay*^{MS} beats *cay* in the majority of the quantiles of the distribution, especially at the upper end.

We can summarize our main results as follows: (a) Linear models involving asset returns and consumption-wealth ratios are misspecified due to the existence of nonlinearity and structural breaks; (b) Given this, it is not always true that the Markov-switching version of the consumption-wealth ratio is a strong predictor relative to its traditional version when we consider a nonparametric framework, which is immune to misspecification due to nonlinearity and regime changes in the relationship between asset returns and the ratios, and; (c) The predictive content of these two versions of the consumption-wealth ratios differ for

the equity and housing markets, with them determining investment decisions in stocks and volatility of the purchasing power of housing irrespective of the market phases (bearish, normal, or bullish) of these two assets, with the latter impossible to detect if we did not consider a higher-order nonparametric causality-in-quantiles method.

As part of future research, it would be interesting to extend our study in order to examine if these results continue to hold in an out-of-sample exercise, since in-sample predictability does not guarantee the same in a forecasting set-up (Rapach and Zhou, 2013; Bonaccolto *et al.*, 2015).

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Results based on housing data obtained from the Lincoln Institute of Land Policy (1960:Q1-2014:Q3)

Figure A1. Causality-in-quantiles: Excess housing returns (*exhr*), *cay* and *cay*^{MS}.
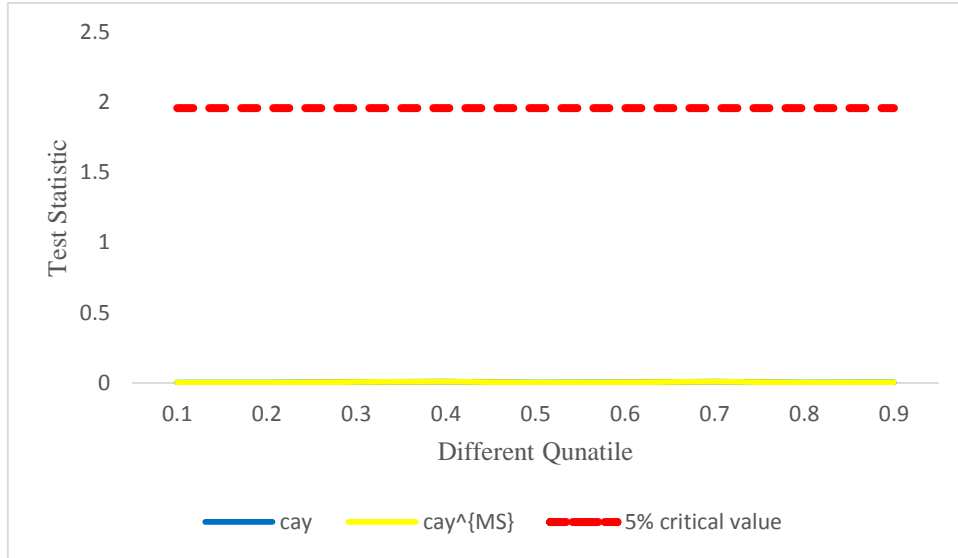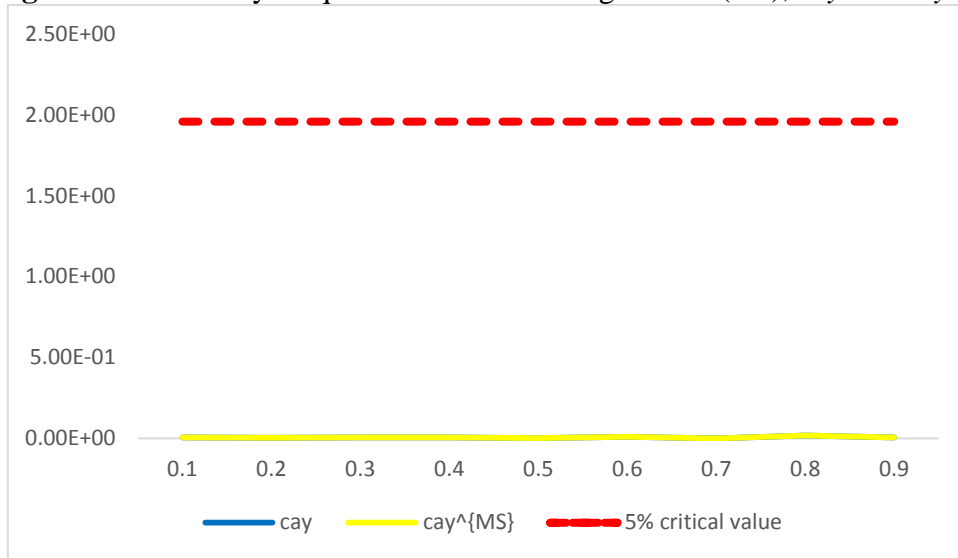

Note: See note to Figure 1.

