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**Consumption-Wealth Ratio and Expected Stock Returns:  
Evidence from Panel Data**

Rio de Janeiro  
2015

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Dissertação submetida a Escola de Pós-Graduação em Economia como requisito parcial para a obtenção do grau de Mestre em Economia.

Área de Concentração: Macroeconometria

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**ANDRESSA SOUZA CAMPOS MONTEIRO DE CASTRO**

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Dissertação apresentada ao Curso de Mestrado em Economia da Escola de Pós-Graduação em Economia para obtenção do grau de Mestre em Economia.

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## Abstract

This paper investigates the role of consumption-wealth ratio on predicting future stock returns through a panel approach. We follow the theoretical framework proposed by Lettau and Ludvigson (2001), in which a model derived from a nonlinear consumer's budget constraint is used to settle the link between consumption-wealth ratio and stock returns. Using G7's quarterly aggregate and financial data ranging from the first quarter of 1981 to the first quarter of 2014, we set an unbalanced panel that we use for both estimating the parameters of the cointegrating residual from the shared trend among consumption, asset wealth and labor income,  $cay$ , and performing in and out-of-sample forecasting regressions. Due to the panel structure, we propose different methodologies of estimating  $cay$  and making forecasts from the one applied by Lettau and Ludvigson (2001). The results indicate that  $\widehat{cay}$  is in fact a strong and robust predictor of future stock return at intermediate and long horizons, but presents a poor performance on predicting one or two-quarter-ahead stock returns.

**KEYWORDS:** *Consumption-wealth ratio, stock returns, unbalanced panel, cointegrating residual.*

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# 1 Introduction

The link between macroeconomics and financial markets has long driven a great amount of empirical work in macroeconometric literature. Motivated by the well known predictability of stock returns (Campbell and Shiller, 1988; Fama and French, 1988; Pesaran and Timmermann, 1995), a branch of this literature has concerned about the forecasting power of macroeconomic variables over future excess returns. There is still little empirical evidence that support such theories, though.

In a seminal paper, Lettau and Ludvigson (2001) study the role of transitory deviations from the common trend in consumption, asset holdings and labor income for predicting stock market fluctuations. They show that, according to forward-looking models of consumer behavior, when investors expect higher future returns, they react by rising current consumption out of its shared trend with asset wealth and labor income in order to maintain a flat consumption path, avoiding sharp variations. Therefore, instead of expecting a subsequent raise on aggregate consumption in a financial market boom scenario, when returns are high, there is an anticipation of this consumption growth. That way, the consumption-wealth ratio may carry information about the future dynamics of excess returns.

Despite the strong empirical evidence provided by Lettau and Ludvigson (2001) ensuring the forecasting power of consumption-wealth ratio over excess stock returns on U.S. market, there was practically no evolution about this issue in further work. Ioannidis et al. (2006), Tsuji (2009) and Gao and Huang (2008) extended the analysis to other countries, following the methodology proposed by Lettau and Ludvigson (2001) to estimate the consumption-wealth ratio and explain either future stock returns or the cross-section of stock returns. Nitschka (2010) have also applied the same estimation method, but used the consumption-wealth ratio of U.S. as a predictor of foreign stock returns, from an American's investor point of view. Most importantly, in all works that include more than one country, the analysis was done separately for each country through time series estimations.

In this work, we take a step forward and study the forecasting relationship between consumption-wealth ratio and excess stock returns through a panel approach. Working with panel data may sometimes change the results derived from a time-series framework due to aggregation bias, just as the case of validity of permanent income hypothesis conditional on consumption liquidity constraints (Zeldes, 1989; Runkle, 1991). Moreover, the panel structure allows us to study a much broader framework, in which we check the theory for several countries together, instead of isolated cases. It is well known that

panel-based tests, such as unit root and cointegration tests, have higher power than tests based on individual time series. With this in mind, using G7's quarterly aggregate and financial data, we verify if consumption-wealth ratio is indeed a strong predictor of future excess stock returns.

After checking the cointegrating relationship among consumption, asset wealth and labor income with a panel version of Johansen (1991) test, we estimate the error correction term of a single vector error correction (VEC) for the entire panel, with consumption, asset wealth and labor income as endogenous variables. The estimated error correction term is what we call  $\widehat{cay}$ , which represents the estimated consumption-wealth ratio. Alternatively, we also compute seven different VEC's for each country, obtaining one specific cointegrating vector for each one of them, which we use to build a  $\widehat{cay}_h$  with heterogeneous parameters and compare its performance on forecasting returns with the performance of the  $cay$  estimated from the single cointegrating vector.

Next, we make several forecasting regressions to investigate the power of  $\widehat{cay}$  and  $\widehat{cay}_h$  as predictors for short and long-term excess stock returns. We find that  $\widehat{cay}_h$  have no power on predicting returns, in contrast to  $\widehat{cay}$ , which forecasting power increases over the time horizon. We also include in these regressions some financial variables widely used to predict stock returns. The results indicate that  $\widehat{cay}$  is the sole robust and strong predictor of future excess returns, but only for two years onward. Non of the predictive variables has shown any capacity of predicting one-quarter-ahead returns.

The remainder of this work proceeds as follows. The next section presents a brief review of the theoretical framework which establishes the relationship between consumption-wealth ratio and expected stock returns. In Section 2, we thoroughly detail the aggregate and financial data that we use to construct our panel. Section 3 shows the VEC estimates from the cointegrating relation among consumption, asset wealth and labor income and specifies how we build the estimated  $cay$ . Section 4 reports the results of forecasting regressions over several time horizons to investigate the predictive power of  $cay$  and some financial variables widely used to forecast stock returns. In Section 5, we re-estimate the forecasting regressions using a different method to check the robustness of the previous results. Finally, on Section 6, we perform out-of-sample forecasts and compare the MSE of models that include  $\widehat{cay}$  with the ones that do not, in order to see if this variable carries significant information about future excess returns out of sample as well.



## 2 Theoretical Framework

To settle the link between consumption-wealth ratio and expected stock returns, consider a representative consumer who invests his total wealth, receiving a time-varying return. Let  $W_t$  and  $C_t$  be the aggregate wealth and aggregate consumption in period  $t$ , respectively.  $R_{w,t+1}$  is the net return on aggregate invested wealth. The intertemporal budget constraint faced by this agent is:

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

To deal with this expression, Campbell and Mankiw (1989) suggest log-linearizing it, obtaining

$$\Delta w_{t+1} \approx r_{w,t+1} + (1 - 1/\rho_w)(c_t - w_t) + k_1, \quad (2)$$

where the lower case letters are used to denote the logs of the corresponding variables,  $r_{w,t+1} \equiv \log(1 + R)$ ,  $\rho_w$  is the steady-state proportion of investment on wealth and  $k_1$  is a constant.

If the consumption-wealth ratio is stationary, it is possible to solve this equation forward. Thus, taking the conditional expectation and assuming that the transversality condition

$\lim_{i \rightarrow \infty} E_t[\rho_w^i (c_{t+i} - w_{t+i})] = 0$  holds, the log consumption-wealth may be written as

$$c_t - w_t = E_t \sum_{i=1}^{\infty} \rho_w^i (r_{w,t+i} - \Delta c_{t+i}) + k_2 \quad (3)$$

which means that the return to wealth or the consumption growth or both could be predicted by consumption-wealth ratio.

