Variants of Consumption-Wealth Ratios and Predictability of U.S. Government Bond Risk Premia: Old is *still* Gold

February 2019

This paper compares the ability of alternative consumption-wealth ratios, based on constant parameter (*cay*), Markov-switching (cay^{MS}) and time-varying parameter (cay^{TVP}) cointegration estimation of the consumption function, for predicting in- and out-of-sample movements of quarterly excess returns of U.S. government bonds over 1953:Q2 to 2015:Q3. Our findings show that after controlling for standard financial and macroeconomic factors, *cay* outperforms the cay^{MS} and cay^{TVP} in predicting the path of excess returns on bonds. Implications of our results for academics, investors and policymakers are discussed.

JEL classification: C22; C53; G12; G17

Keywords: Bond risk premia; Consumption-wealth ratios; In-sample predictability; Out-of-sample forecasts

1. Introduction

Following the seminal contribution of Lettau and Ludvigson (2001), a large number of studies have shown that the traditional consumption-wealth ratio (*cay*), and its recent alternative versions that account for Markov-switching (cay^{MS}) and time-variation (cay^{TVP}) in the consumption function, can predict stock return of the United States (US), with the newer versions performing relatively better at times (e.g., Ludvigson and Ng (2007), Welch and Goyal (2007), Lettau and Ludvigson (2010), Rapach and Zhou (2013), Balcilar et al., (2017), Bianchi et al., (2018), Chang et al., (2018)). Related to this line of research, Afonso and Sousa (2011) made a significant contribution by showing that *cay* can predict 10-year government bond yield of the US (and other the Organisation for Economic Co-operation and Development (OECD) countries), besides stock returns.[1] From a theoretical perspective, this is expected, since consumption-wealth ratios summarize expected returns on aggregate wealth or the market portfolio, and hence, should serve as a strong predictor of asset returns.

Given this, the objective of this paper is to add the nascent literature on the role of the *cay* in affecting the future path of US bond returns, by comparing simultaneously the relative importance of the recently proposed cay^{MS} and cay^{TVP} in predicting bond risk premia (excess returns) of U.S. government bonds. Note that however, there is indeed a large number of studies on forecasting excess returns and bond risk premia of U.S. government bonds (e.g., Cochrane and Piazzesi (2005), Ludvigson and Ng (2009, 2011), Laborda and Olmo (2014), Gargano et al., (2017), Ghysels et al., (2018)).[2] But, these studies highlight the role of macro and financial (often extracted from large data sets), and behavioral factors in predicting (excess) bond returns, over and above the so-called "CP" factor of Cochrane and Piazzesi (2005), which in turn is a linear combination of five forward spreads. In other words, our paper aims to analyze, for the first time, whether the superior predictive ability of the cay^{MS} and cay^{TVP} relative to *cay* observed for the US stock market also translates to the bond market.

[1]However, a disaggregated version of the consumption-wealth ratio based on disaggregated wealth, i.e., financial and housing wealth separated out (termed *cday*) failed to depict any evidence of predictability for the long-term government yield of the US, though positive evidence is observed for the stock markets of the US and other OECD economies. Interestingly, just like *cay*, using the wealth-income ratio (*wy*), Sousa (2015) provided evidence of predictability for the stock and government bond markets of the US and other OECD countries.

[2]Important earlier studies are Keim and Stambaugh (1986), Fama and Bliss (1987), Fama and French (1989), and Campbell and Shiller (1991).

To this end, we use a linear predictive regression framework to forecast excess returns on two- to five-year government bonds (relative to one-year bonds) based on information from the variants of the consumption-wealth ratios after controlling for the CP factor (and a large number of macro and financial factors of Ludvigson and Ng (2009, 2011)), over the quarterly sample period from 1981:Q1 to 2015:Q3 (with an in-sample of 1953:Q2−1980:Q4). We lay out data and methodology in Section 2, results in Section 3, and concluding remarks in Section 4.

