Wealth-to-income ratio and stock market movements:

Evidence from a nonparametric causality test

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ABSTRACT

We use a nonparametric causality-in-quantiles test to analyze the predictive ability of the wealth-to-income ratio (*wy)* for excess stock returns and their volatility. Our results reveal that the wealth-to-income ratio is nonlinearly related with excess stock returns, and hence, results from linear Granger causality tests cannot be deemed robust. When we apply the nonparametric causality-in-quantiles test, we find that the wealth-to-income ratio can predict excess stock returns over the majority of the conditional distribution, with the exception being the extreme ends, i.e. when the market is in deep bear or bull phases. However, the wealth-to-income ratio has no predictability for the volatility of excess stock returns.

Keywords: stock returns, volatility, nonparametric causality-in-quantiles test.
JEL Codes: C22, G10.

1. INTRODUCTION

The seminal paper by Lettau and Ludvigson (2001) had a pivotal role in promoting a line of research that has been assessing the relationship between the dynamics of the consumption-wealth ratio (labelled as *cay*) and the time-varying nature of equity risk premium. Ever since, a large number of studies have confirmed this finding not only for equity markets, but also for bond markets in developed and emerging countries (Sousa, 2010a, 2015; Afonso and Sousa, 2011; Rocha Armada and Sousa, 2012; Rapach and Zhou, 2013; Caporale *et al.*, 2016).

A recent work of Sousa (2015) has made a substantial contribution to the empirical finance literature. The author develops a very simple theoretical model that shows that falls in asset wealth are equivalent to a destruction of collateral or a reduction in utility services. As a result, when hit by negative shocks, investors become more exposed to labour income risk and demand a larger risk premium on assets. Therefore, the fall in the wealth-to-income ratio (labelled as *wy*) forecasts a rise in future asset returns.[1]

Yet, it should also be 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) and Caporale *et al.* (2016) rely on linear predictive regression frameworks. However, as Bianchi *et al.* (2016) and Balcilar *et al.* (2017) put forward with regard to *cay*, the presence of asset price bubbles or irregular changes in the moments of the distribution often leads to infrequent shifts or breaks. Thus, nonlinear frameworks, such as the Markov-switching version of the consumption-wealth ratio, i.e. cay^{MS}, may be more appropriate and display superior forecasting power for stock market returns than linear models.

Against this backdrop, the objective of our paper is to assess the predictive ability of the deviations of asset wealth from its long-run equilibrium relationship with labour income for excess stock returns and its volatility. We accomplish this goal by using a nonparametric causality-in-quantiles test that has been recently developed by Balcilar *et al.* (2016).

This test studies higher order causality over the entire conditional distribution and is inherently based on a nonlinear dependence structure between the variables of interest. 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).

[1] While both *cay* and *wy* can be obtained by considering the household's intertemporal budget constraint, Sousa (2010b) shows that one of the key contributions of *wy* is that the *wy* proxy for time-varying expected returns can also be derived from a theoretical model based on the functional form of the preferences of the representative investor. Thus, *wy* is part of a class of consumption-capital asset pricing (C-CAPM) models, which helps establishing a more direct connection between the theoretical framework and the empirical evidence.

Using quarterly data for the US stock market over the period of 1953:Q2-2016:Q3, we find evidence of nonlinearity and regime changes between excess returns and the wealth-to-income ratio (*wy*), which supports the use of the nonparametric causality-in-quantiles test.

The main novelties of this econometric framework and, thus, the empirical results of our paper are as follows. First, it is robust to mis-specification errors, as it detects the underlying dependence structure between the examined dependent variable (i.e. excess stock returns) vis-à-vis the regressor (i.e. *wy*). In our empirical exercise, we show that this is particularly important given that financial markets data tend to display nonlinear dynamics (Balcilar et al., 2017). Second, this methodology allows us to test not only for causality-in-mean (i.e. the first moment), but also for causality in the tails of the joint distribution of the variables. Our analysis reveals that this aspect is especially relevant in the light of the fact that the unconditional distribution of the dependent variable - i.e. excess stock returns - tends to exhibit fat tails. Thus, the nonparametric causality-in-quantiles test allows us to capture bear, normal and bull market phases corresponding to the lower quantiles, the median, and the upper quantiles of the distribution, respectively.[2] Third, we are also able to investigate causality-in-variance and, thus, study higher-order dependency. This again is highly pertinent since, during some periods, causality in the conditional-mean may not exist, while at the same time higher-order interdependencies may turn out to be significant.[3]