Defining aggregate wealth as asset wealth plus human capital  $W_t = A_t + H_t$ , the log aggregate wealth may be approximated as

$$w_t \approx \gamma a_t + (1 - \gamma)h_t + k_3, \quad (4)$$

where  $\gamma$  is the average share of asset holdings in total wealth. Furthermore, Campbell (1996) shows that the return to aggregate wealth, which is given by

$$1 + R_{w,t} = \gamma_t(1 + R_{a,t}) + (1 - \gamma_t)(1 + R_{h,t}), \quad (5)$$

may be log-linearized to get to a tractable intertemporal model with constant coefficients:

$$r_{w,t} \approx \gamma r_{a,t} + (1 - \gamma) r_{h,t} + k_4. \quad (6)$$

Substituting (4) and (6) into (3), gives

$$c_t - \gamma a_t - (1 - \gamma) h_t = E_t \sum_{i=1}^{\infty} \rho_w^i [\gamma r_{a,t+i} + (1 - \gamma) r_{h,t+i} - \Delta c_{t+i}] + k_5. \quad (7)$$

Unfortunately, as noted by Campbell, human capital is not directly observable. What we do observe is labor income, which can be interpreted as the dividend on human wealth, implying that

$$(1 + R_{h,t+1}) = \frac{(H_{t+1} + Y_{t+1})}{H_t}. \quad (8)$$

Once more, log-linearizing this expression, we obtain

$$r_{h,t+1} \approx \rho_h h_{t+1} + (1 - \rho_h) y_{t+1} - h_t + k_6, \quad (9)$$

where  $\rho_h$  is the steady-state proportion  $H/(H + Y)$ . Solving it forward, taking the expectation and imposing that  $\lim_{i \rightarrow \infty} E_t[\rho_h^i (h_{t+i} - y_{t+i})] = 0$ , the log human capital can be described as

$$h_t = y_t + E_t \sum_{i=1}^{\infty} \rho_h^i (\Delta y_{t+i} - r_{h,t+i}) + k_7. \quad (10)$$

Lettau and Ludvigson (2001) show that the nonstationary component of human capital is captured by labor income, implying that  $h_t = \kappa + y_t + \mu_t$ , where  $\kappa$  is a constant. It is easy to see from (10) that  $\mu_t = E_t \sum_{i=1}^{\infty} \rho_h^i (\Delta y_{t+i} - r_{h,t+i})$ . This term is a stationary random variable, since we are assuming that  $\Delta y_t$  is stationary - labor income has a unit root - and that the return on human wealth is practically constant.

Replacing the log of human wealth in expression (7) by the one obtained in (10), it is possible to rewrite the log consumption-wealth ratio in terms of observable variables:

$$cay_t = c_t - \gamma a_t - (1 - \gamma) y_t \quad (11)$$

$$= E_t \sum_{i=1}^{\infty} \rho_w^i [\gamma r_{a,t+i} + (1 - \gamma) r_{h,t+i} - \Delta c_{t+i}] + (1 - \gamma) \mu_t + k_8. \quad (12)$$

Under the assumption that  $r_{w,t}$ ,  $\Delta c_t$  and  $\Delta y_t$  are stationary<sup>1</sup>, equations (11) and (12) imply

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<sup>1</sup>We test the evidence of unit root process in consumption and labor income in our panel data. Both don't reject at 5% significance level the null hypothesis of unit root, including individual effects and individual

that  $c_t$ ,  $a_t$  and  $y_t$  are cointegrated and  $c_t - \gamma a_t - (1 - \gamma)y_t$  is the cointegrating residual labelled as  $cay_t$ , where  $(1, -\gamma, -(1 - \gamma))$  is the cointegrating vector (Lettau and Ludvigson, 2004). Besides, according to (11) and (12) we may say that  $cay_t$  Granger-causes the right-hand term in brackets. Therefore, provided that the expected future returns on human capital and consumption growth are not too variable, movements on  $cay_t$  should forecast changes in asset returns<sup>2</sup>,  $\sum_{i=1}^H r_{a,t+i}$ ,  $H = 1, 2, \dots, \infty$ .

This result is by and large consistent with a wide range of forward-looking models of investor behavior, where the agents, disliking sharp fluctuations on consumption, will attempt to smooth out transitory movements in asset wealth due to variations in expected asset returns. For instance, when higher returns are expected in the future, the forward-looking investors will currently increase their consumption out of their asset wealth and labor income, rising consumption above its common trend with those variables. Summing up, the detachment of consumption from its shared trend with asset wealth and labor income is likely to be a predictor of stock returns. Our work here is to estimate  $cay$  using consumption, labor income and asset holdings data, and through a panel approach to verify whether this estimated  $cay$  is a strong predictor of real returns and excess returns on stock indexes.

### 3 Aggregate and Financial Data

We work with a typical panel of macroeconomic data, which has a small individual dimension and a large time dimension. More specifically, we analyze an unbalanced panel for G7's countries<sup>3</sup>: Canada, France, Germany, Italy, Japan, United Kingdom and United States. All aggregate variables are quarterly, seasonally adjusted, per capita, measured in 2010 country's own currency. To deflate data we use the CPI from International Financial Statistics (IFS), the FMI's database, and for quarterly population we make an interpolation on annual data provided by OCDE.

The consumption data is private final consumption expenditure from National Accounts Statistics of OCDE's database. Labor income is represented by compensation of employees and provided by Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis, but the original source is OCDE as well. Asset holdings data was taken separately from each country's central banks. As mentioned, the panel is un-

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linear trends.

<sup>2</sup>Lettau and Ludvigson (2001) find that  $cay_t$  is a strong predictor of excess returns on aggregate US stock market indexes for both short and long run.

<sup>3</sup>The reason for choosing G7 is the lack of data availability for other countries in quarterly frequency, specially of households asset wealth.

balanced, thus the length of period is different for each country. More specifically, the length of period for all aggregate data is given by the length of period observed for asset holdings, once there are less observations for this variable than for consumption and income. Therefore, Table 1 specifies the sources, the kind of data used as asset wealth and the length of period for each country.

Table 1: Data Sources

Canada (1990Q1 - 2014Q1)	CANSIM, Statistics Canada: Net worth of households and non-profit institutions serving households (NPISH)
France (1996Q1 - 2014Q1)	Webstat, Banque de France: Net financial assets of households and NPISH
Germany (1991Q1 - 2014Q1)	Deutsche Bundesbank: Financial Asset of households and NPISH
Italy (1995Q1 - 2014Q1)	BDS, Banca D'Italia: Total financial instruments held by households and NPISH
Japan (1997Q4 - 2014Q1)	Bank of Japan: Total assets of households
United Kingdom (1997Q1 - 2014Q1)	Bank of England: Financial assets of households and NPISH
United States (1981Q1 - 2014Q1)	Board of Governors of the Federal Reserve System: Net worth of households and NPISH

The main financial data are real returns and excess returns on stock indexes. In order to obtain the log of real returns  $r_t$ , we take for each country the quarterly closing prices, adjusted for dividends, of the stock indexes provided by Bloomberg, deflate them using the seasonally adjusted CPI from IFS, divide period  $t$  by period  $t - 1$  values and take the log. The stock indexes used are S&P/TSX composite index for Canada, CAC 40 for France, DAX for Germany, FTSEMIB for Italy, Nikkei 225 for Japan, FTSE 100 for United Kingdom and S&P 500 for United States. To obtain quarterly log of excess returns  $r_t - r_{f,t}$ , we need to specify the risk-free rate  $r_{f,t}$ . The raw data is the percent per annum treasury bill rate from government securities for each country, taken from IFS. To get to the quarterly log of real return on the T-bill, we sum a unit to the percent rate, convert the annual returns into quarterly returns, deflate them using a seasonally adjusted inflation rate from the CPI and take the log.

Additionally, we consider some other financial variables such as dividend yield, payout ratio and relative bill rate, in order to extend our analysis and compare the predictive

power between *cay* and these variables. Let  $d-p$  denote the dividend yield, where  $d$  is the log of quarterly dividends per share and  $p$  is the log of the stock index. Since Campbell and Shiller (1988), this variable has been widely used to forecast excess returns<sup>4</sup>, specially for long horizons. Following Lamont (1998), the payout ratio is represented by  $d - e$ , where  $e$  is the log of quarterly earnings per share. As well as the stock index, both dividends per share and earnings per share are provided by Bloomberg. Finally, we build the relative bill rate *RREL* subtracting from the T-bill rate its 12-month backward moving average, a method suggested by Hodrick (1992). For now on, when we refer to any of this variables, aggregate or financial, we are already considering them in logs.

