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ISSN 0034-7140
DOI 10.5935/0034-7140.20160022
Revista Brasileira de Economia, **70**(4), 419–440

Consumption-Wealth Ratio and Expected Stock Returns: Evidence from Panel Data on G7 Countries*

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Contents: 1. Introduction; 2. Present-Value Theory; 3. Macroeconomic and Financial Data; 4. Cointegration Analysis (*cay*); 5. Forecasting Stock Returns In-Sample; 6. Out-of-Sample Forecasts; 7. Cointegration and Forecasting with a FMOLS Estimate of *cay*; 8. Conclusions; Appendix A. VECM Heterogeneous Cointegrating Vectors; Appendix B. FMOLS Heterogeneous Cointegrating Vectors.

Keywords: Consumption-Wealth Ratio, Stock Returns, Unbalanced Panel, Cointegrating Residual.

JEL Code: C22, D91, E21.

Using the theoretical framework of Lettau & Ludvigson (2001), we perform an empirical investigation on how widespread is the predictability of cay—a modified consumption-wealth ratio—once we consider a set of important countries from a global perspective. We chose to work with the set of G7 countries, which represent more than 64% of net global wealth and 46% of global GDP at market exchange rates. We evaluate the forecasting performance of cay using a panel-data approach, since applying cointegration and other time-series techniques is now standard practice in the panel-data literature. Hence, we generalize Lettau and Ludvigson's tests for a panel of important countries. We employ macroeconomic and financial quarterly data for the group of G7 countries, forming an unbalanced panel. For most countries, data is available from the early 1990s until 2014Q1, but for the U.S. economy it is available from 1981Q1 through 2014Q1. Results of an exhaustive empirical investigation are overwhelmingly in favor of the predictive power of cay in forecasting future stock returns and excess returns.

Usando o arcabouço teórico de Lettau & Ludvigson (2001), investigamos a existência de previsibilidade vis-à-vis os excessos de retorno de uma versão modificada da razão

*We are especially grateful for the comments and suggestions given by Wagner Gaglianone, Pedro Cavalcanti Ferreira, Ricardo Sousa and other seminar participants at the *2nd International Workshop on "Financial Markets and Nonlinear Dynamics"* (FMND) in Paris. Any remaining errors are ours. Both Castro and Issler gratefully acknowledge the support from CNPq, FAPERJ, INCT and FGV on different grants. We also thank Marcia Waleria Machado, Marcia Marcos, Andrea Virginia, and Rafael Burjack for excellent research assitence.

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consumo-riqueza para os países do grupo G7. Num exercício empírico exaustivo, confirmamos a potencial previsibilidade da razão consumo-riqueza num arcabouço de dados de painel, algo inédito para esse representativo grupo de paises.

1. INTRODUCTION

The link between macroeconomic and financial markets has long driven a great deal of theoretical and empirical work in the macroeconometric literature. Taking the asset-pricing equation as a starting point, and using a present-value approach, one can derive several interesting implications between macroeconomic data and future returns or excess returns. The work of Campbell (1987), Campbell & Shiller (1987, 1988a), Campbell & Deaton (1989), and Campbell & Mankiw (1989), are good early examples of the connection between macroeconomic and financial variables. Indeed, one should expect some asset-return predictability following this literature, although the evidence is weak. Compare, for example, the results in Fama & French (1988) and Pesaran & Timmermann (1995) with those in Campbell & Thompson (2008). Recently, Guillén, Issler, & Saraiva (2015) examine the usefulness of imposing different layers of present-value-model restrictions in forecasting financial data — a directly related issue.

In an interesting paper, Lettau & Ludvigson (2001) study the role of transitory trend deviations for consumption, asset holdings and labor income in predicting future stock market fluctuations. Using a forward-looking model, with a novel present-value equation, they show that, when investors expect higher returns in the future, they react by raising current consumption relative to its trend vis-a-vis asset wealth and labor income in order to smooth consumption in line with the asset-pricing equation. Therefore, these current transitory fluctuations of consumption about its trend carry information about the future dynamics of returns and excess returns. These issues are investigated using the time-series framework of cointegration and cross-equation restrictions in the context of a vector autoregressive (VAR) model.

Despite the strong empirical evidence provided by Lettau & Ludvigson (2001) for the U.S. stock market, there has been only a few papers trying to investigate this issue with an a broader international perspective. For example, Ioannidis, Peel, & Matthews (2006), Tsuji (2009) and Gao & Huang (2008) extended the time-series analysis of Lettau & Ludvigson (2001) to other countries, which yields country-specific results. Nitschka (2010), on the other hand, used the consumption-wealth ratio of the U.S. economy as a predictor of foreign stock returns. In a more elaborate paper, Sousa (2010) shows that housing wealth could be an important component of aggregate wealth when predicting asset returns.

Despite the unquestionable value-added of the subsequent literature, what we see as lacking in it is the use of a broad enough approach to test the idea that transitory trend deviations for consumption (c), asset-wealth holdings (a) and labor income (y) are able to predict future stock market fluctuations, i.e., the usefulness of cay in forecasting returns. If the present-value model holds, it should hold for every country, and not only to the U.S. economy. Instead of employing a country-specific approach to the matter, we propose to use a panel-data approach for a group of relevant countries, which will be able to test the predictability theory in a broader sense. In order to cover a group of relevant countries, we decided to focus on the G7 group: Canada, France, Germany, Italy, Japan, the United Kingdom and the United States.

The group of G7 countries represents more than 64% of net global wealth (US$ 263 trillion). They also represent 46% of global GDP evaluated at market exchange rates. Thus, the G7 group is definitely relevant from a global perspective. We limit our study to the group of G7 countries because of the lack of data on asset-wealth holdings for a broader group of countries, especially at the quarterly frequency. Since applying cointegration and other time-series techniques is now standard practice in the panel-data literature, generalizing Lettau and Ludvigson's tests for a panel of countries is immediately feasible, and will be highly informative for global financial markets. Additional advantages of employing panel-data tests vis-a-vis country specific tests is the fact that one gathers more information using the former—the cross-sectional dimension.

The first step of our empirical analysis is to test for the existence of a single cointegrating relationship among consumption, asset wealth, and labor income, with panel cointegration tests. Our performed tests allow for heterogeneity in the linear combination forming the cointegrating relationship (cay_h) as well as imposing homogeneity restrictions in it (cay). Here, we also discuss whether or not the estimated linear combinations ($\widehat{cay}$ and $\widehat{cay}_h$) conform to theory in some respects, looking at alternative estimates in the cases where they do not. With our estimates in hand, the next step is to implement an in-sample forecasting exercise, where we investigate whether or not $\widehat{cay}$ and $\widehat{cay}_h$ help to forecast future stock returns and excess returns. We also include in these regressions some financial variables that are widely used in the literature to predict stock returns. Our final forecasting test asks whether or not $\widehat{cay}$ and $\widehat{cay}_h$ help to forecast future stock returns out of sample. Here, the forecasting regression is recursively re-estimated, mimicking closely the exercise a financial analyst will do in practice. Again, we employ a variety of alternative predictors in a horse-race between $\widehat{cay}$ (or $\widehat{cay}_h$) and these potential predictors. Finally, we repeat the in-sample and out-of-sample forecasting tests for cointegrating results that did not conform to theory.

In performing our empirical tests we employ macroeconomic real quarterly data per capita, measured in 2010 country's own currency, as well as financial data for returns and excess returns. Our main sources of data are the National Accounts Statistics of the OECD database, the Federal Reserve Economic Data (FRED) of the FED of St. Louis, and the International Financial Statistics (IFS), provided by the IMF. We have an unbalanced panel. For most countries, data is available from the early 1990s until 2014Q1, but for the U.S. economy it is available from 1981Q1 through 2014Q1.

