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Consumer expectations and short-horizon return predictability

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Abstract

Lettau and Ludvigson [Lettau, M., Ludvigson, S, 2001. Consumption, aggregate wealth and expected stock returns. Journal of Finance 56, 815–849] argue that fluctuations from the equilibrium ratio of consumption to wealth ($\widehat{cay}$) reflect changing expectations of asset returns and document significant short-horizon predictability based on $\widehat{cay}$. This paper further explores the role of consumer expectations in modeling time variation of expected equity returns by considering two measures of consumer expectations: (i) consumer behavior as reflected in $\widehat{cay}$, and (ii) a more-direct measure of expectations captured by the Index of Consumer Sentiment (ICS). We report strong regression-based evidence of return predictability based on $\widehat{cay}$, which remains evident even after accounting for various sources of estimation risk. However, the regression-based evidence of predictability does not necessarily imply that shifts in aggregate consumption and the components of aggregate wealth give rise to economically significant investment signals. The survey-based measure of expectations (ICS) is shown to complement the behavioral measure ($\widehat{cay}$) but has no apparent stand-alone predictive value in forecasting equity returns.

JEL classification: G11; G12

Keywords: Return predictability; Estimation risk; Portfolio choice; Consumer expectations; Consumption-to-wealth ratio; Cay

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1. Introduction

Evidence of return predictability is not necessarily evidence of an anomaly, market inefficiency or investor irrationality. In fact, a degree of systematic equity return predictability is consistent with modern asset pricing theory. While there is little apparent consensus of opinion on the degree of return predictability and its economic implications, the evidence favoring the existence of predictability – particularly over long horizons – is arguably gaining wider acceptance.[1]

A recent paper by Lettau and Ludvigson (2001) (henceforth LL) distinguishes itself from previous predictability studies in two important ways. First, while existing evidence of predictability using 'known' predictors (such as dividend yield) tends to arise at longer horizons, LL provide empirical evidence of predictability over short (quarterly) horizons. Second, LL's predictive variable has sound *ex-ante* theoretical foundations, suggesting strong links between variation in consumer expectations and subsequent equity returns.

LL model a long-run dynamic equilibrium relation between the log of consumption (c), asset returns (a) and labour income (y). Deviations from the cointegrating relation (named cay) can be shown to reflect expectations of return on the true market portfolio in a general, multiperiod consumption-based framework. While cay is not directly observable, LL construct an empirical estimate (denoted by $\widehat{cay}$) and argue that it captures the important predictive components of cay. As such, $\widehat{cay}$ can be expected to forecast asset returns by virtue of the Granger Representation Theorem (GRT). Their findings suggest that $\widehat{cay}$ does indeed have significant in-sample ability to forecast the quarterly return on a broad-based equity portfolio.

To re-emphasize LL's main finding, consider a regression of the quarterly excess return on the S&P500 index (r_t) on lagged $\widehat{cay}$ over the period 1951 Q4 through 2003 Q1. The estimated predictive regression using this extension of LL's sample is:

$$\begin{aligned} r_t = {} & \underset{(3.23)}{0.018} + \underset{(4.60)}{2.0494}\,\widehat{cay}_{t-1} + e_t \qquad (R^2 = 0.0939) \end{aligned}$$

where Newey and West (1987) corrected t-statistics are shown in parentheses. The most striking finding is the degree of in-sample predictability of $\widehat{cay}$ as summarized by the regression R^2 of 9.39%. This level of short-horizon predictability is significantly higher than that which obtains using common alternatives. For example, if lagged dividend yield (DY) is substituted for $\widehat{cay}$ as the predictor, the regression R^2 over the corresponding sample is a mere 1.86%.

The apparently strong predictive properties of $\widehat{cay}$ have been questioned by researchers on several fronts. First, Brennan and Xia (2005) and Hahn and Lee (2001) question the use of a predictor constructed using in-sample data. Specifically, the cointegrating parameters used to construct $\widehat{cay}$ are estimated over the same period used to test its predictive power. Second, Brennan and Xia (2005) emphasize that $\widehat{cay}$'s ability to predict asset returns rests on individuals' ability to take account of future risky investment opportunities in making their current consumption decisions, thus implying that aggregate consumption carries information about future returns.

[1] See, for example, Cochrane (1999).