## 4 Estimating *cay*

Before estimating *cay*, the cointegrating residual of the shared trend in consumption, labor income and asset wealth, we test whether each variable passes a unit root test, since we are assuming a cointegrating process between these variables. Therefore, we perform a panel unit root test proposed by Maddala and Wu (1999), which consists in a Fisher (1932) test<sup>5</sup> that combine the significance levels from individual unit root tests, such as Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF), to derive a panel-specific result. Thus we test for unit root in level for each variable, including in the test equation individual intercepts and individual trends for each country. For all three variables in both tests, PP and ADF, the null hypothesis of presence of unit root is not rejected at a ten percent significance level<sup>6</sup>, which is a good evidence of each process being integrated.

Hence, we conduct another Fisher-type test also suggested by Maddala and Wu (1999) using a Johansen (1991) procedure to determine the number of cointegrating relations among those three variables in the panel. The results summarized on Table 2 strongly indicate that there is indeed a single cointegrating vector for consumption, asset wealth and labor income.

Once the presence of a cointegrating vector is supported by these results, the next step is to estimate the parameters of this vector, which we do in two separate ways. On the first estimation, we make a single Vector Error Correction (VEC) for the entire panel, assuming homogeneity in the cointegrating parameters. On the second one, we make

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<sup>4</sup>Campbell and Shiller (1988) show that the log dividend-price ratio may be written as  $d_t - p_t = E_t \sum_{j=1}^{\infty} \rho_a^j (r_{a,t+j} - \Delta d_{t+j})$ , which means that if the dividend-price ratio is high, agents must be expecting either high future asset returns or low dividend growth rates.

<sup>5</sup>We choose the Fisher test due to the structure of our data. The asymptotic validity for this test depend on  $T$  going to infinity, while for other tests, depend on  $N$  going to infinity.

<sup>6</sup>Probabilities for Fisher test are computed using asymptotic  $\chi^2$  distribution.

Table 2: Johansen Fisher Panel Cointegrating Test

Hypothesized Num. of Coint.	Fisher Stat. Trace Test	P- value*	Fisher Stat. Max-Eigen Test	P- value*
None	40.28	0.0002	36.84	0.0008
At most 1	16.56	0.2805	10.77	0.7044
At most 2	28.45	0.0124	28.45	0.0124

This table reports the panel cointegration test on consumption, asset wealth and income pooled series, assuming that there is a linear deterministic trend in data, including an intercept in the cointegration equation, and using one lag in difference (two lags in level) on the VAR tested.

\*Probabilities are computed using asymptotic  $\chi^2$  distribution.

seven VEC's, one for each country, taking into account the presence of heterogeneity in the cointegrating parameters. On both procedures, we include consumption, asset wealth and labor income as endogenous variables and make the same assumptions we have made for the panel cointegration test - linear deterministic trend in data, an intercept in the cointegration equation and one lag in difference for the endogenous variables -, imposing one cointegrating relationship among the three variables.

On the first VEC estimation, we assume that the cointegration structure is given by  $c_{i,t} = \beta_a a_{i,t} + \beta_y y_{i,t}$  disregarding the constant included in the cointegrating equation, where  $\beta_a$  and  $\beta_y$  are the cointegrating parameters to be estimated, and  $c_{i,t}$ ,  $a_{i,t}$  and  $y_{i,t}$  are consumption, asset wealth and labor income for each country in each period, respectively. Note here that the homogeneity is captured by the invariant parameters  $\beta_a$  and  $\beta_y$ . We report in Table 3 the estimates of this parameters for the panel, obtained on the first part of the VEC<sup>7</sup> estimation and omit the rest of the VEC output.

With the parameters estimates we can easily construct the variable  $\widehat{cay}_t$ , which is the error correction term in one lag forward (current time) and, ignoring the constant, is given by  $\widehat{cay}_{i,t} = c_{i,t} - \widehat{\beta}_a a_{i,t} - \widehat{\beta}_y y_{i,t}$ . Lettau and Ludvigson (2004) argument that this cointegration residual must be covariance stationary, instead of stationary around a deterministic trend. If the contrary was true, it would imply that either consumption or aggregate

<sup>7</sup>With one lag in difference, linear trend and one cointegrating relationship, we estimate the following VEC through a pooled OLS.

$$\begin{aligned}\Delta c_{i,t} &= \alpha_1(c_{i,t-1} - \beta_a a_{i,t-1} - \beta_y y_{i,t-1} - \mu) + \gamma_{11}\Delta c_{i,t-1} + \gamma_{12}\Delta a_{i,t-1} + \gamma_{13}\Delta y_{i,t-1} + \eta_1 + \epsilon_{1,i,t} \\ \Delta a_{i,t} &= \alpha_2(c_{i,t-1} - \beta_a a_{i,t-1} - \beta_y y_{i,t-1} - \mu) + \gamma_{21}\Delta c_{i,t-1} + \gamma_{22}\Delta a_{i,t-1} + \gamma_{23}\Delta y_{i,t-1} + \eta_2 + \epsilon_{2,i,t} \\ \Delta y_{i,t} &= \alpha_3(c_{i,t-1} - \beta_a a_{i,t-1} - \beta_y y_{i,t-1} - \mu) + \gamma_{31}\Delta c_{i,t-1} + \gamma_{32}\Delta a_{i,t-1} + \gamma_{33}\Delta y_{i,t-1} + \eta_3 + \epsilon_{3,i,t}\end{aligned}$$

The right-hand side variable in parenthesis is the error correction term. In long run equilibrium, this term should be zero. However, if any variable of this term deviates from the long run equilibrium, the error correction term would be nonzero and the other variables would adjust to restore the equilibrium relation. The coefficients  $\alpha$  measure the speed of adjustment of each endogenous variable towards the equilibrium (Engle and Granger, 1987).

Table 3: Panel Cointegrating Vector Estimates

One Cointegrating Relationship	Estimated Parameters
Consumption	1.000000
Labor Income	0.640654 (0.36747)
Asset Wealth	-1.458177 (0.42920)
Constant	2.096325

This table presents the estimated parameters of the cointegrating vector  $(1, -\hat{\beta}_y, -\hat{\beta}_a)$ , with respective standard errors in parenthesis. On the specification, we assume there is a linear deterministic trend in data, including an intercept in the cointegrating equation, use one lag in difference and impose one cointegrating relationship. 594 observations are included in this estimation after adjustments. Both estimates are statistically significant at a two-sided 10% level, computed using asymptotic Normal distribution.

wealth would eventually become an infinitesimal fraction of the other, violating the budget set used as starting point. Therefore, as a closure for this estimation, we check if  $\widehat{cay}$  is stationary by performing the Fisher-ADF and PP panel unit root tests, including individual intercepts but not any trends. We obtain p-values of 2.67% and 6.05% for ADF and PP Fisher tests respectively, confirming that  $\widehat{cay}$  is indeed stationary.

Then we proceed to the second VEC estimation, which has an heterogeneous cointegration structure, *i.e.*  $c_{i,t} = \beta_{a,i}a_{i,t} + \beta_{y,i}y_{i,t}$ , ignoring the cointegration constant once more. Thus, to estimate the cointegrating parameters, we perform separated VEC's for each country (not reported here). The estimated heterogeneous  $cay$  is then given by  $\widehat{cay}_{h,i,t} = c_{i,t} - \hat{\beta}_{a,i}a_{i,t} - \hat{\beta}_{y,i}y_{i,t}$ . Then, we make the same panel unit root tests we have made for  $\widehat{cay}$  to check the stationarity of  $\widehat{cay}_h$ . The presence of unit root is strongly rejected on both tests, such that even with different cointegrating parameters for each country, the variable  $\widehat{cay}_h$  can be considered stationary on the panel as a whole.