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

2. ECONOMETRIC FRAMEWORK

2.1. WEALTH-TO-INCOME RATIO: THEORY

Following Sousa (2015), we can write the intertemporal budget constraint of the representative consumer as

$$W_{t+1} = (1 + R_{w,t+1})(W_t - C_t), \tag{1}$$

where W_t represents aggregate wealth, C_t denotes private consumption, and $R_{w,t+1}$ corresponds to the return on aggregate wealth between period t and $t+1$.

[2] This is particularly important not only for predicting risk premium, but also in the context of output growth forecasts given the record of failure to predict recessions (Loungani, 2001).

[3] For instance, Jalles et al. (2015) show that the tendency for forecast smoothing can have relevant costs, especially, around turning points in the economy. And, similarly, Lougani et al. (2013) evaluate how information rigidities evolve during periods of crisis and recessions and how quickly news are incorporated by forecasters into their growth forecasts. See also Ball et al. (2015).

Approximating equation (1) by a Taylor expansion under the assumption that the consumption-aggregate wealth is stationary and that $\lim_{i\to\infty} \rho_w{}^{i}(c_{t+i} - w_{t+i}) = 0$ and taking conditional expectations, we get

$$c_t - w_t = E_t \sum_{i=1}^{\infty} \rho_w^i r_{w,t+i} - E_t \sum_{i=1}^{\infty} \rho_w^i \Delta c_{t+i} + k_w, \tag{2}$$

where $c \equiv logC$, $w \equiv logW$, and k_w is a constant.

If we assume - as in Campbell (1996) - that human wealth can be described by labour income, y_t (i.e., $h_t = y_t + k_h$, where k_h is a constant), then log total wealth can be approximated by

$$w_t \approx \alpha a_t + (1-\alpha) y_t + k_y, \tag{3}$$

where a_t is the log asset wealth, h_t is the log human wealth, and k_y is a constant.

Replacing equation (3) into (2), Lettau and Ludvigson (2001) and Sousa (2010a) show that

$$\underbrace{c_t - \alpha a_t - (1-\alpha) y_t}_{cay_t} = E_t \sum_{i=1}^{\infty} \rho_w^i r_{w,t+i} - E_t \sum_{i=1}^{\infty} \rho_w^i \Delta c_{t+i} + \eta_t + k, \tag{4}$$

where $\eta_t \equiv (1-\alpha) z_t$ is a stationary component, and k is a constant.

If we rearrange terms and take into account that $\xi_t \equiv \frac{1}{\alpha}\left[\underbrace{(c_t - y_t)}_{mpc_y \approx k} - \eta_t - k\right]$ displays stationarity, we obtain:

$$\underbrace{(a_t - y_t)}_{wy_t} = -\frac{1}{\alpha} E_t \sum_{i=1}^{\infty} \rho_w^i r_{w,t+i} + \frac{1}{\alpha} E_t \sum_{i=1}^{\infty} \rho_w^i \Delta c_{t+i} + \xi_t. \tag{5}$$

It can be seen that when the left hand side of equation (5) is falls, consumers expect higher future returns on market wealth. Consequently, when the wealth-to-income ratio decreases, future stock returns are expected to rise. This is because the household's exposure to labor income shocks is larger, thus, the representative investor demands a higher risk premium.

2.2. WEALTH-TO-INCOME RATIO: EMPIRICS

Log real asset wealth (w), and labor income (y) are nonstationary. As a result, using the maximum-likelihood framework of Johansen (1988), we estimate the following vector error correction model (VECM):

$$\begin{bmatrix} \Delta w_t \\ \Delta y_t \end{bmatrix} = \alpha\left[w_t + \varpi y_t + \partial t + \chi\right] + \sum_{k=1}^{K} D_k \begin{bmatrix} \Delta w_{t-k} \\ \Delta y_{t-k} \end{bmatrix} + \varepsilon_t, \tag{6}$$

where χ is a constant, *t* denotes the time trend, ε_t is the error term, and Δ is the first-difference operator. The *k* error-correction terms allow us to eliminate the effect of regressor endogeneity on the distribution of the least-squares estimators of $[1, \varpi, \partial, \chi]$.