2. Data and Methodology

In order to investigate the role of fluctuations in the four measures of the aggregate consumption-wealth ratio for explaining the excess bond returns, we run predictive regressions of the type commonly used in the literature for asset returns predictability. We also include the single forward factor (CP) of Cochrane and Piazzesi (2005) that is widely used in the literature to predict excess bond returns. The predictive regressions framework can be defined as:

$$rx_{t+1}^{(n)} = \alpha_0 + \beta' Z_t + \varepsilon_{t+1}, \tag{1}$$

where $rx_{t+1}^{(n)}$ denote the continuously compounded excess returns on an n-year zero coupon bond in period $t+1$.[3] We obtain quarterly US Treasury bond prices from the Fama and Bliss (1987) dataset, which is available at the Center for Research in Security Prices (CRSP). Depending on the model specification, Z_t includes the single forward factor (CP, constructed based on the bond prices)[4] of Cochrane and Piazzesi (2005), the traditional (cay), and Markov-switching versions of the consumption-wealth ratio cay_s^{MS} and cay_f^{MS} based on filtered and smoothed probabilities respectively as introduced by Bianchi et al. (2018),[5]

[3]In line with Cochrane and Piazzesi (2005), we use the following notation for the (log) yield of an n-year bond $y_t^{(n)} \equiv -\frac{1}{n} p_t^{(n)}$, where $p_t^{(n)} = lnP_t^{(n)}$ is the log bond price of the n-year zero coupon bond at time t. A forward rate at time t for loans between time $t+n-1$ and $t+n$ is defined as: $f_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}$. The log holding period return from buying an n-year bond at time t and selling it as an $n-1$ year bond at time $t+1$ is: $r_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)}$. The risk premium on an n-year discount bond over a short-term bond is the difference between the holding period returns of the n-year bond and the 1-period interest rate, $rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$.

[4]To construct the CP predictor, we regress average excess returns across maturities at each time t on the one-year yield and the four years forward rates $f_t \equiv [y_t^{(1)} f_t^{(2)} f_t^{(3)} f_t^{(4)} f_t^{(t)}]^T$: $\overline{rx}_{t+1} = \gamma_0 + \gamma^T f_t + \overline{\varepsilon}_{t+1}$, where the average excess log returns across the maturity spectrum is defined as: $\overline{rx}_{t+1} \equiv \frac{1}{4} \sum_{n=2}^{5} rx_{t+1}^{(n)}$. Then the predictor is computed from: $CP_{t+1} = \gamma_0 + \gamma^T f_t$.

[5]The regime can be downloaded from the website of Professor Martin Lettau at: `https://sites.google.com/view/martinlettau/data`.

and a time-varying measure of consumption-wealth ratio, i.e., cay^{TVP}, as developed by Chang et al., (2019) based on time-varying co-integration.[6]. Given the availability of the cay^{TVP} data, our sample period runs from 1953:Q2 to 2015:Q3.

We then conduct a recursive out-of-sample forecasting exercise from 1981:Q1 to 2015:Q3, given an in-sample of 1953:Q2 to 1980:Q4, to analyze the predictive accuracy of the variety of alternative consumption-wealth ratio measures by adding each explanatory variable to the random-walk (RW) model one at a time. Put differently, we run a horse-race between a variety of alternative consumption-wealth ratio measures including cay, cay_s^{MS}, cay_f^{MS}, cay^{TVP} individually and the CP factor. We choose the in- and out-of-sample periods following Bianchi et al. (2018). For each quarter, we produce a sequence of six h-quarter-ahead forecasts, i.e., $h = 1, 2, 3, 4, 6, 8$. Finally, we use the mean squared forecast error (MSFE) adjusted test of Clark and West (2007) to compare forecast performance relative to the RW model.