Our final results allow for a very broad examination of the present-value theory behind cay, and its potential forecasting power for future returns. First, we find overwhelming evidence of a single cointegration vector for consumption, asset wealth, and labor income. This is true whether or not we allow for heterogeneity in computing the cointegrating relationship. Despite these results, in some cases the coefficients in the linear combination did not conform to theory. The coefficients of asset wealth and labor income must reflect the participation of asset wealth and human capital in total wealth. Thus, they must lie between zero and one and add up to unity. These theoretical restrictions did not hold in some cases, which required alternative estimation techniques. Second, $\widehat{cay}$ and $\widehat{cay}_h$ help to forecast future stock returns and excess returns in sample. This is true whether or not we consider additional regressors in forecasting. Third, $\widehat{cay}$ and $\widehat{cay}_h$ help to forecast future stock returns and excess returns in the out-of-sample exercise, usually performing better than alternative regressors. Finally, using estimates of cay and cay_h that conform to economic theory does improve forecasts of future accumulated excess returns.

The next section presents a brief review of the theoretical framework which establishes the present-value relationship between cay and expected stock returns. In section 2, we thoroughly detail the aggregate and financial data that we use to construct our panel. Section 3 presents the results of the integration and cointegration analyses in a penal-data context, i.e., we build the estimates of cay and cay_h. Section 4 reports the results of in-sample forecasting. In section 5, we perform out-of-sample forecasts. In section 6, we re-estimate cay and cay_h using the fully-modified OLS (FMOLS) estimator to obtain cointegration estimates that conform to theory. Then, we revisit our previous forecasting exercise. Finally, in section 7, we conclude.

2. PRESENT-VALUE THEORY

Consider a representative consumer who invests her/his total wealth and receive 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 budget constraint faced by this agent is

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

Campbell & Mankiw (1989) suggest log-linearizing (1), obtaining

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

where the lower case letters from now on are used to denote the logs of the corresponding variables, $r_{w,t+1} \equiv \log(1+R)$; ρ_w is the steady-state proportion of investment on wealth; and k_1 is a non-interesting constant. For future reference, all k_i, $i = 2,3,\ldots$, are constants as well.

If the consumption-wealth ratio is stationary, it is possible to solve this equation forward in expectations. Thus, taking the conditional expectation and assuming that the transversality condition $\lim_{i\to\infty} \mathbb{E}_t \left[\rho_w^i (c_{t+i} - w_{t+i})\right] = 0$ holds, the log consumption-wealth may be written as

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

which means that there is a present value relationship between consumption-wealth ratio and the return on aggregate wealth.

A main problem with (3) is that total wealth has two components: asset wealth and human capital. However, the latter is non observable. Lettau & Ludvigson (2001) deal with this issue in an elegant way. They define aggregate wealth as asset wealth plus human capital $W_t = A_t + H_t$, the log of aggregate wealth may be approximated as

$$w_t \approx \gamma a_t + (1-\gamma) h_t + k_3, \tag{4}$$

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

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

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

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

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

$$c_t - \gamma a_t - (1-\gamma) h_t = \mathbb{E}_t \sum_{i=1}^{\infty} \rho_w^i \left[\gamma r_{a,t+i} + (1-\gamma) r_{h,t+i} - \Delta c_{t+i}\right] + k_5. \tag{7}$$

To deal with non observable that human capital, Lettau & Ludvigson (2001) use the fact that labor income can be interpreted as the dividend on human wealth, implying

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

Once more, log-linearizing this expression, we obtain:

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

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

$$h_t = y_t + \mathbb{E}_t \sum_{i=1}^{\infty} \rho_h^i (\Delta y_{t+i} - r_{h,t+i}) + k_7. \tag{9}$$

Lettau & 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 κ is a constant. It is easy to see from (9) that $\mu_t = \mathbb{E}_t \sum_{i=1}^{\infty} \rho_h^i (\Delta y_{t+i} - r_{h,t+i})$. This term is a stationary random variable, since we are assuming that Δy_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 (9), it is possible to rewrite the log consumption-wealth ratio in terms of observable variables:

$$cay_t \equiv c_t - \gamma a_t - (1-\gamma) y_t \tag{10}$$

$$= \mathbb{E}_t \sum_{i=1}^{\infty} \rho_w^i \left[\gamma r_{a,t+i} + (1-\gamma) r_{h,t+i} - \Delta c_{t+i}\right] + (1-\gamma)\mu_t + k_8. \tag{11}$$

Under the assumption that $r_{w,t}$, Δc_t and Δy_t are stationary,[1] equations (10) and (11) imply that c_t, a_t and y_t are cointegrated and $c_t - \gamma a_t - (1-\gamma) y_t$ is the cointegrating linear combination labelled as cay_t, where $(1, -\gamma, -(1-\gamma))$ is the cointegrating vector (Lettau & Ludvigson, 2004). Besides, cay_t Granger-causes the right-hand term in brackets, since these terms are dated from $t+1$ onwards. Therefore, provided that the expected future returns on human capital and consumption growth are relatively smooth, changes in cay_t should forecast future changes on asset returns.[2]

This result is by and large consistent with a wide range of forward-looking models of investor behavior, where agents, disliking sharp fluctuations on consumption, will attempt to smooth out transitory movements in asset wealth due to variations in future 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 trend—an increase in cay_t—and vice-versa for the case when lower returns are expected in the future.

3. MACROECONOMIC AND FINANCIAL DATA

We work with a typical panel of macroeconomic data, where the cross-sectional dimension is small and the time-series dimension is large. As noted above, we possess an unbalanced panel for G7 countries:[3]: Canada, France, Germany, Italy, Japan, United Kingdom and United States. All aggregate variables are quarterly, seasonally adjusted, per capita, and measured in 2010 country's own currency. To deflate data we use the CPI from International Financial Statistics (IFS)—the IMF database—and for quarterly population figures we interpolate annual data provided by OECD.

Consumption data used here is private final consumption expenditure from National Accounts Statistics of OECD's database. Labor income used here is the compensation of employees, provided by the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis, but the original source is OECD as well. Asset holdings data were taken separately from each of the G7 country's central bank.

Asset holdings is a critical variable in our analysis, since it determines the time span for each country in the database. Table 1 specifies the details of the *financial asset holdings* data used in this paper.

Real asset returns and excess returns are obtained from stock indices. To obtain the log of real gross returns r_t for each country, we take their quarterly closing prices, adjusted for dividends. Nominal

[1] 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 linear trends.

[2] Lettau & 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.

[3] The reason for choosing G7 is the lack of data availability for other countries in quarterly frequency, specially of households asset wealth.

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

stock indices are provided by Bloomberg and are deflated using the seasonally adjusted CPI figures from IFS. The stock indices used here 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.

We also considered some additional financial variables such as dividend yield, payout ratio and relative bill rate, in order to extend our analysis and compare the predictive power of cay and that of these variables. Here, we 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 & Shiller (1988b), this variable has been widely used to forecast excess returns,[4] especially 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).

4. COINTEGRATION ANALYSIS (cay)

First, we test whether each of the variables in $cay_t \equiv c_t - \gamma a_t - (1-\gamma) y_t$—consumption ($c_t$), asset wealth ($a_t$), and labor income ($y_t$)—have or not a unit root in (log) levels. We perform a panel unit root test proposed by Maddala & Wu (1999), which consists of a Fisher (1932) test[5] that combine the significance levels from individual unit root tests, such as Phillips–Perron (PP) and Augmented Dickey–Fuller (ADF).

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

[5] 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.

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,[6] which we interpret to mean that their process is integrated of order one.