The time-series *w* and *y* are stochastically cointegrated with the cointegrating vector $[1, \varpi, \chi]$, when the linear combination $w_t + \varpi y_t + \chi$ is trend stationary. Additionally, we impose the restriction that the cointegrating vector eliminates the deterministic trends, so that $w_t + \varpi y_t + \partial t + \chi$ is stationary.

Then, the ratio of asset wealth to income, *wy*, is measured as the deviation from the cointegration relationship:

$$wy_t = w_t + \hat{\varpi} y_t + \hat{\partial} t + \hat{\chi}. \tag{7}$$

Given that the OLS estimators of the cointegration parameters are superconsistent, one can use the ratio of asset wealth to income, *wy*, as a regressor without needing an errors-in-variables standard error correction.

The ratio of asset wealth to income is also measured by estimating the constant, χ, and the coefficient associated with the time trend *(t)*, i.e. ∂, in the cointegrating relationship while imposing the restriction $\varpi = 1$.

2.3. NONPARAMETRIC QUANTILE CAUSALITY TESTING

This section provides a brief description of the quantile based methodology that we use to detect nonlinear causality via a hybrid approach developed by Balcilar *et al.* (2016) based on the frameworks of Nishiyama *et al.* (2011) and Jeong *et al.* (2012). As mentioned earlier, this approach is robust to extreme values in the data and captures general nonlinear dynamic dependencies. Let y_t denote excess stock returns and x_t denote the predictor variable, in our case *wy* (as described in preceding sub-section).

Formally, let $Y_{t-1} \equiv (y_{t-1}, \ldots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \ldots, x_{t-p})$, $Z_t = (X_t, Y_t)$ 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 $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t \mid Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t \mid Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) \mid Z_{t-1}\} = \theta$ with probability one. Consequently, the (non)causality in the q-th quantile hypotheses to be tested can be specified as:

$$H_0: \quad P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} = 1, \tag{8}$$

$$H_1: \quad P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} < 1. \tag{9}$$

Jeong *et al.* (2012) employ the distance measure $J = \{\varepsilon_t E(\varepsilon_t \mid Z_{t-1}) f_z(Z_{t-1})\}$, 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 (8), which can only be true if and only if $E[1\{y_t \le Q_\theta(Y_{t-1}) \mid Z_{t-1}\}] = \theta$ or, equivalently, $1\{y_t \le Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, 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:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s \neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s . \tag{10}$$

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:

$$\hat{\varepsilon}_t = 1\{y_t \le Q_\theta(Y_{t-1})\} - \theta. \tag{11}$$

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

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta \mid Y_{t-1}), \tag{12}$$

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

$$\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1}) = \frac{\sum_{s=p+1, s \neq t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right) 1(y_s \le y_t)}{\sum_{s=p+1, s \neq t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right)}, \tag{13}$$

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

In an extension of Jeong *et al.* (2012)'s framework, Balcilar *et al.,* (2016) also develop a test for the *second* moment. In particular, we can now test the causality running from *wy* to volatility of excess returns. Adopting the approach in Nishiyama *et al.* (2011), higher order quantile causality can be specified as:

$$H_0: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} = 1 \qquad \text{for } k = 1, 2, \ldots, K \tag{14}$$

$$H_1: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} < 1 \qquad \text{for } k = 1, 2, \ldots, K \tag{15}$$

Integrating the entire framework, we define that x_t *Granger causes* y_t *in quantile* θ *up to the* k^{th} *moment* using Eq. (14) to construct the test statistic of Eq. (10) for each k. The causality-in-variance test is then calculated by replacing y_t in Eqs. (10) and (11) with y_t^2. However, it can be shown that it is not easy to combine the different statistics for each $k = 1, 2, \ldots, K$ into one statistic for the joint null, because the statistics are mutually correlated (Nishiyama *et al.*, 2011). To efficiently address this issue, we include a sequential-testing method as described by 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 lead to no-causality in the *second* moment. Thus, we can still construct the tests for $k=2$. Jeong *et al.* (2012) establish that the re-scaled statistics $Th^p \hat{J}_T/\hat{\sigma}_0$ is asymptotically distributed as standard normal, where $\hat{\sigma}_0 = \sqrt{2}\theta(1-\theta)\sqrt{1/(T(T-1)h^{2p})}\sqrt{\sum_{t \neq s} K^2((Z_{t-1}-Z_{s-1})/h)}$. The most crucial element of the test statistics $\hat{J}_T$ is the regression error $\hat{\varepsilon}_t$. Since the regression error in under Eq. (14) is again an error in terms of the quantile, the asymptotic distribution of the test is not affected and the re-scaled statistics $Th^p \hat{J}_T/\hat{\sigma}_0$ is analogously asymptotically distributed as standard normal.