3. Empirical Results

In-sample results, as reported in Table 1, show that the forecasting power of bivariate regressions of excess bond returns incorporating different consumption-wealth ratios is quite weak. Put differently, these regressions express a negligible percentage of next quarter's excess bond return variation across all maturities. But, we observe that the traditional cay is the only measure that has statistically significant predictive power, consistently for bonds at all maturities and produces a non-zero R^2 ranging from 3% to 5%.[7] The predictive content of cay on future excess bond returns is economically large. The point estimate of the coefficient on cay is always positive and increasing in magnitude with the maturity. For example, one-standard-deviation increase in cay leads to 18, 30, 41, 53 basis points rise in excess bond returns for two-, three-, four-, and five-year maturities, respectively. This result in line with the intuition that investors allow consumption to rise above its equilibrium relationship with aggregate wealth and labour income when they have expectations of higher government bond yields, since government bonds are seen as a component of

[6]We thank Professor Tsangyao Chang for making the data on this measure available to us.

[7]Following Afonso and Sousa (2011), we also created a disaggregated measure of the consumption-wealth ratio i.e., *cday* (based on Financial Accounts data of the US derived from the Board of Governors of the Federal Reserve System), but unlike their paper, we found that this measure could predict bond premia equally as well as the *cay*. Complete details of these results are available upon request from the authors.

asset wealth.[8]

The rows (5)-(8) of each panel in Table 1 shows that when both the alternative consumption-wealth measures (in turn) and the *CP* factor are included in the regressions, the R^2 statistic increases to 25% implying that these regressions have more explanatory power than the bivariate model for bond excess returns confirming the importance of information contained in the *CP* factor. Interestingly again, *cay* performs better than the recently developed versions of the consumption-wealth ratios, reflecting that the fixed coefficient version of this ratio, where there is no adjustment for regimes, has much stronger predictive power.

– Insert Table 1 about here. –

Table 2 presents the out-of-sample forecasting results based on alternative model specifications. Models that yield the lowest MSFE values at each horizon are denoted in bold. We observe that the MSFE values generally increase with the forecast horizon. Also, virtually all of the entries in Tables 2 are less than unity, indicating that alternative specifications generally produce better forecasts than the benchmark RW model except for specifications that include only cay_s^{MS}, cay_f^{MS}, cay^{TVP} and a constant. This observation is further supported by the MSFE-adjusted test of Clark and West (2007), implying statistically significant improvements in forecast accuracy compared to the RW model, at all forecast horizons.

Comparing various model specifications, we observe that the model that includes both the *CP* and *cay* usually provides the lowest MSFEs, and attains the top rank in 15 out of 24 cases, outperforming the alternative model specifications that comprise of the different versions of consumption-wealth ratios. On the other hand, the specification including cay_s^{MS} and *CP* also fares quite well, yielding MSFE-best predictions in 6 of 24 cases. Indeed, it is the best MSFE-based model at all forecast horizons, when considering only 3-year excess bond returns. Bianchi et al. (2018) provide evidence of infrequent shifts in the conditional expected value of the real Federal funds rate to coincide with the breaks in the mean of cay_s^{MS}, which in turn characterize the high asset valuation regimes with an expectation of persistently low Federal funds rate. Building on these views, the high asset valuation regimes may imply more favorable prospects for economic growth and result in an increase in consumption. Hence, cay_s^{MS} may contain relevant information for predictability of excess bond returns.

[8]Interestingly, the sign obtained by Afonso and Sousa (2011) for the impact of 10-year US government yield was found to be negative, suggesting that , the issuance of government debt is seen as a symptom of deteriorating public finances, and hence, investors allow consumption to fall below its common trend with aggregate wealth and labour income.