## 5 Forecasting Stock Returns

In this section, we focus on verifying the power of  $cay$  as a predictive variable for real returns and excess returns in a panel structure. The intuition here is that variations on  $cay$  should precede variations on stock returns, since theoretically, the forward-looking investor would increase or decrease current consumption with regard to his wealth, according to future fluctuations on expected stock returns.

Although we restrict our analysis to a panel approach, it is interesting to illustrate the relationship between  $cay$  and stock returns and to see how these variables evolve through time, which has to be done separately for each country. For this purpose, we make individual graphs with both log excess returns - returns on stock indexes minus the return on T-bill - and  $\widehat{cay}$  normalized series, displayed in Figure 1.

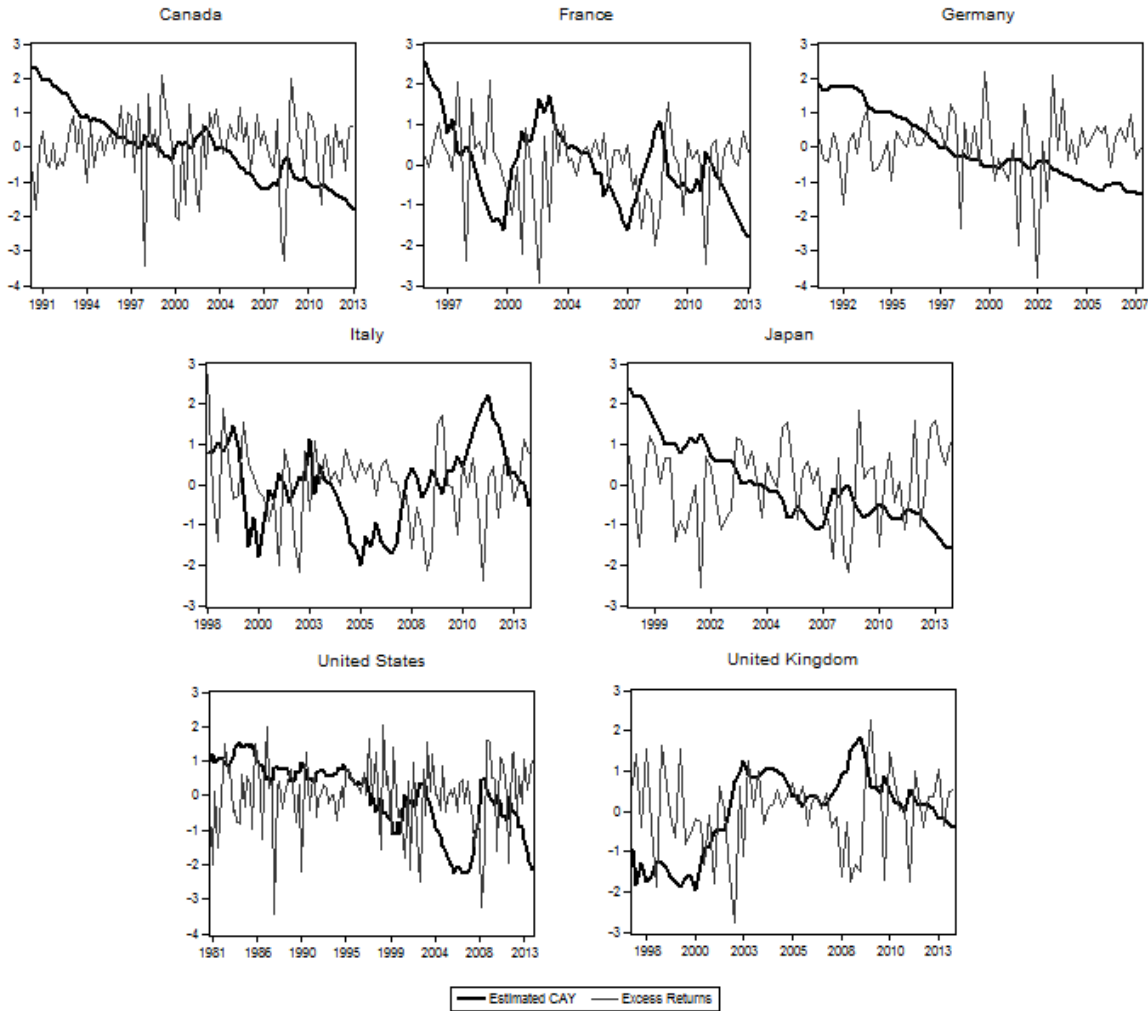


Figure 1: Excess Returns and Estimated  $cay$

This figure shows, for some countries such as France, Italy, United Kingdom and USA, sharp variations of  $\widehat{cay}$  preceding spikes in excess returns, for both positive and negative fluctuations, specially after year 2000. It is also interesting to notice that recently most countries have presented a pronounced decreasing in  $\widehat{cay}$ . Thus, if this variable is indeed a good predictor of excess returns, we should expect a decline in excess return's path in the next few quarters of 2014 and 2015.



Another feature of  $\widehat{cay}$ , which can be noticed in some graphs of Figure 1, is that by and large this variable is counter-cyclical. In fact, when we make a panel regression of consumption growth on contemporaneous  $\widehat{cay}$  controlling for cross section fixed effects, we obtain a coefficient of  $-0.005181$  statistically significant at 1% level. This is consistent with a framework studied by Campbell and Cochrane (1999), in which booms, characterized by high income growth, are periods when consumption rises above habit, inducing a decline in risk aversion. This decline in risk aversion in turn leads to greater demand for risky assets, which reinforces its increase caused by the high income growth. Thus, despite the increase in consumption pushing  $\widehat{cay}$  upwards, the growth on asset wealth overcomes this effect, causing a decline on consumption wealth ratio. For instance, in all countries in Figure 1 there was a remarkable increase of  $\widehat{cay}$  from 2007 to 2008, when the financial crisis was at its peak.

We now turn our attention back to the forecasting power of  $cay$  over the panel stock returns data. First, we make some one-quarter-ahead regressions with real returns and excess returns as dependent variables and both  $\widehat{cay}$  and  $\widehat{cay}_h$  plus other financial variables as regressors, including cross-section fixed effects. In all of these regressions, we make White cross-section corrections<sup>8</sup> to the standard errors, obtaining estimators robust to cross-section heteroskedasticity and cross-section correlation. The estimation results are reported on Table 4.

Regressions with one-period lag of the dependent variable as a regressor are also computed on Table 4. It is well known that the LSDV (least squares dummy variable) - the fixed effects model we have used in the previous regressions - with a lagged dependent variable generates biased estimates when the time dimension of the panel is small (Judson and Owen, 1999). Nevertheless, Nickell (1981) derives an expression for the bias showing that it goes to zero when  $T$  approaches infinity. Thus for our purposes LSDV continues performing well, considering that the number of periods in our data is sufficiently large<sup>9</sup>. We use the White cross-section correction in these regressions as well.

The results in Table 4 show that, at this time horizon length - just one quarter ahead - both  $\widehat{cay}$  and  $\widehat{cay}_h$  are not able to predict stock returns, since they are not statistically

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<sup>8</sup>This method considers the pool regression as multivariate regressions with one equation for each cross-section, and computes for the system of equations robust standard errors. The robust variance matrix estimator is given by  $Avar(\hat{\beta}) \equiv \left( \frac{NT}{NT-K} \right) (\sum_t X_t' X_t)^{-1} (\sum_t X_t' \hat{\epsilon}_t \hat{\epsilon}_t' X_t) (\sum_t X_t' X_t)^{-1}$ , where  $NT$  is the total number of stacked observations and  $K$  is the total number of estimated parameters. See Arellano (1987) and Wooldridge (2010). We choose this estimator because of its consistency for panels with large  $T$  and fixed  $N$ .