Lettau and Ludvigson (2005) respond to Brennan and Xia (2005) and Hahn and Lee (2001) with reference to economic theory and the GRT. First, they note that knowledge of $\widehat{cay}$ parameters (wealth shares) is an implication of the theory, and that even out-of-sample testing does not safeguard against spurious findings of in-sample predictability. Second, if c, a, and y are indeed cointegrated, the GRT implies that lagged $\widehat{cay}$ must forecast growth in the stock-market component of a, given that it has no apparent ability to forecast c, y, or non-stock market wealth. Lettau and Ludvigson (2005, p. 4) conclude that, 'while the explanation for *why* $\widehat{cay}$ forecasts stock returns is open to interpretation, the findings of predictability per se are not.'

The current study contributes to this ongoing debate by extending the LL analysis in two distinct directions. First, we examine the robustness of predictability findings to the assumption that cointegrating parameters are fixed and known. In the spirit of the Kandel and Stambaugh (1996) and Barberis (2000) studies of predictability implied by the dividend yield, we document the impact of $\widehat{cay}$ on asset-allocation choices made by a utility-maximizing investor. The Bayesian framework used in these studies is extended to formally account for estimation risk in both the predictive regression *and* the cointegrating model used to construct $\widehat{cay}$. This approach facilitates an unambiguous assessment of the importance of assuming fixed and known wealth shares (cointegration parameters) in adopting $\widehat{cay}$ as a predictor.

Whilst LL argue the assumption of fixed, known cointegration parameters is reasonable – given that it is an implication of the theory, and given the convergence properties of cointegration parameter estimates – their argument rests on several assumptions and approximations of untested empirical validity. Our results suggest that the evidence of short-horizon return predictability is not driven by the assumption that cointegrating parameters are fixed and known. Both the slope on the $\widehat{cay}$ predictor and the predictive regression R^2 are remarkably insensitive to the uncertainty surrounding the cointegrating regression used to estimate $\widehat{cay}$. However, over long investment horizons, the combination of uncertainty relating to both the cointegrating and predictive regressions negates the economic significance of $\widehat{cay}$ predictability.

The second contribution of the paper relates to the comment of Brennan and Xia (2005) that the predictive ability of $\widehat{cay}$ hinges on individuals' ability to incorporate future investment opportunities into their current consumption decisions. LL's consumption-to-wealth ratio can be regarded as a behavioral summary of expectations about future investment opportunities assuming the representative, rational agent solves a difficult dynamic consumption–investment plan. Accordingly, departures from the steady-state ratio of consumption to wealth occur during times of optimism (characterized by higher consumption and lower risk aversion) and pessimism (lower consumption and higher risk aversion). An alternative to measuring departures from the steady-state relation is to use a more-direct measure of agents' optimism or pessimism; that is, without explicit reliance on deviations from a budget constraint and the implicit assumption about agents' ability solve the dynamic optimization problem.

In this vein, we propose and investigate the University of Michigan's Index of Consumer Sentiment (henceforth ICS) as a predictor of short-horizon equity returns. The ICS provides a composite measure of consumer perceptions of their ability and willingness to buy, especially in relation to discretionary expenditures. To the extent that consumers take account of future risky investment opportunities in formulating current consumption decisions, and that such expectations are reflected in the Michigan survey, the ICS may augment or supplant $\widehat{cay}$ as a predictor of returns.

There are other advantages of adopting the ICS as a measure of agents' expectations. Since the ICS is an off-the-shelf metric, the fact that there can be no suggestion of look-ahead bias is a practical advantage. The ICS also has potential to provide further insight to why $\widehat{cay}$ forecasts asset returns. While Lettau and Ludvigson (2005) emphasize the importance of the GRT as an explanation for the documented predictive ability of $\widehat{cay}$, such an explanation does not shed light on behavioral foundations; that is, whether or not a measure of consumer perception of their willingness and ability to consume reveals information about future asset returns through consumption smoothing.

Our empirical study finds no evidence that the ICS has stand-alone ability to forecast returns, nor of Granger causality between the behavioral ($\widehat{cay}$) and survey-based (ICS) measures of consumer expectations. Stated differently, departures from consumers' intertemporal budget constraint (as captured by $\widehat{cay}$) are not predicted by shifts in consumer sentiment. Shifts in the equity premium appear to presage shifts in sentiment, but not vice versa. To the extent that the ICS can be thought of as a measure of sentiments underpinning consumption-smoothing behavior, we find no empirical evidence consistent with LL's suggestion that $\widehat{cay}$ reflects changing consumer risk aversion. There is, however, a statistically and economically significant interaction between $\widehat{cay}$ and ICS. The short-horizon predictive ability of $\widehat{cay}$ can be improved if $\widehat{cay}$ signals are interpreted in light of measured consumer sentiment.