Next we conduct two panel cointegration tests to verify if there is a single cointegrating relationship among consumption, asset wealth and labor income. The first one is a residual-based test proposed by (Kao, 1999), in which homogeneity restrictions are imposed in the cointegrating vector. We strongly reject the null of no cointegration, with a p-value of 0.29%.[7] This allows the conclusion of the existence of at least one cointegrating vector. The second test is another Fisher-type test suggested by Maddala & Wu (1999) using a Johansen (1991) procedure to determine the number of cointegrating relations among those three variables in the panel. Since the variables are integrated of order one, we can have zero, one, or two cointegrating vectors. In this case, no homogeneity restrictions are imposed for the cointegrating coefficients. Results are presented in Table 2, and indicate that there is indeed a single cointegrating vector for consumption, asset wealth and labor income. Therefore, we are confident that there is a single cointegrating vector for consumption, asset wealth, and labor income, these three variables sharing two common trends.

The next step is to estimate the parameters of the cointegrating vector, $cay_t \equiv c_t - \gamma a_t - (1-\gamma) y_t$. Instead of imposing *a priori* theoretical restrictions, where $0 \leq \gamma \leq 1$, we estimate the coefficients unrestricted, once imposing homogeneity restrictions—all coefficients are the same across the panel, and once without homogeneity restrictions—coefficients vary across cross-sectional units. In the former case, we estimate the following cointegrating vector:

$$cay_t = c_{i,t} - \beta_a a_{i,t} - \beta_y y_{i,t}, \tag{12}$$

whereas in the latter case, we estimate

$$cay_{h_{i,t}} = c_{i,t} - \beta_{a,i} a_{i,t} - \beta_{y,i} y_{i,t}. \tag{13}$$

We estimate cointegrating vectors using Johansen (1991) full-information maximum likelihood (FIML) procedure. Regarding deterministic terms, we assume a linear deterministic trend in data. We chose a vector autoregressive (VAR) model of order two in levels. Table 3 presents the estimates of the cointegrating parameters for (12).[8] One can immediately see that the coefficient of labor income is negative, −0.6406, although it is not significant. Further unit root tests on the cointegrating residual confirm that $\widehat{cay_t}$ does not have a unit root.[9]

We now turn to the estimation of equation (13)—cointegrating vector without imposing homogeneity restrictions. We estimate separately a vector error-correction model (VECM) for each country, with results reported in the Appendix A. Again, further unit root tests on the cointegrating residuals confirms that $\widehat{cay}_{h_{i,t}}$ does not have a unit root.

[6] Probabilities for Fisher test are computed using asymptotic χ^2 distribution.

[7] Probabilities for Kao test are computed using asymptotic Normal distribution

[8] 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 α measure the speed of adjustment of each endogenous variable towards the equilibrium (Engle & Granger, 1987).

[9] Here, and in what follows, we regard this as an informal, but informative test.

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

Notes: This table reports the panel cointegration test on consumption, asset wealth and income, 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 χ^2 distribution.

Table 3. Panel cointegrating vector estimates.

Estimated Parameters	*Asset Wealth*	*Labor Income*	*Constant*
Consumption	**−1.4581*** ** (0.4292)	**0.6406*** (0.3674)	2.0963

Notes: This table presents the estimated parameters of the cointegrating vector $(1, -\widehat{\beta}_y, -\widehat{\beta}_a)$ from the VEC estimation, with respective standard errors in parenthesis. On the specification, we include an intercept in the cointegrating equation, once we assume there is a linear deterministic trend in data, we use one lag in difference and impose one cointegrating relationship. 594 observations are included in this estimation after adjustments. Statistics with * are significant at 10% level, ** at 5% and *** at 1%, computed using asymptotic Normal distribution.

One thing to note is that in the estimation of (12) and (13) we obtained some counter-intuitive results, or results that go against the present-value theory in section 2. These violations happen when $-\beta_a$'s or $-\beta_y$'s are outside the interval $[0,1]$, which happened for $-\beta_y$ in Table 3, and for $-\beta_{a,i}$ and $-\beta_{y,i}$ for a few countries in Appendix A. It is hard to explain why these violations happen. There may be measurement error on the data used; it can be the consequence of using a first-order approximation log linear approximation in building (11); etc. In any case, to deal with this issue, we will also consider alterative estimates of (12) and (13) in which these violations are much more infrequent; see the results in section 7.

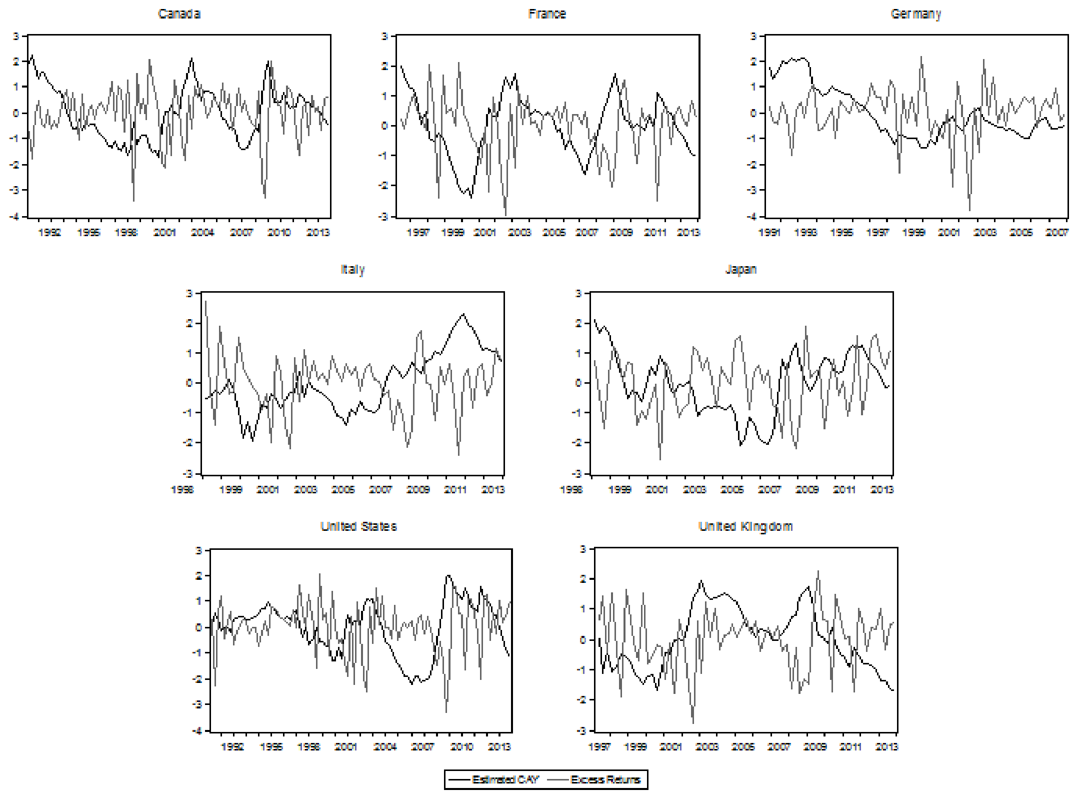
5. FORECASTING STOCK RETURNS IN-SAMPLE

In this section, we investigate if cay can anticipate real stock returns and real excess returns in sample using a panel-data 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. Figure 1 presents individual graphs for log excess returns—log returns on stock indexes minus the log return on T-bill—and $\widehat{cay}$ normalized series.[10]

For some countries such as Canada, France, Japan and United Kingdom, sharp variations of $\widehat{cay}$ clearly preceding spikes in excess returns, for both positive and negative fluctuations. It is also interesting to note that recently most countries have presented a pronounced decreasing in $\widehat{cay}$. Another feature of $\widehat{cay}$ is its counter-cyclical behavior. In fact, when we make a panel regression of consumption

[10]Here, we disaggregate the panel into seven time series, one for each country, and detrend them individually in order to eliminate any individual trend effects.

Figure 1. Excess Returns and Estimated cay.



growth on contemporaneous $\widehat{cay}$ controlling for cross section fixed effects, we obtain a coefficient of -0.005181 statistically significant at the 1% level.