– Insert Table 2 about here. –

In the Appendix of the paper, we conducted additional econometric analyses to check for the robustness of our results by adding the macroeconomic and financial factor (F_s) as an additional control in the predictive regressions, besides the *CP* factor. This factor is a linear combination of nine factors[9] extracted by Ludvigson and Ng (2009, 2011)[10] derived from a large date set of economic and financial variables of the US. As can be seen from the in-sample results in Table A1, the superiority of the *cay* relative to the alternative consumption-wealth ratios continue to hold even in the presence of the *CP* and *LN* factors together. Besides, as reported in Table A2, *cay* is particularly useful in forecasting the bond premia of various maturities at longer horizons, after controlling for both *CP* and *LN* factors. Finally, in Table A3, we report in-sample results of predictability derived from a quantile Bayesian model averaging (QBMA) approach of Korobilis (2017), when we allow for the *CP* factor and all the nine factors of Ludvigson and Ng (2009, 2011), i.e., *LN* instead of one combined factor. Note that, whereas BMA methods are regularly used to deal with model uncertainty in regression models with multiple predictors, the QBMA allows for different predictors to affect different quantiles of the bond premia. In other words, a quantiles-based approach is inherently a time-varying approach as it captures the different phases (regimes) of the bond market, corresponding to various parts of the conditional distribution of the excess bond return (Balcilar et al., 2017). Again, based on the posterior probability of inclusion reported in Table A3, the importance of the *cay* for in-sample predictability is observed particularly strongly for the four- and five-year excess bond returns over the majority of their respective conditional distributions.

In sum, our results highlight the role of the classical consumption-wealth ratio (*cay*) as a significant predictor of excess bond returns, relative to its nonlinear counterparts. The U.S. Treasury securities are well-established as a global safe haven, due to the significant lack of default risk fueled by the vast revenue stream the U.S. government generates (Kopyl and Lee, 2016; Habib and Stracca, 2017). Given that government bonds in the U.S. are considered relatively less riskier to equities (Demirer and Gupta, 2018), might imply relatively lesser nonlinearity in its data generating process, which in turn could be resulting in a weaker role

[9] $\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1\widehat{F_{1t}} + \gamma_2\widehat{F_{1t}^3} + \gamma_3\widehat{F_{2t}} + \gamma_4\widehat{F_{3t}} + \gamma_5\widehat{F_{4t}} + \gamma_6\widehat{F_{5t}} + \gamma_7\widehat{F_{6t}} + \gamma_8\widehat{F_{7t}} + \gamma_9\widehat{F_{8t}} = F_s.$

[10] The factors can be downloaded from Professor Sydney C. Ludvigson's website at: `https://www.sydneyludvigson.com/data-and-appendixes/`, and starts in 1960:Q1. The monthly factors are converted to quarterly values by taking averages over three months.

for the nonlinear counterparts of the consumption wealth-ratios (cay^{MS} and cay^{TVP}) in predicting the future movements of the bond market.

4. Conclusion

We analyze the ability of alternative consumption-wealth ratios, based on the constant parameter, regime-switching and time-varying parameter cointegration estimation of the consumption function, for predicting in- and out-of-sample movements of quarterly excess returns of U.S. government bonds over 1953:Q2 to 2015:Q3. Our findings show that after controlling for standard financial and macroeconomic factors, it is the traditional consumption-wealth ratio based on a standard cointegrating model of the consumption function, that outperforms the recently proposed nonlinear versions of the consumption wealth-ratios in predicting the path of excess returns on bonds.

Our results have implications for bond investors, policymakers, and researchers, who are all looking to predict interest rates movements accurately. The finding that the consumption-wealth ratio, and in particular its traditional version, affects the evolution of future interest rates can help policymakers in fine-tuning monetary policy. Bond investors can improve investment strategies by exploiting the role of the consumption-wealth ratio for interest-rate predictability. Finally, researchers may find our results useful for developing better asset-pricing models that entirely use the information embedded in standard estimates of consumption-wealth ratios.

As part of future research, it would be interesting to re-conduct our analysis for asset (stocks, bonds, and even housing) markets of other developed and emerging countries.