The remainder of the paper proceeds as follows. Section 2 outlines the econometric approach to modeling the cointegrating relation and the predictive regressions, along with the Bayesian posterior densities that are integral to the empirical analysis. Data series are described in Section 3. All results for $\widehat{cay}$ and ICS predictors are presented in Section 4, while Section 5 concludes the paper.

2. Econometric approach

The econometric approach to utilizing $\widehat{cay}$ in a predictive regression is a two-step procedure. First, to construct $\widehat{cay}$, the parameters of the cointegrating relationship are estimated. Second, the time-series of $\widehat{cay}$ is deployed as the independent variable in a predictive regression.

LL follow Stock and Watson (1993) in using dynamic least squares to obtain consistent estimates of the cointegrating parameters. In this paper, we adopt a Bayesian approach to estimate posterior densities of the parameters of both the predictive and cointegrating regressions. It is through these densities that we are able to account for estimation risk in assessing the predictive power of $\widehat{cay}$. An added advantage of the Bayesian approach is that, rather than assuming knowledge of fixed wealth shares, the posterior distribution of the cointegrating regression parameters can be utilized to assess the evidence of predictability conditioned only on the data (c, a and y) – as opposed to conditioning on $\widehat{cay}$ and ignoring the uncertainty surrounding parameter estimates in the cointegrating regression. This goes some way towards alleviating the concerns of Brennan and Xia (2005) that LL's in-sample estimate of $\widehat{cay}$ is assumed fixed and known.

2.1. Bayesian estimation of the cointegrating relation

Our analysis of cointegration between c, a and y adopts the estimation approach presented in Strachan (2003), which can be thought of as a Bayesian analogue of the Johansen

(1988) and Johansen (1991) approach to identification in a classical setting. This section briefly introduces essential notation relating to the estimation of the cointegrating regression (especially the cointegrating weights and the adjustment coefficients), as well as the relevant posterior densities.[2]

Consider the p-dimensional vector-valued process x_t:

$$x_t = \sum_{i=1}^{K} \Pi_i x_{t-i} + \Phi d_t + \varepsilon_t. \tag{1}$$

Writing (1) as an error correction model (ECM) gives:

$$\Delta x_t = \Pi x_{t-1} + \sum_{i=1}^{K-1} \Gamma_i \Delta x_{t-i} + \Phi d_t + \varepsilon_t, \tag{2}$$

where $\Delta x_{t-i} = x_{t-i} - x_{t-i-1}$, $\Pi = \sum_{i=1}^{K} \Pi_i - I_p$ is a $p \times p$ long-run impact matrix, Γ_i is a $p \times p$ matrix of coefficients governing the short-run dynamics, d_t is a $w \times 1$ vector of deterministic variables, Φ is the $p \times w$ coefficient matrix and ε_t is a zero-mean vector of errors with covariance Ω.

If all p time series comprising x_t are $I(1)$ and $rank(\Pi) = r < p$, then r linear combinations of the series are stationary and the time-series are said to be cointegrated. Further, Π can be written as the product of two $p \times r$ full rank matrices α' and β so that:

$$\Delta x_t = \beta \alpha x_{t-1} + \sum_{i=1}^{K-1} \Gamma_i \Delta x_{t-i} + \Phi d_t + \varepsilon_t. \tag{3}$$

We can interpret $\beta' x_{t-1} - E(\beta' x_{t-1})$ as deviations from the r equilibria and α as a matrix of coefficients governing the adjustment to equilibrium after a disturbance. In the context of the current paper, $x_t = (c_t\ a_t\ y_t)'$. In relation to the cointegrating regression, the posterior density of interest is $p(\theta_c \mid \mathscr{D})$, where $\theta_c \equiv (\alpha, \beta, \Gamma, \Phi, \Omega)$ and $\mathscr{D}$ denotes the sample data. Posterior means are used as point estimates of parameters to construct $c\hat{a}y$ and the full density is utilized to account for estimation risk surrounding the cointegrating regression.

2.2. Predictive regression and asset-allocation framework

Our approach to assessing the economic significance of return predictability using $c\hat{a}y$ is to document the horizon effects associated with optimal asset-allocation decisions made by a utility-maximizing investor. The investor chooses weightings in a portfolio comprising one risky asset (a stock portfolio) and one riskless asset, then holds this portfolio for J periods. Portfolio weights are chosen to maximize the expected power utility of terminal wealth. Since the optimal allocation to risky stocks is horizon dependent if stock returns are predictable, horizon effects are a measure of the economic significance of return predictability.