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 $L(\cdot)$ respectively. In this study, we make use of lag order of one, which is consistent with the linear predictive regression framework used to predict excess stock returns (see Balcilar *et al.* (2017) for a detailed discussion in this regard). The bandwidth value is chosen by employing the leave-one-out least squares cross-validation techniques of Racine and Li (2004) and Li and Racine (2004). Finally, for $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels was employed.

3. Data analysis and Empirical results

3.1. Data

Our quarterly dataset comprises excess stock returns and *wy*. The data on asset wealth and labour income, which were used in the construction of *wy*, span over the period 1952:Q1-2016:Q3 and are obtained from Professor Sydney C. Ludvigson's website: http://www.econ.nyu.edu/user/ludvigsons/. The start and end dates are driven by data availability of the two time-series at the time of the writing of this paper. Differencing of the variables to estimate the VECM and use of 4 lags to compute the unrestricted (*wyu*) and restricted (*wyr*) version of the *wy* variable, implies that the effective sample starts from 1953:Q2.

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, with data for the latter obtained from the FRED database of Federal Reserve Bank of St. Louis. We also compute the volatility of excess stock market returns (*exsv*) using the squared values of *exsr*.

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 non-human components of total asset wealth because it is a much broader measure than the S&P 500 index. As can be seen from the summary statistics, reported in Table 1, the *exsr* (*exsv*) is skewed to the left (right), with excess kurtosis, resulting in non-normal distributions for both excess stock returns and volatility. This result, in turn, provides a preliminary motivation to use the causality-in-quantiles test. Note that, we standardize the *wyu* and *wyr* variables (by dividing with their respective standard deviations) to compare the strength of the predictability for excess stock returns and its volatility across these two measures.

Table 1. Summary Statistics

	Variable			
Statistic	*exsr*	*exsv*	*wyu*	*wyr*
Mean	0.02	0.01	0.00	0.00
Median	0.03	0.00	0.00	-0.01
Maximum	0.21	0.07	0.18	0.21
Minimum	-0.27	0.00	-0.16	-0.21
Std. Dev.	0.08	0.01	0.07	0.09
Skewness	-0.58	3.11	0.25	0.18
Kurtosis	3.94	15.46	2.95	2.56
Jarque-Bera	23.57	2053.03	2.57	3.36
Probability	0.00	0.00	0.28	0.19
Observations	254			

Note: Std. Dev: stands for standard deviation. Probability corresponds to the *p*-value of the Jarque-Bera test with the null of normality.

3.2. Empirical Results

We start off with the estimation of the VECM model, which in turn gives us the generated predictors *wyu* and *wyr*. Table 2 summarizes the estimates for the shared trend among asset wealth and labour income. It shows that the coefficient associated with labour income is positive, which suggests that the asset wealth and labour income share a positive long-run path and that the elasticity of asset wealth with respect to human wealth is positive. The table also presents the unit root test to the residuals of the cointegration relationship based on the Engle and Granger (1987) methodology and shows that they are stationary at the conventional level of significance (i.e., one can reject the null of a unit root). Note that, since the pre-requisite for the cointegration test is to ensure that the asset wealth and labor income variables are non-stationary, we also conducted the Augmented Dickey-Fuller (ADF) test, results of which have been reported in Table A1 in the Appendix of the paper.[4] As can be seen, the null of unit root cannot be rejected for both the variables, i.e., both asset wealth and labor income are I(1) processes, and hence, the VECM is correctly specified.