Figure A2. Causality-in-quantiles: Volatility of excess housing returns (*exhv*), *cay* and *cay*^{MS}.
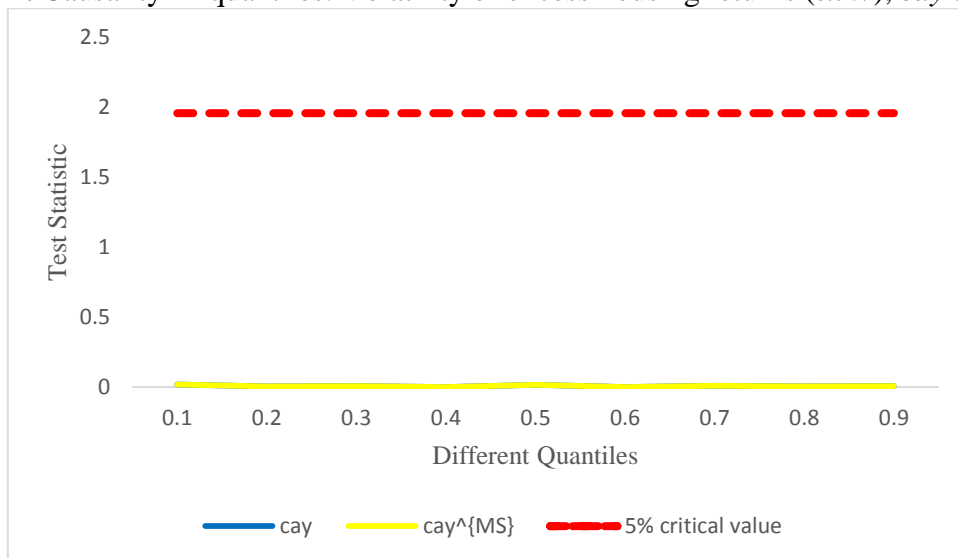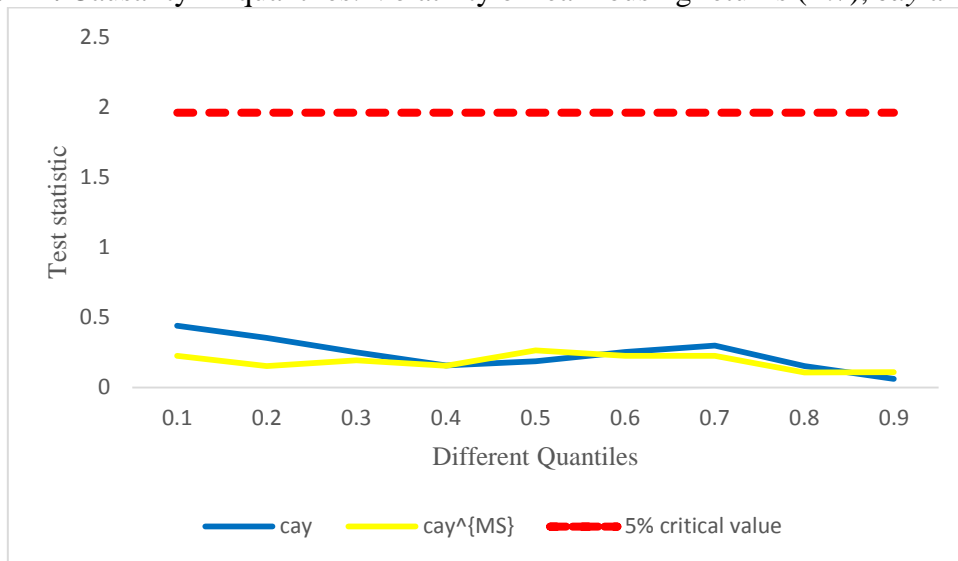

Note: See note to Figure 1.