The key input to the optimization problem is the distribution of forecasted cumulative returns to the risky asset over the J-period investment horizon, which is estimated using a predictive regression. Following Kandel and Stambaugh (1996) and Barberis (2000), a vector autoregression (VAR) is used to model the joint dynamics of returns and the predictor

[2] Technical detail relating to all Markov chain Monte Carlo sampling schemes is contained in an Appendix available from the corresponding author on request.

variable. Consider a predictive regression with $\widehat{cay}$ as the sole predictor. The system of equations estimated is:

$$\begin{aligned} r_t &= b_{10} + b_{11}\widehat{cay}_{t-1} + e_{1t}, \\ \widehat{cay}_t &= b_{20} + b_{21}\widehat{cay}_{t-1} + e_{2t}. \end{aligned} \tag{4}$$

The equations in (4) can be viewed as a VAR with the coefficient on lagged returns r_{t-1} restricted to zero. In the discussion that follows, the matrix of regression coefficients is denoted B and the variance–covariance matrix of the innovations is denoted Σ, with elements σ_{ij}. Again, a Bayesian approach is adopted to estimate the joint posterior density of the predictive VAR parameters $p(\theta_{\mathrm{p}} \mid \mathscr{D})$, where $\theta_{\mathrm{p}} \equiv (B, \Sigma)$.

2.3. Parameters and uncertainty

The Bayesian posterior densities of the cointegrating parameters (θ_{c}) and the predictive regression (θ_{p}) allow the analysis of return predictability to proceed in a number of interesting directions. First, point estimates of the cointegrating parameters (θ_{c}) can be used to construct estimates of $\widehat{cay}$. Conditioning on $\widehat{cay}$, the estimation risk associated with the parameters of the predictive regression (θ_{p}) can be accounted for in asset-allocation decisions. As noted earlier, the key input to the optimal asset-allocation decision is the distribution of forecasted J-period cumulative returns to the risky asset which, under this scenario, is:

$$p(r_{t+J}|\mathscr{D}_t, \widehat{cay}_t) = \int p(r_{t+J}|\mathscr{D}_t, \widehat{cay}_t, \theta_{\mathrm{p}})p(\theta_{\mathrm{p}}|\mathscr{D}_t, \widehat{cay}_t)d\theta_{\mathrm{p}}. \tag{5}$$

Note that conditioning on $\widehat{cay}$ (or equivalently, the cointegrating parameters θ_{c}) is directly analogous to the approach of Kandel and Stambaugh (1996) and Barberis (2000), with the exception that $\widehat{cay}$ is employed here in place of dividend yield. Nonetheless, assessing predictability using (5) is subject to the criticism of Brennan and Xia (2005); namely, that predictability findings are conditioned on $\widehat{cay}$ being fixed and known.

With this in mind, an alternative approach is to integrate out the uncertainty surrounding both θ_{c} and θ_{p}. In doing so, the optimal asset-allocation decision is conditioned only on the data $\mathscr{D} \equiv (c, a, y, r)$. Under this scenario, the distribution of J-period cumulative returns is:

$$p(r_{t+J}|r_t, c_t, a_t, y_t) = p(r_{t+J} \mid \mathscr{D}_t) = \int\int p(r_{t+J}|\mathscr{D}_t, \theta_{\mathrm{p}}, \theta_{\mathrm{c}})p(\theta_{\mathrm{p}}, \theta_{\mathrm{c}}|\mathscr{D}_t)d\theta_{\mathrm{p}}\,d\theta_{\mathrm{c}}. \tag{6}$$

Comparison of the equity allocation of risk-averse investors based on the predictive densities (5) and (6) provides a measure of the importance of assuming the parameters θ_{c} are fixed and known. To the extent that allocations differ, the criticism of Brennan and Xia (2005) becomes increasingly important. By contrast, if evidence of predictability using $\widehat{cay}$ is insensitive to the uncertainty surrounding wealth shares, Lettau and Ludvigson's (2005) defence of $\widehat{cay}$ predictability is strengthened.