Table 2. Cointegration estimations.

$$wy_t = w_t + \hat{v} y_t + \hat{¶} t + \hat{c}$$

Panel A: $\hat{v}$ freely estimated			
$\hat{v}$	$\hat{\partial}$	$\hat{c}$	ADF *t*-statistic
0.22	-0.01	-12.78	-3.53***
Panel B: $\hat{v}$ restricted to -1			
$\hat{v}$	$\hat{\partial}$	$\hat{c}$	ADF *t*-statistic
1	-0.01	-19.83	-3.05**

Note: The estimated coefficients are obtained from the regression of the Vector Error-Correction Model (VECM) model described by system (6) in Section 2.2. In the estimation, we use the maximum-likelihood framework of Johansen (1988). The unit root test to the residuals of the cointegration relationship is based on the Engle and Granger (1987) methodology. *** and ** denote statistical significance at the 1% and 5% level, respectively.

Though our objective is to analyse the causality-in-quantiles running from *wyu and wyr* to *exsr* and *exsv*, for the sake of completeness and comparability, we also conduct the standard linear Granger causality test based on a VAR(1) model.

The results are reported in Table 3. The null hypotheses that *wyu* and *wyr* does not Granger-cause excess stock returns are overwhelmingly rejected at the 1% significance level, with *wyr* being a stronger predictor than *wyu*.

Table 3. Linear Granger causality test.

Null hypothesis	$c^2(1)$ test statistic	*p*-value
wyu does not Granger cause *exsr*	13.49***	0.00
wyr does not Granger cause *exsr*	16.58***	0.00

Note: *exsr* stands for excess stock returns; *wyu* and *wyr* are freely estimated (unrestricted) and restricted wealth–income ratios, respectively (See Table 2); *** 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.* (1996) (hereforth, BDS) test on the residuals of an AR(1) model for excess returns, and the

[4] Given the low power of the ADF test, we also conducted other unit root tests like the Phillips-Perron, DF-GLS and Ng-Perron tests; which too confirmed the unit root behaviour of the asset wealth and labor income variable. These results have been suppressed to save space, but are available upon request from the authors.

excess returns equation in the VAR(1) model involving *wyu* or *wyr*. The *p*-values of the BDS test are reported in Table 4 and, in general, they reject the null hypothesis of no serial dependence. These results provide strong evidence of nonlinearity in not only excess stock returns, but also in its relationship with *wyu* or *wyr*. Consequently, the evidence of predictability for the excess stock returns emanating from the linear Granger causality test cannot be relied upon.

Table 4. Brock *et al.* (1996) BDS test.

	Dimension				
	2	3	4	5	6
AR(1): exsr	0.01	0.00	0.00	0.00	0.00
VAR(1): [exsr,wyu]	0.11	0.01	0.00	0.00	0.00
VAR(1): [exsr, wyr]	0.02	0.00	0.00	0.00	0.00

Note: Entries correspond to the *p*-value of the BDS test statistic, with the test applied to the residuals recovered from the AR(1) model of *exsr* and the residuals from the *exsr* equations of the VAR(1) model with *wyu* or *wyr*.

Next, we turn to the tests of multiple structural breaks (Bai and Perron, 2003), applied again to the AR(1) model for excess returns, and the excess return equations from a VAR(1) model involving *wyu* or *wyr*. We were able to detect six breaks for the AR(1) model of excess returns and nine breaks each for the excess returns equation in the VAR(1) model with *wyu* and *wyr*. The results are summarized in Table 5 and corroborate the existence of structural breaks. Therefore, the Granger causality tests involving *exsr* and *wyu* and *wyr* based on a linear framework are, again, likely to suffer from mis-specification.

Table 5. Bai and Perron (2003)'s test of multiple structural breaks.

Models	Break Dates
AR(1): exsr	1956:Q3, 1995:Q1, 2000:Q2, 2003:Q2, 2006:Q2, 2009:Q2
VAR(1): [exsr, wyu]	1960:Q1, 1963:Q1, 1974:Q3, 1977:Q3, 1997:Q2, 2000:Q4, 2004:Q1, 2008:Q4, 2012:Q2
VAR(1): [exsr, wyr]	1960:Q1, 1963:Q1, 1970:Q3, 1974:Q3, 1977:Q3, 1997:Q2, 2000:Q2, 2003:Q2, 2008:Q1

Note: See notes to Table 3. Break dates are based on the Bai and Perron (2003) test of multiple structural breaks applied to the AR(1) models of *exsr* and the *exsr* equations of the VAR(1) model with *wyu* or *wyr*.