Table 4 presents in-sample one-quarter-ahead regressions with real returns and excess returns as dependent variables and both $\widehat{cay}$ and $\widehat{cay}_h$ and other financial variables as regressors, including cross-section fixed effects. On all of these regressions, we make White cross-section corrections to the standard errors.[11] 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 & Owen, 1999). Nevertheless, Nickell (1981) derives an expression for the bias showing that it goes to zero when T approaches infinity. For our purposes, since we are under a large T, small N, environment, the LSDV model bias should be very small, we thus take these in-sample results seriously. Again, we use the White cross-section correction in these regressions as well.

[11]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

$$Avar(\hat{\beta}) \equiv \left(\frac{NT}{NT-K}\right)\left(\sum_t X_t' X_t\right)^{-1}\left(\sum_t X_t'\hat{\epsilon}_t\hat{\epsilon}_t' X_t\right)\left(\sum_t X_t' X_t\right)^{-1},$$

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.

Table 4. In-sample one-quarter-ahead regressions.

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

Notes: 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 R^2. White cross-section corrected standard errors appear in parenthesis.

In Table 4, at one-quarter ahead, both $\widehat{cay}$ and $\widehat{cay}_h$ are not able to predict stock returns, since their coefficients are not statistically significant. The same is true for the other financial variables considered in Table 4. It is also worth noting that the $\overline{R}^2$ are extremely low, especially on the regressions with either $\widehat{cay}$ or $\widehat{cay}_h$ as a single regressor.

From equation (11), one can conclude that cay should be a good predictor of consumption growth as well as of asset returns. Thus, we investigate whether or not it helps to forecast either accumulated consumption growth or accumulated excess returns. Table 5 presents the results over horizons spanning 1 to 24 quarters, where regressions are estimated by the LSDV model. Results are presented in Table 5.

From Table 5, we conclude the following. First, $\widehat{cay}$ 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 about consumption growth or excess returns using 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. This is a rather convenient result, since $\widehat{cay}$'s estimating method is a much more parsimonious way of obtaining the cointegrating vector for the entire panel. Second, comparing results in Table 4 with those in 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. In fact, regression 3 from Table 5 shows $\widehat{cay}$'s forecasting power as well as its adjusted R^2 increasing through time, which is probably due to the strong persistence in cay and excess return series. Third, when we

Table 5. In-sample 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	$\widehat{cay}_t$	**-0.0047***	**-0.0069***	**-0.0080***	-0.0072	0.0014	0.0091	0.0141	0.0131
		(0.0026)	(0.0036)	(0.0043)	(0.0052)	(0.0107)	(0.0146)	(0.0180)	(0.0208)
		[0.0267]	[0.0454]	[0.0580]	[0.0660]	[0.0962]	[0.1218]	[0.1540]	[0.2407]
2	$\widehat{cay}_{h\,t}$	0.0040	0.0073	0.0081	-0.0008	-0.0290	-0.0425	-0.0597	**-0.1312****
		(0.0077)	(0.0125)	(0.0169)	(0.0186)	(0.0285)	(0.0350)	(0.037802)	(0.0575)
		[0.0163]	[0.0363]	[0.0512]	[0.0621]	[0.0982]	[0.1229]	[0.1552]	[0.2490]
		Panel B: Excess Stock Returns, $\sum_{i=1}^{H} (r_{t+i} - r_{f,t+i})$							
3	$\widehat{cay}_t$	0.0214	**0.0669***	**0.1331*****	**0.2302*****	**0.5800*****	**0.9233*****	**1.1272*****	**1.2443*****
		(0.0244)	(0.0392)	(0.0503)	(0.0642)	(0.1308)	(0.1521)	(0.1294)	(0.1312)
		[-0.0069]	[0.0034]	[0.0175]	[0.0438]	[0.0809]	[0.1639]	[0.2379]	[0.3824]
4	$\widehat{cay}_{h\,t}$	0.0996	0.1534	0.1857	0.2003	**0.2902****	0.2672	-0.0323	**-0.7786*****
		(0.0732)	(0.1032)	(0.1290)	(0.1495)	(0.1371)	(0.1967)	(0.2269)	(0.2311)
		[-0.0059]	[0.0010]	[0.0079]	[0.0145]	[0.0526]	[0.1019]	[0.1560]	[0.3652]
5	$d_t - p_t$	0.0117	0.0348	0.055985	**0.0657****	**0.1585*****	**0.1911****	**0.2802*****	**0.3126*****
		(0.0201)	(0.0302)	(0.0351)	(0.0304)	(0.0596)	(0.0787)	(0.0703)	(0.0783)
		[-0.0072]	[0.0031]	[0.0134]	[0.0214]	[0.0429]	[0.0783]	[0.1537]	[0.2783]
6	$d_t - e_t$	0.0009	-0.0087	-0.020391	**0.0391****	**0.0941*****	**0.1445*****	**0.3224*****	**0.2911*****
		(0.0138)	(0.0306)	(0.0397)	(0.0180)	(0.0360)	(0.0393)	(0.0360)	(0.0420)
		[-0.0077]	[-0.0035]	[0.0047]	[0.0251]	[0.0554]	[0.1202]	[0.3018]	[0.3788]
7	$RREL_t$	0.5207	3.6982	**6.0328***	-3.5101	-4.7525	**-13.174****	**-13.635****	-7.1375
		(2.1074)	(2.7613)	(3.1641)	(2.7862)	(5.2727)	(5.7636)	(6.8009)	(8.0032)
		[-0.0041]	[0.0086]	[0.0219]	[0.0149]	[0.0243]	[0.0685]	[0.1038]	[0.1633]
8	$d_t - p_t$	0.0180	0.0557	**0.0900***	**0.0621***	**0.1332***	0.1162	0.0873	0.1577
		(0.0262)	(0.0438)	(0.0509)	(0.0340)	(0.0692)	(0.0814)	(0.0757)	(0.0979)
	$d_t - e_t$	-0.0016	-0.0165	-0.0348	0.0217	0.0590	**0.1107****	**0.2950*****	**0.2561*****
		(0.0146)	(0.0330)	(0.0426)	(0.0192)	(0.0433)	(0.0459)	(0.0410)	(0.0494)
	$RREL_t$	2.2272	**8.1993****	**12.2728*****	**-6.1581****	**-9.5835***	**-17.3299*****	**-15.2702*****	**-20.3082****
		(3.1878)	(3.8109)	(3.8679)	(3.1330)	(5.7054)	(5.7694)	(5.6160)	(9.1230)
		[0.0002]	[0.0513]	[0.0903]	[0.0430]	[0.0723]	[0.1436]	[0.3143]	[0.3972]
9	$\widehat{cay}_t$	0.0179	0.0663	**0.1404*****	**0.2311*****	**0.6340*****	**1.0124*****	**1.0701*****	**0.8687*****
		(0.0312)	(0.0443)	(0.0523)	(0.0808)	(0.1524)	(0.1489)	(0.1413)	(0.1695)
	$d_t - p_t$	0.0173	0.0524	0.0814	0.0468	0.0859	0.0232	-0.0213	0.055328
		(0.0267)	(0.0438)	(0.0516)	(0.0363)	(0.0740)	(0.0828)	(0.0758)	(0.1126)
	$d_t - e_t$	-0.0016	-0.0168	-0.0368	0.0181	0.0489	**0.1011****	**0.2959*****	**0.2569*****
		(0.0146)	(0.0332)	(0.0429)	(0.0189)	(0.0416)	(0.0431)	(0.0389)	(0.0499)
	$RREL_t$	2.4396	**8.6521****	**12.686*****	**-6.2927****	**-9.8741***	**-17.736*****	**-14.923*****	**-16.368***
		(3.3107)	(3.9507)	(3.9608)	(3.1389)	(5.3831)	(5.2806)	(5.0180)	(9.1167)
		[-0.0002]	[0.0572]	[0.1012]	[0.0740]	[0.1366]	[0.2733]	[0.4733]	[0.5058]

Notes: This table reports the 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 $\overline{R}^2$ are in brackets at the end of each regression. Statistics with * are significant at 10% level, ** at 5% and *** at 1%.

add alternative financial variables on the longer-term regressions, we observe that $\widehat{cay}$ is a much better predictor of excess returns than $d-p$ in regression 5, the same being true for the payout ratio, on regression 6. On the other hand, comparing the $\overline{R}^2$ of regressions 3 and 7 we observe a better fit for $RREL$ as a predictor up to one year ahead. However, for longer horizons, $\widehat{cay}$ has a better fit. Fourth, in regression 9, we use $\widehat{cay}$ together with all other financial variables. It is interesting to notice that the forecasting power of dividend yield has vanished. The only two important predictors of excess returns are cay and $RREL$. For longer horizons, the payout ratio $d-e$ may be considered a good predictor as well.