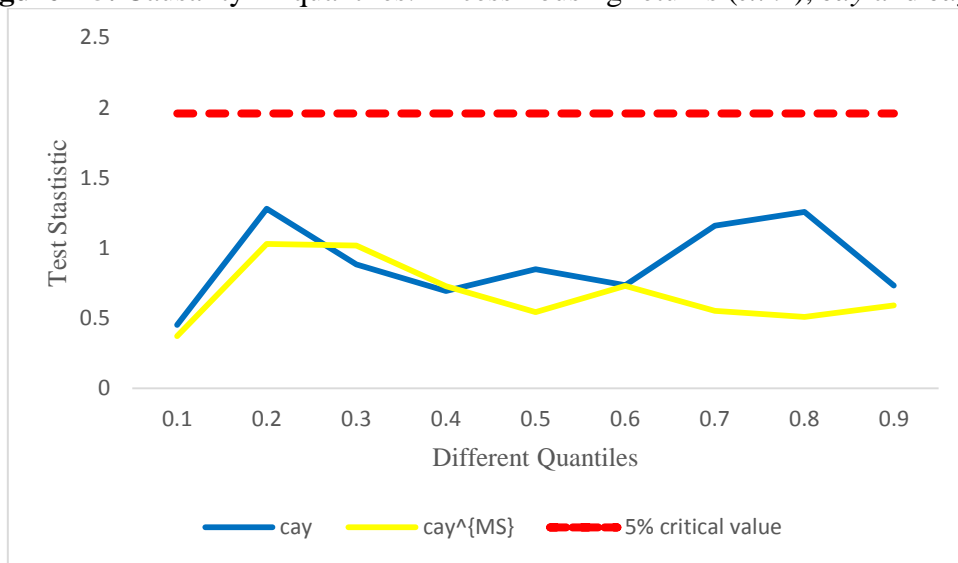**Figure A3.** Causality-in-quantiles: Real housing returns (*rhr*), *cay* and *cay*^{MS}.

Note: See note to Figure 1.

Figure A4. Causality-in-quantiles: Volatility of real housing returns (*rhv*), *cay* and *cay*^{MS}.
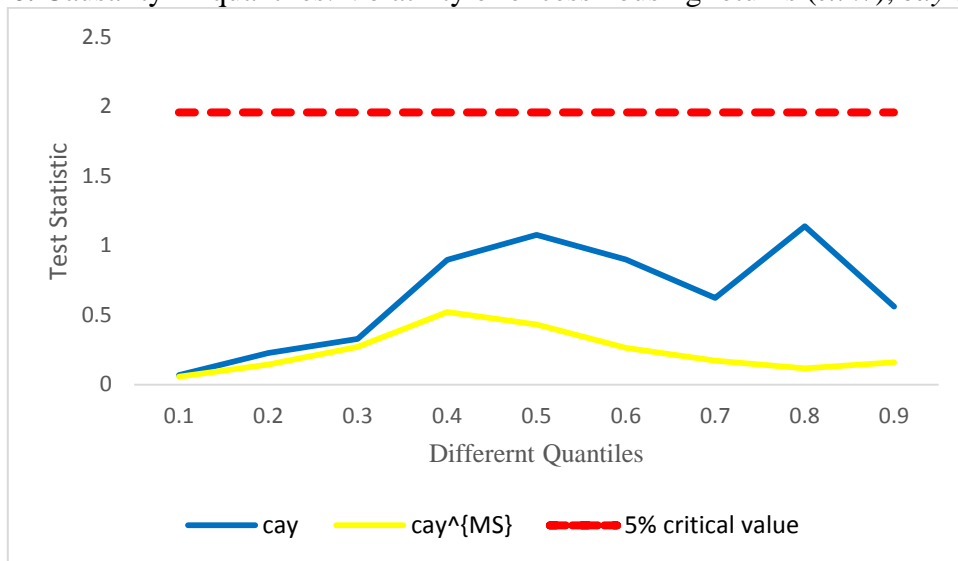

Note: See note to Figure 1.