Thus, due to nonlinearity and regime changes the linear model of Granger causality test is mis-specified and hence, cannot be deemed robust. Given this, 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 and 2 display the results from the causality-in-quantiles test for excess stock returns (*exsr*) and its volatility (*exsv*).[5] We find that *wyu* and *wyr*

[5] As in Rocha Armada and Sousa (2012), and Sousa (2012a,b, 2015), we also analysed whether the wealth income ratios can predict returns and volatility of the housing and bond markets. Linear causality tests did show that these ratios can predict movements of real yields of bonds, but not real housing returns. But, again based on the BDS and Bai and Perron (2003) tests, the linear model was found to be mis-specified, and hence, results from it could not be considered reliable. Given this, when we applied the causality-in-quantiles test, we were, however, unable to detect

fail to predict *exsv* over its entire conditional distribution, i.e., the wealth-income ratio has no predictability of excess stock returns volatility. But, *wyu* and *wyr* predict *exsr* over the quantile range of [0.10, 0.80] and [0.05, 0.85] respectively. So even after guarding for possible misspecification, the conditional mean-based results of the linear Granger causality holds, but only at certain parts of the conditional distribution of *exsr*, with the exceptions being the extreme ends of the distribution, i.e., when the stock market is in deep bear or bullish phases. In other words, if we had relied on a linear Granger causality test, besides being mis-specified, we would have wrongly concluded that *wyu* and *wyr* always predicts *exsr*, but as we show, that this is only the case when the market is not at its extreme phases. We are able to capture this via the causality-in-quantiles test, since it is more general and covers the entire conditional distribution of the equity premium, besides being a correctly specified model in the presence of nonlinearity and regime changes, since it is a nonparametric approach.

Intuitively, the result suggests that when the stock market is at its extreme ends, investors most likely herd and do not need any information from the wealth-income ratios to predict stock returns. In other words, it seems that the efficient market hypothesis holds at the extreme quantiles for the equity market relative to the predictive ability of the wealth-income ratios. However, barring the extreme bear and bull phases, investors clearly use information from the wealth-income ratios to predict future movements of the stock market. Clearly, using a conditional-mean based model, such information would not be available to us.

In addition, it is important to note that while in general, like the conditional mean-based results *wyr* outperforms *wyu* in terms of the strength of its predictability for excess returns, and also in terms of the coverage of the quantile range, there are some exceptions. For instance, *wyu* is a stronger predictor than *wyr* at quantiles of 0.15, 0.30, 0.60 and 0.75. This is again an important information for the investor, since our results show that predictability of the stock market based on information from the unrestricted and restricted wealth-income ratios are quantile dependent, and not universally in favour of a specific measure of the ratio.