3. Data

The data employed in this study are drawn from a number of public sources. In all predictive regressions, the dependent variable is the quarterly return on the CRSP

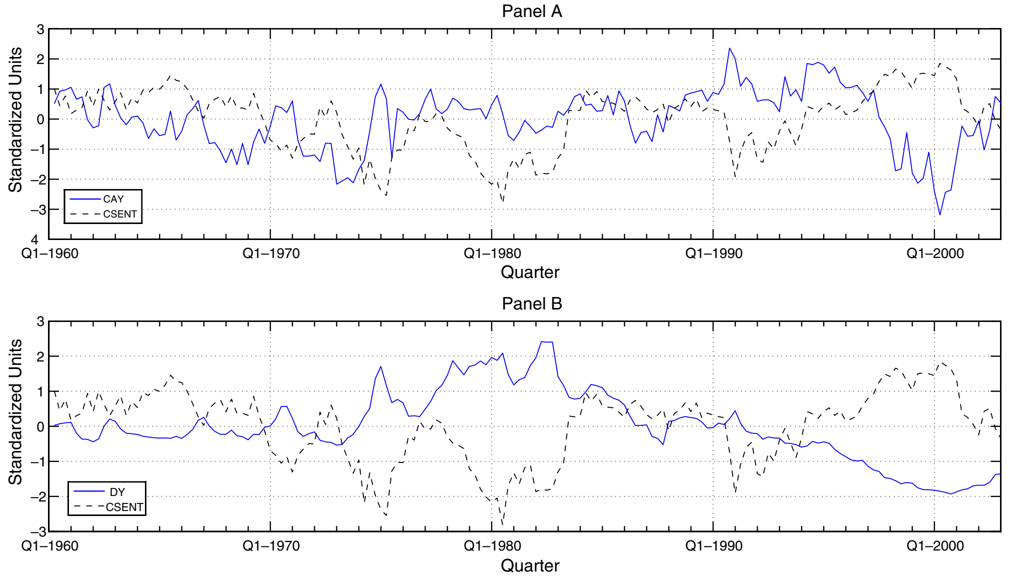


Fig. 1. Time-series plots of $\widehat{cay}$, ICS and DY. The solid line in Panel A plots the path of standardized $\widehat{cay}$ based on the posterior mean of cointegrating parameter estimates. The solid line in Panel B plots the path of the standardized dividend yield DY. In both panels, the dashed line plots the (standardized) quarterly Index of Consumer Sentiment (ICS).

value-weighted market portfolio, in excess of the one-month Treasury bill rate. The corresponding dividend yield on the market portfolio is imputed from the total return index and price index from CRSP.

The definition and construction of macroeconomic time-series data for consumption (c), asset holdings (a) and labour income (y) are identical to LL, albeit over an extended time period extending from Q1 1951 to Q1 2003.[3] These data are quarterly, seasonally adjusted, per capita variables measured in 1992 chain-weighted dollars.

The Index of Consumer Sentiment (ICS) has been published by the University of Michigan since 1960. It provides a composite measure of consumer perceptions of their 'ability and willingness to buy'. Specifically, the index seeks to capture consumers' ability and willingness to undertake discretionary expenditures.[4] Commencing in Q1 1960, time series of the sentiment index is freely available on the University of Michigan website.

Fig. 1 summarizes the time series properties of the standardized predictive variables. As may be expected, both $\widehat{cay}$ and the ICS are more volatile than DY, crossing their sample means far more often than the dividend yield over the sample period. However, the time

[3] This data is available on Martin Lettau's web page: http://pages.stern.nyu.edu/~mlettau/index.htm. The reader is referred to the appendix in Lettau and Ludvigson (2001) for details on variable construction and original data sources.

[4] Refer to Curtin (2002) for detailed discussion of interpretation and performance of the expectation measures. It is interesting to note that the discretionary expenditures captured by the consumer-sentiment surveys are excluded from the consumption data used to construct $\widehat{cay}$ on the grounds that expenditures on durable goods are replacements and additions to a stock rather than a 'service flow' from the existing stock (Lettau and Ludvigson, 2005, p. 822).

series plots are highly suggestive of links between shifts in measured sentiment and both $\widehat{cay}$ and DY. These apparent linkages are explored in Section 4.4.

4. Results

4.1. Estimates of model parameters

As a starting point, the parameters of the error correction model (3) are estimated following the Bayesian approach outlined in Section 2. Table 1 presents summary statistics for the posterior densities of the cointegrating parameters (β) and adjustment factors (α) which govern the long-run dynamics of log consumption (c), asset returns (a) and labour income (y).