<sup>9</sup>We work with an unbalanced panel in which the time dimension goes from 66 to 134 observations. Most of researches consider  $T \geq 30$  large enough.

Table 4: Forecasting Stock Returns

Panel A: Real Returns, $r_{t+1}$									
#	Total Obs	Constant	$lag$	$\widehat{cay}_t$	$\widehat{cay}_{ht}$	$d_t - p_t$	$d_t - e_t$	$RREL_t$	$\bar{R}^2$
1	584	0.0065 (0.0098)		0.0326 (0.0240)					-0.0045
2	433	0.0924 (0.0917)	0.1596 (0.1091)	0.0369 (0.0320)		0.0239 (0.0252)	-0.0042 (0.0141)	3.7276 (2.9619)	0.0248
3	584	0.0065 (0.0097)			0.0708 (0.0718)				-0.0060
4	450	0.1130 (0.0951)	0.1636 (0.1160)		-0.0025 (0.1193)	0.0311 (0.0261)	-0.0094 (0.0151)	3.5497 (2.9224)	0.0234
Panel B: Excess Returns, $r_{t+1} - r_{f,t+1}$									
#	Total Obs.	Constant	$lag$	$\widehat{cay}_t$	$\widehat{cay}_{ht}$	$d_t - p_t$	$d_t - e_t$	$RREL_t$	$\bar{R}^2$
5	559	0.0033 (0.0097)		0.0214 (0.0244)					-0.0069
6	432	0.0943 (0.0932)	0.1605 (0.1100)	0.0317 (0.0314)		0.0249 (0.0255)	-0.0042 (0.0142)	3.3996 (2.9338)	0.0209
7	559	0.0034 (0.0096)			0.0996 (0.0732)				-0.0059
8	449	0.1179 (0.0965)	0.1667 (0.1169)		0.0311 (0.1214)	0.0328 (0.0264)	-0.0096 (0.0151)	3.2541 (2.9118)	0.0201

This table shows some regressions of one-step-forward returns forecasts. Total Obs. refers to the total panel unbalanced observations included after adjustments, and  $lag$  is the one-lag backward dependent variable, *i.e.* on  $t$ , used as a regressor. The Constant is an overall fixed effects mean and we omit the specific fixed effects of each country. The last column reports the adjusted  $\bar{R}^2$ . White cross-section corrected standard errors appear in parenthesis.

significant. The same is true for the other financial variables included in the regressions. It is also worth noting that the  $\bar{R}^2$  are extremely low, specially on the regressions with either  $\widehat{cay}$  or  $\widehat{cay}_h$  as a single regressor.

Nevertheless, it may be inferred from the benchmark model (12) that  $cay$  should track longer-term tendencies in asset returns rather than provide accurate short-term forecasts of movements in this market. Indeed, for some countries in Figure 1 there are several episodes that fluctuations in  $\widehat{cay}$  have persisted for many periods, supporting the idea of long horizon responsiveness of stock returns due to changes in  $cay$ .

Furthermore, the model in (12) indicates that  $cay$  could be a good predictor of consumption growth as well as of asset returns. Thus we extend our analysis by making forecasts regressions using either accumulated consumption growth or accumulated excess returns as dependent variables to see the impact of  $cay$  on these variables over longer horizons. Table 5 presents the results over horizons spanning 1 to 24 quarters of regres-

sions of accumulated consumption growth and accumulated excess returns on  $\widehat{cay}$ ,  $\widehat{cay}_h$  and the financial variables, also estimated by LSDV.

Table 5: Long-Horizon Regressions

#	Reg.	Forecast Horizon $H$							
		1	2	3	4	8	12	16	24
Panel A: Consumption Growth, $\sum_{i=1}^H \Delta c_{t+i}$									
1	$\widehat{cay}_t$	<b>-0.0047*</b> (0.0026) [0.0267]	<b>-0.0069*</b> (0.0036) [0.0454]	<b>-0.0080*</b> (0.0043) [0.0580]	-0.0072 (0.0052) [0.0660]	0.0014 (0.0107) [0.0962]	0.0091 (0.0146) [0.1218]	0.0141 (0.0180) [0.1540]	0.0131 (0.0208) [0.2407]
2	$\widehat{cay}_h$	0.0040 (0.0077) [0.0163]	0.0073 (0.0125) [0.0363]	0.0081 (0.0169) [0.0512]	-0.0008 (0.0186) [0.0621]	-0.0290 (0.0285) [0.0982]	-0.0425 (0.0350) [0.1229]	-0.0597 (0.037802) [0.1552]	<b>-0.1312**</b> (0.0575) [0.2490]
Panel B: Excess Stock Returns, $\sum_{i=1}^H (r_{t+i} - r_{f,t+i})$									
3	$\widehat{cay}_t$	0.0214 (0.0244) [-0.0069]	<b>0.0669*</b> (0.0392) [0.0034]	<b>0.1331***</b> (0.0503) [0.0175]	<b>0.2302***</b> (0.0642) [0.0438]	<b>0.5800***</b> (0.1308) [0.0809]	<b>0.9233***</b> (0.1521) [0.1639]	<b>1.1272***</b> (0.1294) [0.2379]	<b>1.2443***</b> (0.1312) [0.3824]
4	$\widehat{cay}_h$	0.0996 (0.0732) [-0.0059]	0.1534 (0.1032) [0.0010]	0.1857 (0.1290) [0.0079]	0.2003 (0.1495) [0.0145]	<b>0.2902**</b> (0.1371) [0.0526]	0.2672 (0.1967) [0.1019]	-0.0323 (0.2269) [0.1560]	<b>-0.7786***</b> (0.2311) [0.3652]
5	$d_t - p_t$	0.0117 (0.0201) [-0.0072]	0.0348 (0.0302) [0.0031]	0.055985 (0.0351) [0.0134]	<b>0.0657**</b> (0.0304) [0.0214]	<b>0.1585***</b> (0.0596) [0.0429]	<b>0.1911**</b> (0.0787) [0.0783]	<b>0.2802***</b> (0.0703) [0.1537]	<b>0.3126***</b> (0.0783) [0.2783]
6	$d_t - e_t$	0.0009 (0.0138) [-0.0077]	-0.0087 (0.0306) [-0.0035]	-0.020391 (0.0397) [0.0047]	<b>0.0391**</b> (0.0180) [0.0251]	<b>0.0941***</b> (0.0360) [0.0554]	<b>0.1445***</b> (0.0393) [0.1202]	<b>0.3224***</b> (0.0360) [0.3018]	<b>0.2911***</b> (0.0420) [0.3788]
7	$RREL_t$	0.5207 (2.1074) [-0.0041]	3.6982 (2.7613) [0.0086]	<b>6.0328*</b> (3.1641) [0.0219]	-3.5101 (2.7862) [0.0149]	-4.7525 (5.2727) [0.0243]	<b>-13.174**</b> (5.7636) [0.0685]	<b>-13.635**</b> (6.8009) [0.1038]	-7.1375 (8.0032) [0.1633]
8	$\widehat{cay}_t$	0.0179 (0.0312)	0.0663 (0.0443)	<b>0.1404***</b> (0.0523)	<b>0.2311***</b> (0.0808)	<b>0.6340***</b> (0.1524)	<b>1.0124***</b> (0.1489)	<b>1.0701***</b> (0.1413)	<b>0.8687***</b> (0.1695)
	$d_t - p_t$	0.0173 (0.0267)	0.0524 (0.0438)	0.0814 (0.0516)	0.0468 (0.0363)	0.0859 (0.0740)	0.0232 (0.0828)	-0.0213 (0.0758)	0.055328 (0.1126)
	$d_t - e_t$	-0.0016 (0.0146)	-0.0168 (0.0332)	-0.0368 (0.0429)	0.0181 (0.0189)	0.0489 (0.0416)	<b>0.1011**</b> (0.0431)	<b>0.2959***</b> (0.0389)	<b>0.2569***</b> (0.0499)
	$RREL_t$	2.4396 (3.3107) [-0.0002]	<b>8.6521**</b> (3.9507) [0.0572]	<b>12.686***</b> (3.9608) [0.1012]	<b>-6.2927**</b> (3.1389) [0.0740]	<b>-9.8741*</b> (5.3831) [0.1366]	<b>-17.736***</b> (5.2806) [0.2733]	<b>-14.923***</b> (5.0180) [0.4733]	<b>-16.368*</b> (9.1167) [0.5058]