From the theoretical framework (equation (11)), cay should Granger-cause asset returns. We perform Granger causality tests[12] investigating if $\widehat{cay}$ Granger-causes excess stock returns. Indeed, with a lag length from four quarters onwards, we reject the null that $\widehat{cay}$ does not Granger-cause excess returns, at 1% significance.

6. OUT-OF-SAMPLE FORECASTS

In our view, a true test for predictability should be out-of-sample, since this is the context that is of interest to academics, practitioners, and financial analysts alike. To address this issue, we estimate nested and non-nested models and make out-of-sample forecast comparisons using their mean-squared forecast error (MSFE). Because our results in the previous section using the heterogeneous version of the cointegrating vector ($\widehat{cay}_h$) were disappointing, from now on we focus only on the homogeneous version, $\widehat{cay}$. Nested and non-nested models are first estimated using data from the beginning of the sample until 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. Our forecast accuracy measure is the trace of the MSFE matrix for all countries (implies equal weights across countries).

The so-called Nested Model consists of two regressions. The unrestricted model, which includes $\widehat{cay}$ and an alternative regressor explaining future excess returns, and the restricted model, where we exclude $\widehat{cay}$ from the unrestricted model, justifying its name. The so-called Non-Nested Model consists also of two regressions. Model 1, which includes $\widehat{cay}$ alone, and model 2, which includes only an alternative regressor, so both models are non-nested.

We analyze the MSFE of models using either $\widehat{cay}$, with cointegrating parameters estimated using the full sample, or *reest* $\widehat{cay}$, with the cointegrating parameters re-estimated every period. The target variables are the one-step-forward excess returns ($r_{t+1} - r_{f,t+1}$), and also the two years accumulated excess returns, $\sum_{i=1}^{8}(r_{t+i} - r_{f,t+i})$. Table 6 presents the results for nested regressions. From Table 6, it is clear that adding $\widehat{cay}$ to the benchmark models always decrease the MSFE of the regressions on a two-year horizon. This happens whether the cointegrating coefficients are re-estimated or not. For one quarter ahead, $\widehat{cay}$ and *reest* $\widehat{cay}$ also do better than the constant and lagged benchmarks, but not when we include $d_t - p_t$, $d_t - e_t$, and $RREL_t$. Again, the benefit of adding $\widehat{cay}$ in these regressions is greater over the two years accumulated excess returns, which is consistent with the results from long-term regressions above.

In Table 7, we extend our analysis by making nonnested forecasts. 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 MSFEs in relation to lagged

[12]The tests consist of running regressions with different lags, l, of the form

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

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

Table 6. 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	$\widehat{cay}_t$ vs. $(d_t-p_t)+(d_t-e_t)+RREL_t$	1.0097	0.9822
4	$reest\ \widehat{cay}_t$ vs. $r_t-r_{f,t}$	0.9988	0.9954
5	$reest\ \widehat{cay}_t$ vs. $const$	0.9980	0.9897
6	$reest\ \widehat{cay}_t$ vs. $(d_t-p_t)+(d_t-e_t)+RREL_t$	1.0076	0.9872

Notes: This table shows the results of the nested comparisons, displaying the MSE ratio from the unrestricted model, which includes either $\widehat{cay}$ or *reest* $\widehat{cay}$, over the restricted model without this variables. The first valued column refers to one-quarter-ahead excess returns forecasts and the second one refers to two years accumulated excess returns predictions. The first three rows are computed with $\widehat{cay}$ estimated from the full sample and the last three with its parameters recursively re-estimated (*reest* $\widehat{cay}$).

Table 7. 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

Notes: 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 valued column 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.

excess returns. Except for *RREL*, the impact of $\widehat{cay}$ and *reest* $\widehat{cay}$ over the MSFE 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 in all, we find that $\widehat{cay}$ beats most alternatives across both horizons investigated here. Out-of-sample results are consistent with the in-sample results as a whole, confirming the predictability of $\widehat{cay}$ embedded in equation (11).

7. COINTEGRATION AND FORECASTING WITH A FMOLS ESTIMATE OF *cay*

As pointed out in the Introduction, from a theoretical perspective, the cointegrating vector should be

$$cay_t = (1,-\gamma,-(1-\gamma))\begin{pmatrix} c_t \\ a_t \\ y_t \end{pmatrix},$$

where $0 \leq \gamma \leq 1$ should be the share of asset wealth in total wealth. However, inspection of our empirical results in section 4 and the Appendices, shows that not always these theoretical restrictions were obeyed. Two possible reasons for that are measurement error on the components of cay_t or the fact that we obtain the present-value equation (11) using a first-order log-linear approximation.

Lettau & Ludvigson (2001) and some subsequent papers in the literature also present these problems, especially the fact that coefficients did not add up to unity, which was not viewed as major issue. So, we follow the early literature and try to estimate the cointegrating vector using a method that could in principle yield estimates of the homogeneous cointegrating vector $(1, -\beta_a, -\beta_y)$, where $0 \leq \beta_a, \beta_y \leq 1$, with an analogous restriction binding also for the heterogeneous case. However, we do not impose that $\beta_a + \beta_y = 1$. To implement that, we apply the Fully Modified Ordinary Least Squares (FMOLS) proposed by Phillips & Hansen (1990). This approach, in contrast to the standard OLS, eliminates problems of asymptotic bias of the estimates caused by the long run correlation between the cointegrating equation and stochastic regressors innovations. This allows inference on the cointegrating vector.

Table 8 reports the results on the homogeneous cointegrating vector, obtained from the FMOLS for the entire panel. In Appendix B, we present the heterogeneous vectors results, derived from the time-series FMOLS regressions estimated separately for each country.

Table 8. Panel homogeneous cointegrating vector.

Estimated Parameters	*Asset Wealth*	*Labor Income*	R^2
Consumption	**−0.1952*****	**−0.8244*****	0.99
	(0.0144)	(0.0327)	

Notes: This table presents the estimated parameters of the cointegrating vector $(1, -\widehat{\beta}_y, -\widehat{\beta}_a)$ from the FMOLS estimation, with respective standard errors in parenthesis. On the specification, we include an intercept in the cointegrating equation. 601 observations are included in this estimation after adjustments. Both estimates are statistically significant at 1% level (***), computed using asymptotic χ^2 distribution.