As may be expected, the standard deviation of the cointegrating vector components are small relative to the means. Also consistent with expectations, the posterior standard deviation of the adjustment coefficients for consumption and income are large (of the same order of magnitude or larger than their expected values), whilst the dispersion of the adjustment coefficient on asset wealth is relatively small. This is consistent with LL's finding that deviations from the long-run relation between consumption, income and asset wealth are offset by adjustments in asset wealth rather than consumption or income – arguably this is why $\widehat{cay}$ forecast shifts in asset wealth rather than consumption or income.

The posterior estimates of the cointegrating parameters are broadly consistent with LL's estimates obtained using dynamic least squares (over a slightly shorter sample period). LL's estimates suggest that asset wealth accounts for 34% of aggregate wealth. The posterior densities of cointegrating parameters in this paper suggest a mean value of 31% with a standard deviation of 5.5%.

Given the error correction model estimates, the predictive variable $\widehat{cay}$ at any time t is constructed using the posterior means; that is, $\widehat{cay}_t = c_t - 0.2766a_t - 0.6119y_t$. Moving to the second stage of estimation, parameters from the predictive regression (4) are estimated. Table 2 Panel A reports the posterior means of the predictive VAR parameters for quarterly returns using $\widehat{cay}$ as the predictor. For the purpose of comparison, Panel B reports analogous estimates for a VAR using lagged dividend yield as the predictor.

The time series of estimated $\widehat{cay}$ exhibits some persistence ($b_{21} = 0.835$), although it is stationary. In contrast, the DY predictor is highly persistent ($b_{21} = 0.9883$), as is common. Arguably, the most notable point in Table 2 is the magnitude of the correlations between innovations in returns and each predictor. At -58% (-69%), the correlation between

Table 1
Point estimates for cointegrating regression

	Cointegrating parameters		Adjustment coefficients		
	β_a	β_y	α_c	α_a	α_y
Mean	−0.2766	−0.6119	−0.0344	0.4671	−0.0529
Median	−0.2727	−0.6160	−0.0325	0.4760	−0.0563
Standard deviation	0.0481	0.0526	0.0342	0.1670	0.0728

The error correction model (3) is estimated using sample data from 1951 Q4 through 2003 Q1 (202 observations). Summary statistics for the cointegrating vector $\beta = (\beta_c\ \beta_a\ \beta_y)'$ and adjustment coefficient vector $\alpha = (\alpha_c\ \alpha_a\ \alpha_y)'$ are based on the joint posterior density $p(\theta_c|\mathscr{D})$. The cointegrating vector β incorporates the normalization $\beta_c = 1$.

Table 2
Point estimates for predictive VAR

Equation	Predictor	b_{i0}	b_{i1}	σ_{i1}	σ_{i2}
r_t	$\hat{cay}_{t-1}$	0.0175	0.0254	0.0063	**−0.58**
$\hat{cay}_t$	$\hat{cay}_{t-1}$	0	0.835		0.4805e−005
r_t	DY_{t-1}	0.0854	0.03	0.0068	**−0.69**
DY_t	DY_{t-1}	−0.0325	0.9883		0.004

The predictive VAR (4) is estimated using sample data from 1951 Q4 through 2003 Q1 (202 observations) where r_t is the excess return on the CRSP market index. Point estimates for the VAR parameters $\theta_{\mathrm{p}} = (B, \Sigma)$ are the posterior means of $p(\theta_{\mathrm{p}}|\mathscr{D})$. Diagonal elements of the covariance matrix Σ are reported as correlations. Note that the intercept in the $\hat{cay}$ autoregression is zero since the time series of $\hat{cay}$ are standardized to have zero mean.

innovations in quarterly returns and $\hat{cay}$ (DY) is substantially smaller than the −94% reported in Barberis (2000) for a predictive VAR involving returns and DY (albeit for monthly sampling over a somewhat shorter period). The magnitude of these correlations is important in the context of the asset-allocation problem and the issue will be re-visited in Section 4.2.

4.2. Economic significance of $\hat{cay}$ as a predictor

Following Kandel and Stambaugh (1996) and Barberis (2000), the economic significance of return predictability is documented in terms of the horizon effects in a buy-and-hold asset-allocation problem. This analysis involves shocking the predictive variable of interest and measuring the impact of the shock on the optimal allocation. As such, the analysis can be thought of as an elaboration of the study of impulse response functions based on point estimates of VAR parameters. However, richer economic insights obtain through modeling the propagation of the shock through the full predictive distribution (rather than just the expected value), and in so doing, accounting for various sources of estimation risk through Eqs. (5) and (6).