This table reports estimates from the long-horizon regressions of accumulated consumption growth and accumulated excess stock returns on  $\widehat{cay}$ ,  $\widehat{cay}_h$  and the financial variables. We omit the constants of all regressions. Reg. indicates the regressors included in each regression. The forecast horizon length is in quarters. White cross-section corrected standard errors are displayed in parenthesis and  $\bar{R}^2$  are in brackets at the end of each regression. Statistics with (\*) are significant at 10% level, (\*\*) at 5% and (\*\*\*) at 1%.

From Table 5 we may conclude that as a whole,  $\widehat{cay}$  is a much better predictor for both consumption growth and excess returns than  $\widehat{cay}_h$ . This means that if one wants to make forecasts for any of those two variables in a panel, it is better to estimate a single cointegrating vector for the entire panel and build a  $cay$  with homogeneous coefficients rather than estimate one cointegrating vector for each country and make an heterogeneous  $cay$ .

It is also clear that, comparing Table 4 with Table 5,  $\widehat{cay}$  has a better performance on predicting excess returns over longer horizons than just one period ahead. In fact, regressions 1 and 3 of Table 5 show that for short horizons,  $\widehat{cay}$  is more likely to predict

consumption growth, and for longer periods, its forecasting power is greater on excess returns. Thus we can see a strong persistence of  $\widehat{cay}$  through time with an increasing of its forecasting power.

To check the effectiveness of  $\widehat{cay}$  as a predictor for excess returns, we add the financial variables on the longer-term regressions. Row 5 reports regressions using the dividend yield as the sole forecasting variable and, considering the  $\bar{R}^2$  of this regression set against  $\widehat{cay}$ 's, we may say that  $\widehat{cay}$  is a much better predictor of excess returns than  $d - p$ , ignoring the first period when both variables are not statistically significant. The same is true for the payout ratio, on 6. On the other hand, comparing the  $\bar{R}^2$  of rows 3 and 7 we observe a better fit with  $RREL$  as a predictor up to one year and with  $\widehat{cay}$  so on.

Finally, on Row 8 we make the long-horizon regressions on  $\widehat{cay}$  and all financial variables. It is interesting to notice that the forecasting power of dividend yield has vanished when we use all variables together. This means that  $\widehat{cay}$  and  $RREL$  capture all the effect of  $d - p$  over accumulated excess returns. From 3 to 8,  $\widehat{cay}$ 's coefficients stay almost the same, so that it must not be considered replaceable by any financial variables. When comparing rows 7 and 8 there is a considerable change in  $RREL$ 's coefficients. This is maybe due to an omitted variable error in 7, which produces biased estimates. Then, on 8 we remain with  $cay$  and  $RREL$  as stronger predictors of excess returns over three quarters and forth, and for longer horizons - more than three years -, the payout ratio  $d - e$  may be considered a predictor as well. Comparing the  $\bar{R}^2$ 's from rows 3 and 8 we may say that it is worth including the financial variables together with  $\widehat{cay}$  when making forecasting about excess returns.

From the theoretical framework we have seen that  $cay$  should Granger-cause asset returns, once movements on  $cay$  were supposed to precede wealth variations caused by asset returns fluctuations. Therefore, in order to improve our forecasting analysis, we perform Granger causality tests<sup>10</sup> checking if  $\widehat{cay}$  Granger-causes the excess stock returns. Indeed, with a lag length from four onward we reject at 1% the null of  $\widehat{cay}$  does not Granger-cause excess returns. This result is in line with the forecasting outcome from the previous regressions, which indicates that  $\widehat{cay}$  provides statistically significant information about future values of excess returns only after one year.

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<sup>10</sup>The tests consist of running regressions with different lags,  $l$ , of the form

$$(r_t - r_{f,t}) = \alpha_0 + \alpha_1(r_{t-1} - r_{f,t-1}) + \dots + \alpha_l(r_{t-l} - r_{f,t-l}) + \beta_1\widehat{cay}_{t-1} + \dots + \beta_l\widehat{cay}_{t-l} + u_t$$

and checking the F-statistics for the joint hypothesis of  $\beta_1 = \beta_2 = \dots = \beta_l = 0$ .

## 6 Robustness Checks

How robust are these forecasting results? On all previous regressions we have used the White cross-section correction to obtain standard errors robust to cross-section heteroskedasticity and cross-section correlation. This approach however does not take into account any time-series dependence. Therefore, in this section we use another estimation method in order to correct the standard errors for both cross-section and serial correlation and heteroskedasticity.

We begin with a within transformation of the linear unobserved effects model we want to estimate. This transformation is obtained through a time demeaning of the panel equation, removing the individual specific effects (Wooldridge, 2010). Consider the linear model with unobserved effects for  $T$  periods and  $i$  individuals

$$y_{it} = c_i + \mathbf{x}_{it}\boldsymbol{\beta} + u_{it}. \quad (13)$$

Then, by averaging this equation over  $t = 1, \dots, T$ , we get to the cross section equation

$$\bar{y}_i = c_i + \bar{\mathbf{x}}_i\boldsymbol{\beta} + \bar{u}_i, \quad (14)$$

where  $\bar{y}_i = T^{-1} \sum_{t=1}^T y_{it}$ ,  $\bar{\mathbf{x}}_i = T^{-1} \sum_{t=1}^T \mathbf{x}_{it}$  and  $\bar{u}_i = T^{-1} \sum_{t=1}^T u_{it}$ . Subtracting equation (13) from (14) for each  $t$ , we obtain the transformed equation

$$\ddot{y}_{it} = \ddot{\mathbf{x}}_{it}\boldsymbol{\beta} + \ddot{u}_{it}, \quad (15)$$

where  $\ddot{y}_{it} \equiv y_{it} - \bar{y}_i$ ,  $\ddot{\mathbf{x}}_{it} \equiv \mathbf{x}_{it} - \bar{\mathbf{x}}_i$ ,  $\ddot{u}_{it} \equiv u_{it} - \bar{u}_i$  and the specific effects removed. In our case, the dependent variable would be the excess returns and the explanatory variables would be lagged  $\widehat{cay}$  and the lag of the financial variables.

With the fixed effects out of the picture, we follow the example given by Driscoll and Kraay (1998) in which there are cross-sectional and time dependence in the linear model. The procedure consists of taking the cross-sectional average of the variables in the model, which in our case are already time demeaned, reducing the panel to a single time series

$$\frac{1}{N} \sum_{i=1}^N \ddot{y}_{it} = \frac{1}{N} \sum_{i=1}^N \ddot{\mathbf{x}}_{it}\boldsymbol{\beta} + \frac{1}{N} \sum_{i=1}^N \ddot{u}_{it}, \quad (16)$$

$$\tilde{y}_t = \tilde{\mathbf{x}}_t\boldsymbol{\beta} + \tilde{u}_t. \quad (17)$$

Then we apply the Newey and West (1987) consistent covariance matrix estimator<sup>11</sup>, in order to correct heteroskedasticity and serial correlation.