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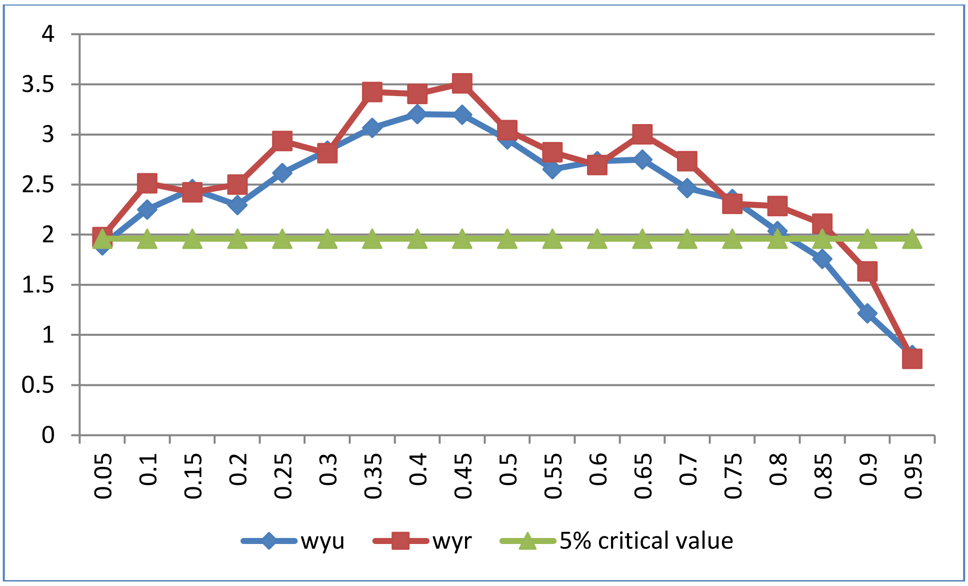
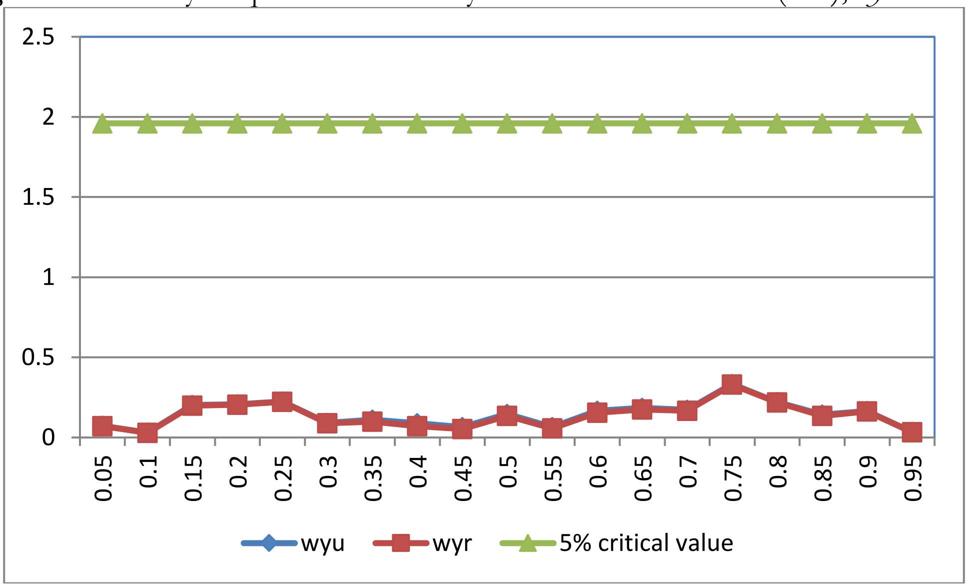
any evidence of predictability from the wealth-income ratios to bond and housing returns and their volatilities. Complete details of these results are available upon request from the authors.

Figure 1. Causality-in-quantiles: Excess stock returns (*exsr*), *wyu* and *wyr*.



Note: Horizontal axis depicts the various quantiles, while the vertical axis measures the test statistic..

Figure 2. Causality-in-quantiles: Volatility of excess stock returns (*exsv*), *wyu* and *wyr*.



Note: See note to Figure 1.

4. Conclusion

This paper assesses the predictive ability of the deviations of asset wealth from its cointegrating relationship with labour income (labelled as *wy* and introduced by Sousa (2015)) for excess stock returns in the US, as well as its volatility, over the period 1953Q2-2016Q3, 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 excess stock returns and *wy*, which gives support to the use of the above mentioned test and also implies that results from linear Granger causality tests cannot be deemed reliable.

Our results also indicate that the wealth-income ratio is mainly relevant for excess stock returns, but not for their volatility. Furthermore, the wealth-ratio has predictive content for excess stock returns, barring the extreme ends of its conditional distribution.

As part of future research, it would be interesting to extend our study to examine if these results hold in an out-of-sample exercise given that in-sample predictability does not guarantee the same in a forecasting set-up (Rapach and Zhou, 2013).

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Appendix

Table A1. Augmented Dickey-Fuller unit root tests.

	Log-Level		First-Differences	
Variable	C	C+T	C	C+T
Asset Wealth	-0.06	-2.85	-12.63***	-12.61***
Labor Income	-2.03	-1.11	-15.57***	-15.76***

Note: C and C+T stand for the model with constant only, and constant and trend, respectively; *** indicates rejection of the null hypothesis of unit root at the 1% level of significance, given critical values of -3.46 (1%), -2.87 (5%), -2.57 (10%) for model with C only, and for C+T, the corresponding critical values are: -3.99 (1%), -3.43 (5%), -3.14 (10%); Lag lengths chosen by the Schwarz Information Criterion (SIC).