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Table 1: In-sample regressions of quarterly excess bond returns on predictor factors

Model: $rx_{t+1}^{(n)} = \alpha_0 + \beta' Z_t + \varepsilon_{t+1}$

		CP	cay	cay_f^{MS}	cay_s^{MS}	cay^{TVP}	R^2
$rx_{t+1}^{(2)}$	(1)		0.188***				0.05
	(2)			0.076			0.00
	(3)				0.045		0.00
	(4)					-0.002	0.00
	(5)	0.384***	0.128***				0.26
	(6)	0.405***		-0.036			0.24
	(7)	0.406***			-0.046		0.24
	(8)	0.399***				-0.001	0.25
$rx_{t+1}^{(3)}$	(1)		0.305***				0.03
	(2)			0.083			0.00
	(3)				0.028		0.00
	(4)					-0.002	0.00
	(5)	0.722***	0.193**				0.26
	(6)	0.762***		-0.129			0.25
	(7)	0.760***			-0.144		0.25
	(8)	0.745***				-0.001	0.25
$rx_{t+1}^{(4)}$	(1)		0.413***				0.03
	(2)			0.174			0.00
	(3)				0.100		0.00
	(4)					-0.002	0.00
	(5)	1.001***	0.258**				0.25
	(6)	1.047***		-0.117			0.24
	(7)	1.047***			-0.136		0.24
	(8)	1.032***				-0.001	0.24
$rx_{t+1}^{(5)}$	(1)		0.538***				0.03
	(2)			0.268			0.00
	(3)				0.172		0.00
	(4)					-0.001	0.00
	(5)	1.237***	0.346**				0.25
	(6)	1.293***		-0.091			0.24
	(7)	1.294***			-0.121		0.24
	(8)	1.281***				-0.001	0.24

The table reports the estimates from OLS regressions of excess bond returns on the variables in columns. For example, the first row in panel $rx_{t+1}^{(2)}$ reports the results from the predictive model that includes only the *cay*. A constant is always included in the regressions. Entries superscripted with an asterisk denote the statistical significance (*** p < 0.01, ** p < 0.05, * p <0.1).

Table 2: Out-of-sample forecasting of excess bond returns based on alternative model specifications