Results based on housing data obtained from the Organisation for Economic Co-operation and Development (OECD) (1970:Q1-2013:Q4)

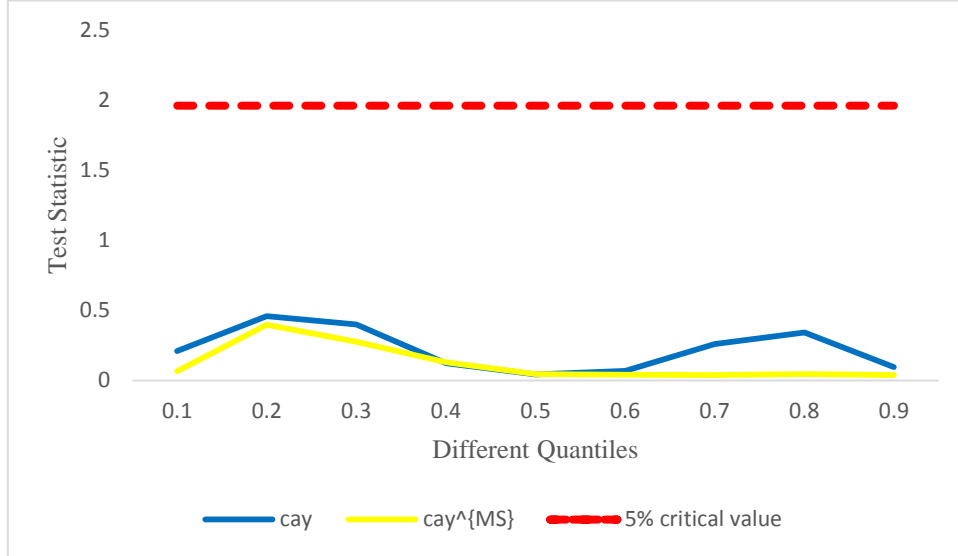**Figure A5.** Causality-in-quantiles: Excess housing returns (*exhr*), *cay* and *cay*^{MS}.

Note: See note to Figure 1.

Figure A6. Causality-in-quantiles: Volatility of excess housing returns (*exhv*), *cay* and *cay*^{MS}.
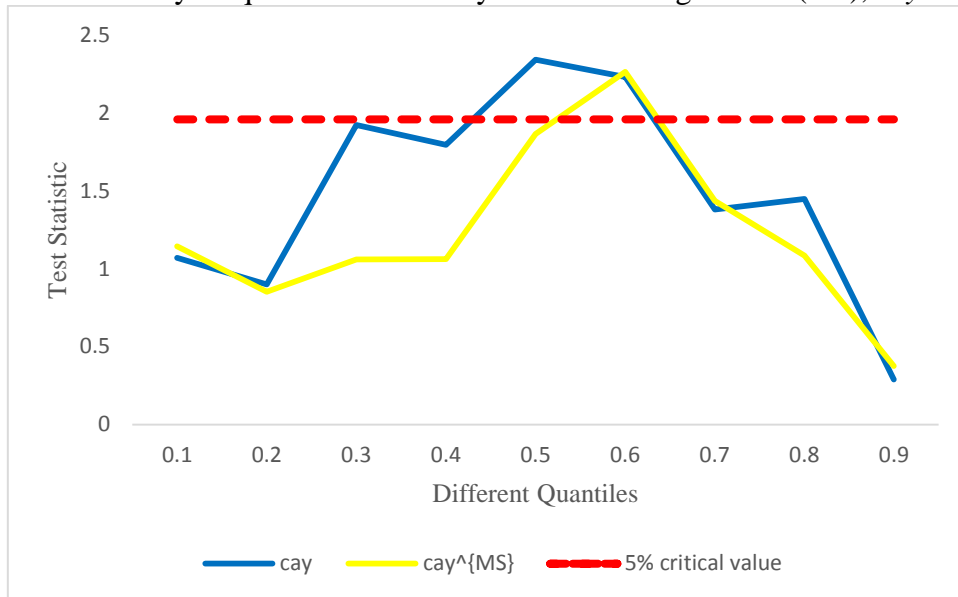

Note: See note to Figure 1.

Figure A7. Causality-in-quantiles: Real housing returns (*rhr*), *cay* and *cay^{MS}*.

Note: See note to Figure 1.

Figure A8. Causality-in-quantiles: Volatility of real housing returns (*rhv*), *cay* and *cay^{MS}*.

Note: See note to Figure 1.