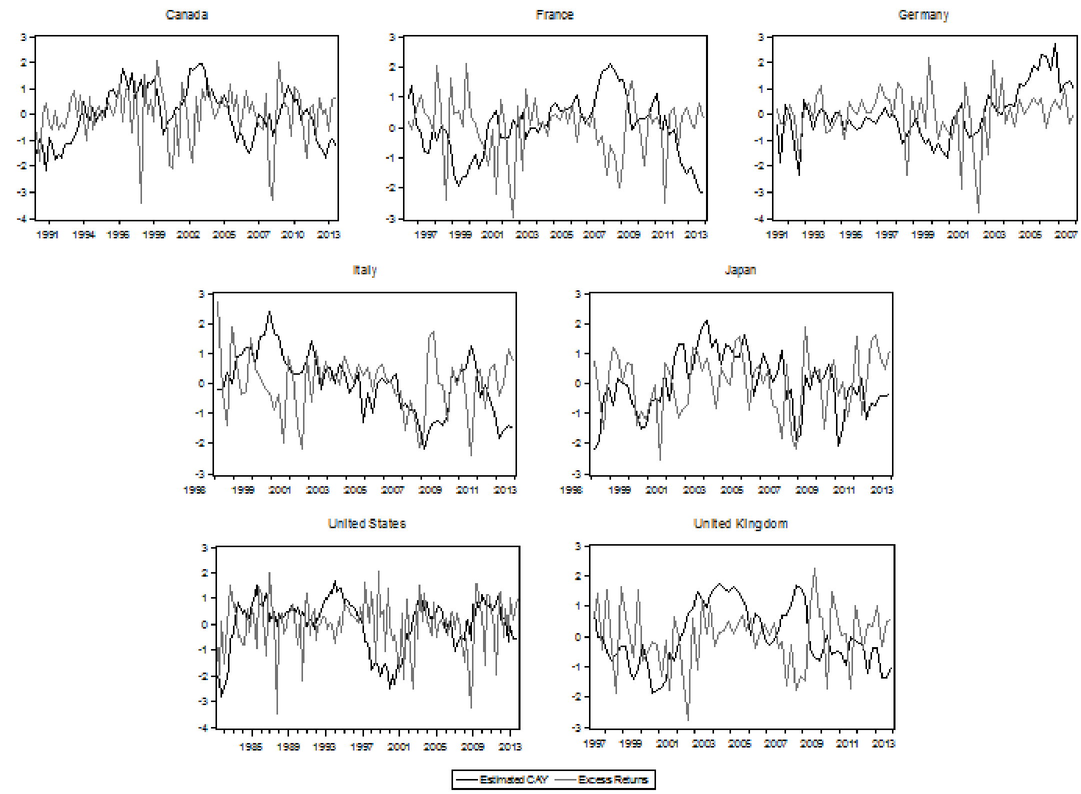
For the homogeneous cointegrating vector, contrary to previous results, we now do not observe a negative share for human-capital wealth. Also, for the heterogeneous case, we only observed two instances with negative shares for asset wealth (France and the UK), which are very small numerically and statistically insignificant. Thus, from a practical and statistical point-of-view, our FMOLS cointegrating vectors are theoretically valid.

With these new results in hand, we build $\widehat{cay}_f$, the homogeneous version of the cointegrating residual using FMOLS, and $\widehat{cay}_{fh}$, its heterogenous counterpart. Once again, we check the stationarity of $\widehat{cay}_f$ and $\widehat{cay}_{fh}$ by performing the Fisher-ADF and PP panel unit root tests, including individual intercepts but not any trends. For both variables, the presence of unit root is strongly rejected on both ADF and PP tests, confirming their stationarity.

Figure 2 shows variations of $\widehat{cay}_f$ preceding some movements on excess returns for countries such as Canada, France, Germany and United Kingdom. In addition, we notice that some countries present a faster responsiveness of excess returns over movements on $\widehat{cay}_f$. For instance, considering the year of 2013, the excess returns of France, Italy, Japan and United Kingdom have already followed the latest $\widehat{cay}_f$ swings. On the other hand, United States and Canada still show opposite movements between those two variables. Thus, if $\widehat{cay}_f$ 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 for both Canada and United States.

Next, we perform the in-sample one-quarter-ahead predictability tests using $\widehat{cay}_f$ or $\widehat{cay}_{hf}$. Results are presented in Table 9. Contrary to previous results, now, both $\widehat{cay}_f$ and $\widehat{cay}_{fh}$ can significantly

Figure 2. Excess Returns and Estimated cay.



forecast one-quarter-ahead stock returns and excess returns. But, other financial variables included in the regressions cannot.

Table 10 we presents the results of forecasting tests for in-sample long-term regressions, investigating the impact of $\widehat{cay}_f$ and $\widehat{cay}_{fh}$ over accumulated consumption growth and accumulated excess returns.

From Panel A on Table 10 we notice that $\widehat{cay}_{fh}$ is a better predictor of consumption growth than $\widehat{cay}_f$, based on a larger adjusted R^2. In contrast, in Panel B, $\widehat{cay}_f$ is a better predictor overall. Comparing $\widehat{cay}_f$ with the other financial variables (rows 4 and 5) $\widehat{cay}_f$ is a much better predictor of excess returns than $d-p$, except for a horizon of six years. The same is not true for the payout ratio, on row 6. On the other hand, comparing the $\overline{R}^2$ of rows 3 and 7 we observe a better fit with $RREL$ as a predictor only up to three quarters ahead. On row 9, we make the long-horizon regressions on $\widehat{cay}_f$ and all financial variables together, results are still the same as in Table 5—$\widehat{cay}_f$ and $RREL$ as stronger predictors of excess returns for intermediate horizons, and for longer horizons the payout ratio $d-e$ may also be considered a good predictor.

Table 11 presents the results of the out-of-sample forecasting exercise for excess returns. Again, we make both nested and nonnested comparisons and use either $\widehat{cay}_f$ or $reest\,\widehat{cay}_f$, which has its coefficients recursively re-estimated using FMOLS.

At the one-quarter-ahead horizon, results for $reest\,\widehat{cay}_f$ in Table 11 are disappointing, but $\widehat{cay}_f$ still beats lagged excess returns and the constant-return model. For the accumulated excess returns up to two years ahead, both $\widehat{cay}_f$ or $reest\,\widehat{cay}_f$ forecast much better than any of the alternatives. The

Table 9. In-sample one-quarter-ahead regressions.

#	Total Obs	*Constant*	*lag*	$\widehat{cay}_{f\,t}$	$\widehat{cay}_{fh\,t}$	$d_t - p_t$	$d_t - e_t$	$RREL_t$	$\overline{R}^2$
				Panel A: Real Returns, r_{t+1}					
1	584	0.0069		**0.3547***					0.0018
		(0.0097)		(0.1267)					
2	433	0.1120	0.1549	**0.3232**		0.0284	-0.0001	3.7247	0.0309
		(0.0941)	(0.1104)	(0.1919)		(0.0254)	(0.0146)	(3.0236)	
3	584	0.0069			0.3127				-0.0041
		(0.0098)			(0.2421)				
4	450	0.1076	0.1649		0.1577	0.0294	-0.0089	3.5740	0.0243
		(0.0880)	(0.1161)		(0.2196)	(0.0244)	(0.0151)	(2.9221)	
				Panel B: Excess Returns, $r_{t+1} - r_{f,t+1}$					
#	Total Obs.	Constant	*lag*	$\widehat{cay}_{f\,t}$	$\widehat{cay}_{fh\,t}$	$d_t - p_t$	$d_t - e_t$	$RREL_t$	$\overline{R}^2$
5	559	0.0037		**0.4244***					0.0051
		(0.0096)		(0.1297)					
6	432	0.1148	0.1540	**0.3903**		0.0295	0.0004	3.3901	0.0317
		(0.0955)	(0.1112)	(0.1950)		(0.0257)	(0.0146)	(3.0125)	
7	559	0.0039			0.3881				-0.0033
		(0.0096)			(0.2421)				
8	449	0.1075	0.1673		0.2300	0.0297	-0.0086	3.2640	0.0219
		(0.0891)	(0.1171)		(0.2205)	(0.0246)	(0.0152)	(2.9111)	

Notes: 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 R^2. White cross-section corrected standard errors appear in parenthesis. Statistics with * are significant at 10% level, ** at 5% and *** at 1%.

decrease in MSFE can reach up to 14%, which is impressive compared to previous results.