It is worth mentioning that this method comprises a broad class of spatial and temporal dependence, requiring no prior knowledge of the exact form of the serial and cross-unit correlations. Table 6 shows the estimates of the log-term regressions obtained from the procedure described above, which we use to compare with the results of the previous section.

Table 6: Robustness Regressions

#	Reg.	Forecast Horizon $H$							
		1	2	3	4	8	12	16	24
Panel A: Consumption Growth, $\sum_{i=1}^H \Delta c_{t+i}$									
1	$\widehat{cay}_t$	-0.0002 (0.0067) [-0.0034]	0.0029 (0.0128) [-0.0047]	0.0101 (0.0182) [-0.0007]	0.0195 (0.0228) [0.0086]	<b>0.0644*</b> (0.0386) [0.0626]	<b>0.0993*</b> (0.0506) [0.0940]	<b>0.1304**</b> (0.0596) [0.1203]	<b>0.1586**</b> (0.0658) [0.1352]
Panel B: Excess Stock Returns, $\sum_{i=1}^H (r_{t+i} - r_{f,t+i})$									
2	$\widehat{cay}_t$	0.0074 (0.0489) [0.000073]	0.0618 (0.0887) [0.0035]	0.1377 (0.1377) [0.0116]	0.2410 (0.1702) [0.0273]	<b>0.6163**</b> (0.2958) [0.1070]	<b>0.9301**</b> (0.3688) [0.1752]	<b>1.1550***</b> (0.3868) [0.2433]	<b>1.1138***</b> (0.2750) [0.3113]
3	$\widehat{cay}_t$	0.0354 (0.0536)	0.2064 (0.0993)	0.1074 (0.1356)	<b>0.3231*</b> (0.1733)	<b>0.6864**</b> (0.2884)	<b>1.0563***</b> (0.3521)	<b>1.1041**</b> (0.4450)	<b>1.0329**</b> (0.4027)
	$d_t - p_t$	0.0286 (0.0284)	0.0608 (0.0548)	0.0803 (0.0726)	0.0867 (0.0810)	0.0624 (0.1094)	0.0695 (0.1333)	0.0193 (0.1389)	0.0103 (0.1245)
	$d_t - e_t$	-0.0350 (0.0347)	-0.0690 (0.0678)	-0.1004 (0.0785)	-0.1204 (0.0802)	-0.1167 (0.0974)	-0.1305 (0.1272)	0.0686 (0.1269)	0.0684 (0.0934)
	$RREL_t$	-0.5165 (3.8742) [-0.0041]	4.3880 (6.8932) [0.0336]	12.0227 (8.3910) [0.0902]	11.8797 (9.1119) [0.1003]	6.6752 (9.4622) [0.1170]	-9.3486 (10.4292) [0.1937]	-4.0422 (10.6266) [0.2458]	-4.4971 (13.0993) [0.2982]

This table reports estimates from the long-horizon time series regressions of the average accumulated consumption growth and average accumulated excess stock returns on  $\widehat{cay}$ 's and financial variables' averages. There are no the constants on these regressions, since the fixed effects were eliminated after time demeaning. The Newey-West corrected standard errors are displayed in parenthesis and  $\bar{R}^2$  are in brackets at the end of each regression. Statistics with (\*) are significant at 10% level, (\*\*) at 5% and (\*\*\*) at 1%.

Analyzing Table 6, we notice from Rows 1 and 2 that  $\widehat{cay}$  is able to predict both consumption growth and excess returns only in the long run, but its forecasting power is higher for excess returns as well as its impact. Furthermore, when we make the regressions with all variables together,  $\widehat{cay}$  is the sole statistically significant variable.

Considering the accumulated consumption growth, we can see that Panel A has considerably changed from Table 5 to Table 6. On the first,  $\widehat{cay}$  is a statistically significant predictor for consumption growth over short horizons, while on the latter, this variable starts being significant only after two years. Hence, with such different results, there is no confirmation about the robustness of  $\widehat{cay}$  as a consumption growth predictor.

<sup>11</sup>See Driscoll and Kraay (1998) for more details about the consistency of this estimator.

Comparing Row 3 from Table 5 and Row 2 from Table 6, it is clear that  $\widehat{cay}$  may be used as a predictor for excess returns over short horizons only if one is applying the first estimation method - LSDV with White cross-section corrected standard errors. However, over two years, both methods present almost the same results for the impact of  $\widehat{cay}$  over excess returns and for its forecasting power, which supports the robustness of this variable as a predictor for excess returns over higher period lengths.

The last row of both tables show that together with all financial variables,  $\widehat{cay}$  is a robust predictor of excess returns from two years onward, since that their coefficients and significance level present negligible differences. On the other hand, the forecasting power of  $RREL$  and  $d_t - e_t$  have disappeared on the robustness regressions, suggesting that they are not as strong as  $\widehat{cay}$  for predicting returns. In addition and in contrast to Table 5, when comparing the  $\bar{R}^2$ 's from Rows 2 and 3 of Table 6 we see that the financial variables can be considered disposable as predictors for excess returns.

We may conclude from this robustness analysis<sup>12</sup> and from the long-term regressions of the last section that  $\widehat{cay}$  should in fact be considered a strong predictor for future excess stock returns over long horizons - more than one year. It is the only predicting variable that survived our robustness tests. In addition, scanning the  $\bar{R}^2$ 's from Tables 5 and 6 we may say that both estimation methods have almost the same forecasting power for excess returns, with respect to  $\widehat{cay}$ , as a whole.

## 7 Out-of-Sample Tests

Several forecasting researches indicate that some variables with strong predictive power in-sample do not necessarily perform out-of-sample forecasts that well. This is probably due to "look-ahead" bias when coefficients are estimated using the full sample. We address this problem by making some nested and non-nested out-of-sample forecast comparisons, analyzing the mean-squared error (MSE) of one-quarter-ahead panel forecasts.

Both nested and non-nested models are first estimated using data from the first quarter of 1981 to the first quarter of 2004 and then recursively re-estimated adding one quarter at a time and calculating one-step-ahead forecasts until the fourth quarter of 2013. In order to remain with just one MSE for the panel, we compute the out-of-sample forecasting error for each country and take the trace of the matrix of cross product of this errors,

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<sup>12</sup>We have also performed this robustness exercise without the within transformation, such that the fixed effects remained in the model when we took the cross-sectional average and the intercept of the time series was an average of this fixed effects. The results present slightly differences on coefficients and  $\bar{R}^2$  and bring about the same conclusions.

obtaining a sum of the MSE's.

We analyze the MSE of models using either  $\widehat{cay}$ , with cointegrating parameters estimated in the full sample, or  $reest \widehat{cay}$ , with the parameters re-estimated every period. The former case gives an idea of the results if one used the existing estimates of the parameters and faced the same distribution of data, while the latter is a more realistic scenario using only data available at the time of forecast.

This exercise is done not only for one-step-forward excess returns ( $r_{t+1} - r_{f,t+1}$ ), but also for two years accumulated excess returns ( $\sum_{i=1}^8 (r_{t+i} - r_{f,t+i})$ ), since the results of the last two sections indicate that in-sample  $\widehat{cay}$  should not be a good predictor one-step-forward but present strong and robust forecasting power two years onward. Therefore, we would be able to evaluate the impact of  $\widehat{cay}$  over the MSE of excess returns with different period lengths.

On the nested regressions, we begin with two parsimonious models, the *lagged benchmark* using just one-period lagged value of excess return as a predictors and the *constant benchmark* with a constant as the sole explanatory variable assuming constant expected returns. Then we make the comparisons by augmenting the benchmarks with the one-period lagged value of  $\widehat{cay}$ . The results of this nested comparisons are presented on Table 7.