Fig. 2 presents optimal allocations based on predictive models employing dividend yield (Panels A and B) and $\hat{cay}$ (Panels C and D).[5] Each subplot contains six sets of results. The lines labeled 'No Shock' plot asset allocations over a J-quarter holding period conditional on the predictor being at its sample mean at the time the allocation decision is made. The lines labeled '+ve shock' or '−ve shock' plot asset allocations conditional on the predictor being, respectively, one standard deviation above or below its sample mean. Finally, each graph shows results where the estimation risk associated with the predictive VAR is ignored (solid line) and accounted for (dotted line).

4.2.1. Ignoring estimation risk in predictive regression

When dividend yield is at its sample mean (No Shock case), the solid line in Fig. 2 Panel A shows that an investor with low risk aversion ($A = 5$) and an investment horizon of one quarter allocates just over 60% of wealth to equity (and the remainder to the short term riskless asset) when using lagged DY to predict future returns. The same investor with a

[5] For each predictor, two levels of risk aversion ($A = 5, 20$) are presented for an investor with power utility over terminal wealth.

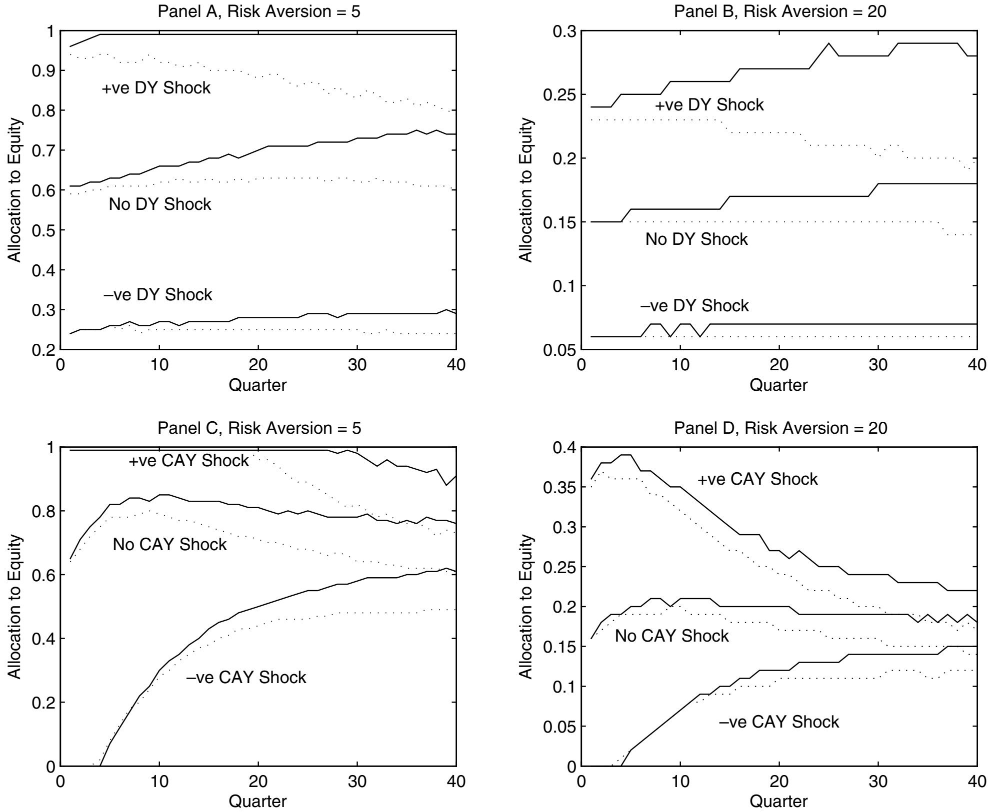


Fig. 2. Optimal asset allocations using *cây* and DY predictors. The figure shows the optimal buy-and-hold allocations to equity by a risk-averse investor who uses a predictive model to forecast quarterly returns. The predictive variable is DY (in Panels A and B) and *cây* (in Panels C and D). Two levels of risk aversion are shown ($A = 5, 20$). Each subplot shows several sets of results. The 'No Shock' plot assumes that the predictor is at its sample mean, while +ve (−ve) shocks denote cases where the observed value of the predictor is one standard deviation above (below) its time series mean. Solid lines plot equity allocations based of point estimates of the predictive VAR parameters, while dotted lines account for estimation risk in VAR parameters. *Note*: scale differs between the panels.