$rx_{t+1}^{(2)}$	h=1	h=2	h=3	h=4	h=6	h=8
RW	0.019	0.019	0.019	0.019	0.019	0.018
$RW + cay$	0.967***	0.972***	0.976***	0.978***	0.980***	0.982***
$RW + cay_s^{MS}$	1.003	1.005	1.007	1.009	1.007	1.007
$RW + cay_f^{MS}$	1.001	1.004	1.006	1.006	1.004	1.003
$RW + cay^{TVP}$	1.005	1.010	1.015	1.016	1.019	1.023
$RW + CP$	0.812***	0.813***	0.828***	0.844***	0.849***	0.841***
$RW + cay + CP$	**0.807*****	**0.810*****	**0.825*****	**0.840*****	**0.842*****	**0.829*****
$RW + cay_s^{MS} + CP$	0.810***	0.812***	0.827***	0.843***	0.846***	0.837***
$RW + cay_f^{MS} + CP$	0.812***	0.815***	0.830***	0.846***	0.849***	0.841***
$RW + cay^{TVP} + CP$	0.816***	0.820***	0.835***	0.850***	0.855***	0.848***
$rx_{t+1}^{(3)}$						
RW	0.036	0.036	0.036	0.035	0.035	0.034
$RW + cay$	0.977***	0.982***	0.986***	0.988***	0.989***	0.990***
$RW + cay_s^{MS}$	1.005	1.008	1.013	1.016	1.017	1.015
$RW + cay_f^{MS}$	1.003	1.007	1.010	1.013	1.011	1.009
$RW + cay^{TVP}$	1.006	1.010	1.014	1.015	1.018	1.021
$RW + CP$	0.822***	0.828***	0.841***	0.858***	0.860***	0.854***
$RW + cay + CP$	0.821***	0.830***	0.844***	0.861***	0.858***	0.848***
$RW + cay_s^{MS} + CP$	**0.819*****	**0.825*****	**0.840*****	**0.857*****	**0.856*****	**0.846*****
$RW + cay_f^{MS} + CP$	0.822***	0.828***	0.843***	0.860***	0.859***	0.849***
$RW + cay^{TVP} + CP$	0.826***	0.834***	0.847***	0.862***	0.864***	0.857***
$rx_{t+1}^{(4)}$						
RW	0.052	0.052	0.051	0.050	0.050	0.048
$RW + cay$	0.978***	0.984***	0.987***	0.989**	0.990**	0.991**
$RW + cay_s^{MS}$	1.005	1.009	1.014	1.017	1.018	1.017
$RW + cay_f^{MS}$	1.003	1.007	1.010	1.013	1.012	1.009
$RW + cay^{TVP}$	1.006	1.011	1.014	1.015	1.018	1.021
$RW + CP$	0.832***	**0.841*****	**0.853*****	**0.867*****	0.865***	0.856***
$RW + cay + CP$	**0.831*****	0.842***	0.855***	0.870***	**0.864*****	**0.851*****
$RW + cay_s^{MS} + CP$	0.833***	0.843***	0.857***	0.872***	0.869***	0.855***
$RW + cay_f^{MS} + CP$	0.834***	0.844***	0.858***	0.874***	0.870***	0.857***
$RW + cay^{TVP} + CP$	0.836***	0.847***	0.859***	0.872***	0.870***	0.860***
$rx_{t+1}^{(5)}$						
RW	0.065	0.065	0.064	0.062	0.062	0.060
$RW + cay$	0.975***	0.980***	0.983***	0.984***	0.984***	0.985***
$RW + cay_s^{MS}$	1.005	1.009	1.014	1.018	1.019	1.018
$RW + cay_f^{MS}$	1.002	1.006	1.010	1.013	1.013	1.010
$RW + cay^{TVP}$	1.005	1.010	1.012	1.014	1.017	1.019
$RW + CP$	0.846***	0.856***	0.869***	0.886***	0.883***	0.878***
$RW + cay + CP$	**0.843*****	**0.855*****	**0.869*****	**0.886*****	**0.878*****	**0.869*****
$RW + cay_s^{MS} + CP$	0.848***	0.860***	0.875***	0.893***	0.889***	0.881***
$RW + cay_f^{MS} + CP$	0.849***	0.861***	0.876***	0.894***	0.890***	0.881***
$RW + cay^{TVP} + CP$	0.849***	0.860***	0.873***	0.889***	0.886***	0.879***

Entries in the first row of the table are point MSFEs based on the benchmark random walk (RW) model, while the rest are relative MSFEs. Hence, a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (*** = 1% level; ** = 5% level) are significantly superior than the RW model, based on the Clark and West (2007) predictive accuracy test.

Appendix

Table A1: In-sample regressions of quarterly excess bond returns on predictor factors

		F_s	CP	cay	cay_f^{MS}	cay_s^{MS}	cay^{TVP}	R^2
$rx_{t+1}^{(2)}$	(1)	0.41***	0.12**					0.41
	(2)	0.39***	0.11**	0.11**				0.43
	(3)	0.41***	0.11*		0.04			0.41
	(4)	0.41***	0.11*			0.05		0.41
	(5)	0.41***	0.11**				0.0006	0.42
$rx_{t+1}^{(3)}$	(1)	0.74***	0.23**					0.41
	(2)	0.72***	0.22**	0.16*				0.42
	(3)	0.74***	0.23**		0.002			0.41
	(4)	0.75***	0.23**			0.009		0.41
	(5)	0.77***	0.21**				0.002	0.41
$rx_{t+1}^{(4)}$	(1)	0.99***	0.34**					0.39
	(2)	0.97***	0.33**	0.22*				0.40
	(3)	0.99***	0.33**		0.076			0.39
	(4)	1.00***	0.33**			0.085		0.39
	(5)	1.03***	0.33**				-0.0007	0.39
$rx_{t+1}^{(5)}$	(1)	1.16***	0.47**					0.37
	(2)	1.13***	0.45**	0.29*				0.38
	(3)	1.17***	0.45**		0.133			0.38
	(4)	1.17***	0.45**			0.135		0.38
	(5)	1.23***	0.44**				0.004	0.38