Table 12 present the results of the non-nested tests. For accumulated excess returns, note that $\widehat{cay}_f$ or *reest* $\widehat{cay}_f$ produce superior forecasts than any other alternative predictor. For one-step-ahead, the same can be said about $\widehat{cay}_f$, with an excellent out-of-sample performance beating alternative predictors by more than 15%. However, *reest* $\widehat{cay}_f$ is beaten almost by all alternative predictors, with the exception of $d - e$.

The results in the current section show that taking into account theoretical restrictions may improve forecasting performance – compare the results in Tables 6 and 11, and results in Tables 7 and 12—especially those of accumulated excess returns over the two-year horizon. These empirical results are in line with those obtained by Guillén et al. (2015), who compared the out-of-sample forecasting performance of present-value models for the long- and short-interest rates, and for prices and dividends, with those of an unrestricted VAR, a cointegrating VAR, and a VAR with imposed cointegration and common-cycle restrictions, for these same variables. There, it became clear the advantages of imposing a fully-fledged theoretical model, although an intermediately restricted model produced forecasting winners more frequently.

8. CONCLUSIONS

Using the theoretical framework of Lettau & Ludvigson (2001), we perform an empirical investigation on how widespread is the predictability of *cay*—a modified consumption-wealth ratio—once we consider

Table 10. In-sample 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	$\widehat{cay}_{f\,t}$	**-0.0323*** **	**-0.0578*** **	**-0.1537*** **	**-0.0838*** **	**-0.1079** **	**-0.1348***	**-0.1691***	**-0.3456** **
		(0.0108)	(0.0166)	(0.0329)	(0.0248)	(0.0474)	(0.0733)	(0.1017)	(0.1621)
		[0.0305]	[0.0549]	[0.0830]	[0.0767]	[0.1043]	[0.1272]	[0.1586]	[0.2533]
2	$\widehat{cay}_{fh\,t}$	**-0.0714*** **	**-0.1219*** **	**-0.1537*** **	**-0.1839*** **	**-0.2159*** **	-0.1741	-0.1082	-0.2700
		(0.0148)	(0.0241)	(0.0329)	(0.0423)	(0.0807)	(0.1141)	(0.1368)	(0.1940)
		[0.0459]	[0.0718]	[0.0830]	[0.0922]	[0.1106]	[0.1254]	[0.1532]	[0.2435]
		Panel B: Excess Stock Returns, $\sum_{i=1}^{H}(r_{t+i} - r_{f,t+i})$							
3	$\widehat{cay}_{f\,t}$	**0.4244*** **	**0.8800*** **	**1.3672*** **	**1.4580*** **	**3.7857*** **	**5.3733*** **	**5.2354*** **	**3.0325*** **
		(0.1297)	(0.1943)	(0.2509)	(0.2800)	(0.5579)	(0.6422)	(0.7373)	(1.0610)
		[0.0051]	[0.0248]	[0.0462]	[0.0529]	[0.0984]	[0.1619]	[0.1855]	[0.2547]
4	$\widehat{cay}_{fh\,t}$	0.3881	**0.8770** **	**1.4381*** **	**2.1433*** **	**5.4529*** **	**7.9904*** **	**8.5069*** **	**6.6140*** **
		(0.2421)	(0.3621)	(0.4265)	(0.5020)	(0.7686)	(0.8105)	(0.8090)	(1.0691)
		[-0.0033]	[0.0097]	[0.0249]	[0.0440]	[0.1436]	[0.2298]	[0.2730]	[0.4250]
5	$d_t - p_t$	0.0117	0.0348	0.055985	**0.0657** **	**0.1585*** **	**0.1911** **	**0.2802*** **	**0.3126*** **
		(0.0201)	(0.0302)	(0.0351)	(0.0304)	(0.0596)	(0.0787)	(0.0703)	(0.0783)
		[-0.0072]	[0.0031]	[0.0134]	[0.0214]	[0.0429]	[0.0783]	[0.1537]	[0.2783]
6	$d_t - e_t$	0.0009	-0.0087	-0.020391	**0.0391** **	**0.0941*** **	**0.1445*** **	**0.3224*** **	**0.2911*** **
		(0.0138)	(0.0306)	(0.0397)	(0.0180)	(0.0360)	(0.0393)	(0.0360)	(0.0420)
		[-0.0077]	[-0.0035]	[0.0047]	[0.0251]	[0.0554]	[0.1202]	[0.3018]	[0.3788]
7	$RREL_t$	0.5207	3.6982	**6.0328***	-3.5101	-4.7525	**-13.174** **	**-13.635** **	-7.1375
		(2.1074)	(2.7613)	(3.1641)	(2.7862)	(5.2727)	(5.7636)	(6.8009)	(8.0032)
		[-0.0041]	[0.0086]	[0.0219]	[0.0149]	[0.0243]	[0.0685]	[0.1038]	[0.1633]
8	$d_t - p_t$	0.0180	0.0557	**0.0900***	**0.0621***	**0.1332***	0.1162	0.0873	0.1577
		(0.0262)	(0.0438)	(0.0509)	(0.0340)	(0.0692)	(0.0814)	(0.0757)	(0.0979)
	$d_t - e_t$	-0.0016	-0.0165	-0.0348	0.0217	0.0590	**0.1107** **	**0.2950*** **	**0.2561*** **
		(0.0146)	(0.0330)	(0.0426)	(0.0192)	(0.0433)	(0.0459)	(0.0410)	(0.0521)
	$RREL_t$	2.2272	**8.1993** **	**12.272*** **	**-6.1581** **	**-9.5835***	**-17.329*** **	**-15.270*** **	**-20.308** **
		(3.1878)	(3.8109)	(3.8679)	(3.1330)	(5.7054)	(5.7694)	(5.6160)	(9.1230)
		[0.0002]	[0.0513]	[0.0903]	[0.0430]	[0.0723]	[0.1436]	[0.3143]	[0.3972]
9	$\widehat{cay}_{f\,t}$	**0.3949** **	**0.8832*** **	**1.3711*** **	**2.0112*** **	**4.8117*** **	**5.8325*** **	**5.3440*** **	**3.1608** **
		(0.1956)	(0.2642)	(0.2819)	(0.3194)	(0.5854)	(0.6328)	(0.7381)	(1.2583)
	$d_t - p_t$	0.0214	0.0630	**0.1003** **	**0.0762** **	**0.1678*** **	**0.1664** **	**0.1423***	**0.2175** **
		(0.0269)	(0.0437)	(0.0496)	(0.0322)	(0.0612)	(0.0757)	(0.0739)	(0.1037)
	$d_t - e_t$	0.0026	-0.0067	-0.0201	**0.0438** **	**0.1092** **	**0.1668*** **	**0.3511*** **	**0.3004*** **
		(0.0150)	(0.0329)	(0.0424)	(0.0197)	(0.0436)	(0.0439)	(0.0393)	(0.0535)
	$RREL_t$	2.4770	**8.7199** **	**12.705*** **	**-6.2200** **	-9.2138	**-16.235*** **	**-14.157*** **	**-17.045***
		(3.3823)	(3.9924)	(3.9796)	(3.0262)	(5.6297)	(5.7525)	(5.3590)	(9.3017)
		[0.0120]	[0.0808]	[0.1333]	[0.1373]	[0.2186]	[0.3077]	[0.4666]	[0.4734]

Notes: This table reports estimates from the long-horizon regressions of accumulated consumption growth and accumulated excess stock returns on $\widehat{cay}_f$, $\widehat{cay}_{fh}$ 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 $\overline{R}^2$ are in brackets at the end of each regression. Statistics with * are significant at 10% level, ** at 5% and *** at 1%.

a set of important countries from a global perspective. We chose to work with the set of G7 countries, which represent more than 64% of net global wealth (US$ 263 trillion), and 46% of global GDP at market exchange rates. We evaluate the forecasting performance of cay using a panel-data approach, since applying cointegration and other time-series techniques is now standard practice in the panel-data literature. Hence, generalizing Lettau and Ludvigson's tests for a panel of countries is feasible and highly informative for global financial markets.