Table 7: Out-of-Sample Nested Comparisons

#	Comparison	$MSE_u/MSE_r$	
		$r_{t+1} - r_{f,t+1}$	$\sum_{i=1}^8 (r_{t+i} - r_{f,t+i})$
1	$\widehat{cay}_t$ vs. $r_t - r_{f,t}$	0.9978	0.9893
2	$\widehat{cay}_t$ vs. $const$	0.9981	0.9851
3	$reest \widehat{cay}_t$ vs. $r_t - r_{f,t}$	0.9988	0.9954
4	$reest \widehat{cay}_t$ vs. $const$	0.9980	0.9897

This table shows the results of the nested comparisons, displaying the MSE ratio from the unrestricted model, which includes  $\widehat{cay}$ , over the restricted model with either lagged excess returns ( $r_t - r_{f,t}$ ) or a constant ( $const$ ) as the sole predictor. The first column with values refers to one-quarter-ahead excess returns forecasts and the second one refers to two years accumulated excess returns predictions. The first two rows are computed with  $\widehat{cay}$  estimated from the full sample and the last two with its parameters recursively re-estimated ( $reest \widehat{cay}$ ).

We can see from Table 7 that adding  $\widehat{cay}$  to the benchmark models always decrease the MSE of the regressions, suggesting that this variable improves the forecasts when put together with either a constant or lagged excess returns, regardless of whether the cointegrating coefficients are re-estimated or not. We may say that this improvement is greater over the two years accumulated excess returns, which is consistent with the results from long-term regressions of the previous sections.



The column of one-step-ahead excess returns indicates that  $\widehat{cay}$  and its re-estimated version have almost the same impact over the MSE ratio when added to the constant benchmark and to the lagged benchmark. On the other hand, for two years accumulated excess returns,  $\widehat{cay}$  reduces the MSE by more than the model that uses  $reest \widehat{cay}$ . We can also see from the second column of MSE values that the gains from augmenting the models with both  $\widehat{cay}$ 's are greater on the constant benchmark than on the lagged benchmark.

Next, we extend our analysis by making nonnested forecasts to see if  $\widehat{cay}$  and its re-estimated version as sole predictive variables exhibit more information and smaller MSE relatively to the models with financial variables - dividend yield, payout ratio and the relative bill rate - and lagged excess returns as the sole predictor. The results from nonnested comparisons are given in Table 8.

Table 8: Out-of-Sample Nonnested Comparisons

#	Comparison	$MSE_1/MSE_2$	
		$r_{t+1} - r_{f,t+1}$	$\sum_{i=1}^8 (r_{t+i} - r_{f,t+i})$
1	$\widehat{cay}_t$ vs. $r_t - r_{f,t}$	1.0032	0.9862
2	$\widehat{cay}_t$ vs. $d_t - p_t$	0.9956	0.9938
3	$\widehat{cay}_t$ vs. $d_t - e_t$	0.9822	0.9616
4	$\widehat{cay}_t$ vs. $RREL_t$	0.9863	0.9874
5	$reest \widehat{cay}_t$ vs. $r_t - r_{f,t}$	1.0035	0.9915
6	$reest \widehat{cay}_t$ vs. $d_t - p_t$	0.9959	0.9992
7	$reest \widehat{cay}_t$ vs. $d_t - e_t$	0.9825	0.9668
8	$reest \widehat{cay}_t$ vs. $RREL_t$	0.9866	0.9928

This table reports the results of nonnested comparisons, displaying the MSE ratio from the first model, with either  $\widehat{cay}$  or  $reest \widehat{cay}$  as the sole predictor, over the second model, with financial variables or lagged excess returns. Once more, the first column with values refers to one-quarter-ahead excess returns forecasts and the second one refers to two years accumulated excess returns predictions. The first four rows are computed with  $\widehat{cay}$  estimated from the full sample and the last two with its parameters recursively re-estimated.

Compared to the financial variables,  $\widehat{cay}$  produces superior forecasts regardless of whether its coefficients are re-estimated or whether we want to predict the next quarter or two years accumulated excess returns. The strength of  $\widehat{cay}$  as a predictor may be noticed specially with regard to the payout ratio,  $d - e$ . However, when making forecasts over one quarter ahead, both  $\widehat{cay}$  and  $reest \widehat{cay}$  produce higher MSE's in relation to lagged excess returns.

Except for  $RREL$ , the impact of  $\widehat{cay}$  and  $reest \widehat{cay}$  over the MSE ratio is greater for two years accumulated excess returns. At this time length, the forecasting power of  $\widehat{cay}$  even overcomes the predictive power of lagged excess returns. Moreover, comparing the first four rows with the last four, we see that  $\widehat{cay}$  has a superior forecasting power than its

re-estimated version, as one would expect.

All of these findings indicate that for longer horizons  $\widehat{cay}$  produces forecasts superior to any of the competitor models. In addition,  $\widehat{cay}$  should be included together with a constant or lagged excess returns to improve the forecasts, regardless of the time horizon. We conclude that these out-of-sample results are consistent with the in-sample results as a whole.

## 8 Conclusion

Our work here was to settle the link between the consumption-wealth ratio and expected stock returns through a panel approach, estimating the cointegrating residual from the shared trend among consumption, asset wealth and labor income,  $cay$ , and verifying its forecasting power over stock returns. According to the theoretical framework, when agents expect higher asset returns in the future they increase current consumption in order to smooth out their purchasing power, which leads to a detachment of consumption from its shared trend with asset wealth and labor income. Therefore, movements on  $cay_t$  should forecast future asset returns.

Using quarterly data from 1981 to 2014, we set a panel for G7's countries and, after testing the cointegrating relationship between consumption, asset wealth and labor income, we estimate  $cay$  with a VEC. Then, using our panel data, we make one-step-forward forecasts as well as long horizon regressions to investigate the power of  $\widehat{cay}$  as a predictor for excess stock returns. Neither  $\widehat{cay}$  nor the financial variables that we include on regressions are able to predict excess returns one quarter ahead. Nevertheless, the forecasting power of  $\widehat{cay}$  surprisingly increases as the forecast horizon becomes longer. In fact, the impact of  $\widehat{cay}$  over future excess returns starts being statistically significant over three quarters and increases together with  $\widehat{cay}$ 's forecasting power thereafter.

On our robustness analysis, we study another way of estimating the forecasting parameters and correcting standard errors. Once more, none of the predictive variables is capable of predicting excess returns one quarter ahead. However,  $\widehat{cay}$  exhibits substantial forecasting power at horizons ranging from two years and so on, and among the financial variables, is the only predictor which outlasts our robustness exercise.

In addition, we perform nested and nonnested out-of-sample excess returns forecasts adding one quarter at a time and recursively estimating the predictors parameters. On the nested comparisons,  $\widehat{cay}$  has improved the forecasting performance for both constant returns benchmark and lagged benchmark, regardless of whether the forecasting horizon was one quarter or two years ahead. From nonnested comparisons we may say that

the MSE of forecasts with  $\widehat{cay}$  as the sole predictive variable is consistently lower than the MSE of prediction with the financial variables. However, for one-quarter-ahead forecasts on these nonnested comparisons, the performance of  $\widehat{cay}$  falls short of the predictive power of lagged excess returns, although this effect is reversed when making two-year-ahead predictions.

We may conclude from our analysis that, when estimated with panel data, *cay* is indeed a strong and robust predictor of future excess returns from two years onward. One possible explanation to this delayed response is that we could be estimating a long-run equilibrium tendency and that *cay* is not able to capture short-term volatility of excess returns.

In a nutshell, the predictive relationship between *cay* and excess returns implies that expected sharp fluctuations on assets returns, which directly affects the investors wealth, are not necessarily attached to subsequent abrupt movements on consumption. The forward-looking investors anticipate and dilute the impact of this wealth variation in order to avoid sharp swings in their consumption.

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