The table reports the estimates from OLS regressions of excess bond returns on the variables in columns. For example, the first row in panel $rx_{t+1}^{(2)}$ reports the results from the predictive model that includes only the CP and F_s. A constant is always included in the regressions. Entries superscripted with an asterisk denote the statistical significance (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table A2: Out-of-sample forecasting of excess bond returns based on alternative model specifications

$rx_{t+1}^{(2)}$	h=1	h=2	h=3	h=4	h=5	h=6	h=7	h=8	h=9
RW	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.018	0.017
$RW + CP + F_s$	0.649***	**0.651*****	**0.661*****	**0.667*****	0.657***	0.658***	0.661***	0.667***	0.676***
$RW + CP + F_s + cay$	**0.646*****	0.653***	0.665***	0.669***	**0.657*****	**0.655*****	**0.655*****	**0.659*****	**0.667*****
$rx_{t+1}^{(3)}$									
RW	0.036	0.036	0.036	0.035	0.035	0.035	0.035	0.034	0.033
$RW + CP + F_s$	**0.686*****	**0.693*****	**0.702*****	**0.708*****	**0.693*****	**0.692*****	0.694***	0.700***	0.707***
$RW + CP + F_s + cay$	0.687***	0.700***	0.712***	0.718***	0.700***	0.696***	**0.693*****	**0.696*****	**0.700*****
$rx_{t+1}^{(4)}$									
RW	0.051	0.051	0.051	0.050	0.050	0.049	0.049	0.048	0.046
$RW + CP + F_s$	**0.715*****	**0.725*****	**0.734*****	**0.739*****	**0.724*****	**0.722*****	0.723***	0.728***	0.734***
$RW + CP + F_s + cay$	0.716***	0.731***	0.744***	0.749***	0.731***	0.725***	**0.722*****	**0.723*****	**0.725*****
$rx_{t+1}^{(5)}$									
RW	0.064	0.064	0.063	0.062	0.061	0.061	0.061	0.060	0.058
$RW + CP + F_s$	0.743***	**0.753*****	**0.763*****	**0.768*****	**0.753*****	**0.751*****	0.752***	0.759***	0.765***
$RW + CP + F_s + cay$	**0.742*****	0.758***	0.770***	0.776***	0.757***	0.752***	**0.749*****	**0.751*****	**0.754*****

Entries in the first row of the table are point MSFEs based on the benchmark random walk (RW) model, while the rest are relative MSFEs. Hence, a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (*** = 1% level; ** = 5% level) are significantly superior than the RW model, based on the Clark and West (2007) predictive accuracy test.

Table A3: Quantile Bayesian model averaging predictive regression results for the model including , LN, CP and cay

quantiles	**0.05**	**0.10**	**0.20**	**0.25**	**0.35**	**0.40**	**0.45**	**0.50**	**0.55**	**0.60**	**0.70**	**0.75**	**0.80**	**0.85**	**0.90**
$rx_{t+1}^{(2)}$	0.01	0.16	0.02	0.20	0.18	0.10	0.95	0.32	0.12	0.87	0.09	0.28	0.52	0.11	0.09
$rx_{t+1}^{(3)}$	0.35	0.60	0.20	0.11	0.18	0.26	0.05	0.42	0.00	0.66	0.72	0.33	0.63	0.05	0.07
$rx_{t+1}^{(4)}$	0.07	0.06	0.03	0.02	0.14	0.04	0.00	0.60	0.22	0.04	0.04	0.79	0.04	0.02	0.04
$rx_{t+1}^{(5)}$	0.01	0.21	0.89	0.07	0.01	0.05	0.22	0.00	0.03	0.00	0.13	0.01	0.00	0.00	0.28

Entries in the table are posterior inclusion probabilities of cay at specific quantiles based on the regression of excess returns on nine LN (Ludvigson and Ng, 2009; 2011) factors, the CP factor and the cay.