We employ macroeconomic and financial quarterly data for the group of G7 countries, forming an unbalanced panel. For most countries, data is available from the early 1990s until 2014Q1, but for the U.S. economy it is available from 1981Q1 through 2014Q1. Our final results allowed a very broad examination of the present-value theory behind cay, which conclusions we list below:

1. We find overwhelming evidence of a single cointegration vector for consumption, asset wealth, and labor income, in forming cay.

Table 11. 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	$\widehat{cay}_{f_t}$ vs. $r_t - r_{f,t}$	0.9887	0.8833
2	$\widehat{cay}_{f_t}$ vs. $const$	0.9892	0.8804
3	$\widehat{cay}_{f_t}$ vs. $(d_t - p_t) + (d_t - e_t) + RREL_t$	1.0005	0.8603
4	$reest\ \widehat{cay}_{f_t}$ vs. $r_t - r_{f,t}$	1.0192	0.8727
5	$reest\ \widehat{cay}_{f_t}$ vs. $const$	1.0169	0.8759
6	$reest\ \widehat{cay}_{f_t}$ vs. $(d_t - p_t) + (d_t - e_t) + RREL_t$	1.0169	0.8767

Notes: This table shows the results of the nested comparisons, displaying the MSE ratio from the unrestricted model, which includes either $\widehat{cay}_f$ or *reest* $\widehat{cay}_f$, over the restricted model, without these variables. The first value column refers to one-quarter-ahead excess returns forecasts and the second one refers to two years accumulated excess returns predictions. The first three rows are computed with $\widehat{cay}_f$ estimated from the full sample and the last three with its parameters recursively re-estimated (*reest* $\widehat{cay}_f$).

Table 12. 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	$\widehat{cay}_{f_t}$ vs. $r_t - r_{f,t}$	0.9916	0.8798
2	$\widehat{cay}_{f_t}$ vs. $d_t - p_t$	0.9841	0.8866
3	$\widehat{cay}_{f_t}$ vs. $d_t - e_t$	0.9708	0.8578
4	$\widehat{cay}_{f_t}$ vs. $RREL_t$	0.9748	0.8809
5	$reest\ \widehat{cay}_{f_t}$ vs. $r_t - r_{f,t}$	1.0192	0.8695
6	$reest\ \widehat{cay}_{f_t}$ vs. $d_t - p_t$	1.0116	0.8762
7	$reest\ \widehat{cay}_{f_t}$ vs. $d_t - e_t$	0.9979	0.8477
8	$reest\ \widehat{cay}_{f_t}$ vs. $RREL_t$	1.0020	0.8706

Notes: This table reports the results of nonnested comparisons, displaying the MSE ratio from the first model, with $\widehat{cay}_f$ as the sole predictor, over the second model, with financial variables or lagged excess returns. Once more, the first valued column 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 $\widehat{cay}_f$ estimated from the full sample and the last two with its parameters recursively re-estimated.

2. In some cases, the coefficients in the cointegrating linear combination did not conform to theory, since they must lie between zero and one and add up to unity. This issue required alternative estimation techniques and forecast evaluation.

3. Estimates of *cay* help to forecast future stock returns and excess returns in sample. This is true whether or not we consider additional regressors in forecasting.

4. Estimates of *cay* help to forecast future stock returns and excess returns in the out-of-sample exercise, usually performing better than alternative regressors.

5. Finally, using estimates of *cay* that conform to economic theory does improve forecasts of future accumulated excess returns up to the two-year horizon.

All in all, we believe that our evidence has shown that the predictive power of *cay* is not a phenomenon restricted to the U.S. economy, but a much wider phenomenon, which deserves to be studied more broadly.

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APPENDIX A. VECM HETEROGENEOUS COINTEGRATING VECTORS

This appendix provides the results from the VEC regressions for each country separately. Table A-1 shows the cointegrating vector parameters estimates when we relax the homogeneity restrictions, leading to heterogeneous coefficients among countries. On every VEC specification, we include an intercept in the cointegrating equation, we use one lag in difference for the endogenous variables and impose on cointegrating relationship among them.

With these estimated parameters we construct the variable $\widehat{cay}_h$, which represents the cointegrating residual when we allow for heterogeneity on coefficients, just as we describe in section 4.

Table A-1. Heterogeneous cointegrating vectors.

Estimated Parameters *Consumption*	*AssetWealth*	*LaborIncome*	*Constant*
Canada	**1.0091*****	**-3.0200*****	9.5197
	(0.2245)	(0.4719)	
France	**0.7842*****	**-2.7832*****	6.4006
	(0.1925)	(0.3837)	
Germany	**-0.2011*****	**-0.4126*****	-2.7835
	(0.0107)	(0.0772)	
Italy	-0.1789	0.5172	-10.4017
	(0.1215)	(0.3965)	
Japan	**-0.3486*****	**-0.3826*****	-2.0229
	(0.0331)	(0.0709)	
United Kingdom	**-0.1073****	**-0.8947*****	0.0846
	(0.0452)	(0.0451)	
United States	**-0.6898*****	0.1587	-2.1200
	(0.23672)	(0.4907)	

Notes: This table presents the estimated parameters of the cointegrating vectors $(1, -\widehat{\beta}_{y,i}, -\widehat{\beta}_{a,i})$ for each country from the VEC estimations, with respective standard errors in parenthesis. On every VEC specification, we include an intercept in the cointegrating equation, we use one lag in difference for the endogenous variables and impose one cointegrating relationship among them. Statistics with * are significant at 10% level, ** at 5% and *** at 1%, computed using asymptotic Normal distribution.

APPENDIX B. FMOLS HETEROGENEOUS COINTEGRATING VECTORS

This appendix provides the results from the FMOLS regressions for each country separately. Table B-2 shows the cointegrating vector parameters estimates when we relax the homogeneity restrictions, leading to heterogeneous coefficients among countries. In addition, in the specification, we include distinct constants in the cointegrating structure for each country.

With these estimated parameters we construct the variable $\widehat{cay}_{fh}$, which represents the cointegrating residual when we allow for heterogeneity on coefficients, just as we describe in section 7.

Table B-2. Heterogeneous cointegrating vectors.

Estimated Parameters *Consumption*	*AssetWealth*	*LaborIncome*	*Constant*	R^2
Canada	**-0.2322***** (0.0324)	**-0.5455***** (0.0695)	0.4957 (0.3412)	0.99
France	0.0008 (0.0381)	**-0.9523***** (0.0694)	0.4770* (0.2856)	0.97
Germany	**-0.1931***** (0.0087)	**-0.3664***** (0.0575)	3.2525*** (0.4430)	0.95
Italy	**-0.2874***** (0.0339)	**-0.1677*** (0.0995)	3.8119*** (0.5481)	0.89
Japan	**-0.3107***** (0.0272)	**-0.3372***** (0.0606)	3.298*** (1.2337)	0.76
United Kingdom	0.0006 (0.0286)	**-0.8837***** (0.0267)	1.1555*** (0.4118)	0.97
United States	**-0.4810***** (0.1046)	**-0.4591**** (0.2180)	-1.4607 (0.9745)	0.96

Notes: This table presents the estimated parameters of the cointegrating vectors $(1, -\widehat{\beta}_{y,i}, -\widehat{\beta}_{a,i})$ for each country, with respective standard errors in parenthesis. We include individual intercepts in the cointegrating specification. Statistics with * are significant at 10% level, ** at 5% and *** at 1%, computed using asymptotic χ^2 distribution.