10-year horizon allocates over 72% of wealth to equity. The magnitude of this horizon effect weakens significantly if risk aversion is higher ($A = 20$ in Panel B). The corresponding results for an investor using *cây* to predict is shown Panels C and D. The solid line (No Shock case) shows that an investor with lower risk aversion ($A = 5$) invests approximately 65% of wealth in equity for a one-quarter horizon, and 76% for a 10-year horizon.

This horizon effect for *cây* predictability (using quarterly returns) is small relative to Barberis's finding for dividend yield (using monthly returns). However, the most notable aspect of Fig. 2 Panels C and D is that the *cây* horizon effect is *not* monotonic – the optimal equity allocation initially climbs for short investment horizons, peaks at 85% (for 10- and 11-quarter horizons) and then declines to 76% as horizon increases to 10 years.

Barberis (2000) explains his monotonic horizon effect by arguing that stocks are more appealing over longer horizons if the conditional variance of stock returns grows less than linearly with horizon. He uses a simple two-period example to illustrate the mathematics and explain the intuition in terms of negative correlation between innovations in returns and the predictor (dividend yield in his case). That is, a negative shock to dividend yield is likely to be associated with a positive shock to expected return. A lower dividend yield implies a lower expected return. This sequence of a high (low) realized return followed by a low (high) expected return implies that realized returns will exhibit a degree of negative serial correlation, and the conditional variance of cumulative returns does not scale with horizon.

To understand the non-monotonicity in the present case, note from Table 2 that the correlation between innovations in returns and the $\widehat{cay}$ predictors (−58%) is significantly lower than the −94% reported by Barberis for monthly returns and dividend yield. The impact of correlation is subtle but important. To illustrate, Fig. 3 plots the conditional periodic volatility of returns implied by Barberis's predictive regression estimates (see Barberis (2000), Table 2). When correlation is −94%, the volatility of return declines monotonically with investment horizon (solid line). As a consequence, if expected returns are positive and grow linearly with horizon, the implied Sharpe ratio of equity increases with horizon and equity becomes more attractive to risk averse investors. If, however, the correlation is halved, the periodic volatility initially falls with investment horizon, flattens out, then begins to rise with horizon (dashed line). Viewed in this light, the non-monotonicity of optimal allocations based on $\widehat{cay}$ predictability in Fig. 2 is consistent with the pattern in annualized volatility, and hence the time-varying Sharpe ratio implied by Fig. 3.

While the horizon effects induced by predictive variables are modest, optimal allocations are highly sensitive to shocks in the predictors. For example, in Fig. 2 Panel D, if the most-recently observed value of $\widehat{cay}$ is one standard deviation above its historical mean, the one-quarter allocation to equity more than doubles (from 16% to 36%). Similarly, if observed $\widehat{cay}$ is one standard deviation below its historical mean, the one-quarter

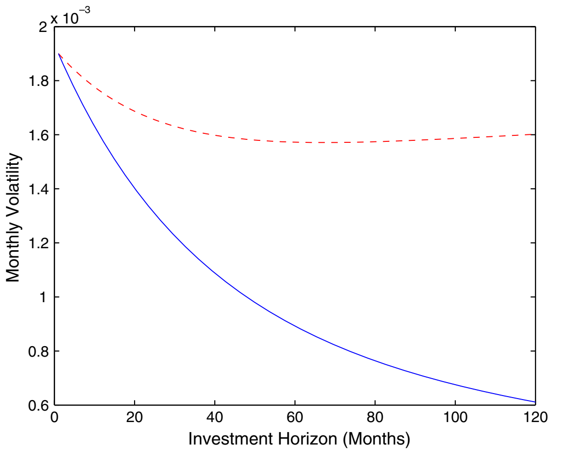


Fig. 3. Impact of correlation on monthly return volatility. The figure plots the monthly return volatility by investment horizon using the predictive regression estimates reported in Barberis (2000). The solid line represents the −94% correlation between innovations in dividend yield and return estimated by Barberis. The dashed line plots the same monthly return volatility by investment horizon assuming the correlation is halved to −43.5%, all else being equal.

equity allocation falls to zero. Over longer investment horizons, the impact of shocks to the *cây* predictor are less dramatic.

4.2.2. Impact of estimation risk in the predictive regression

The dotted lines in each subplot in Fig. 2 represent optimal equity allocations when the estimation risk associated with the predictive regression parameters (θ_{p}) is accounted for. That is, the distribution of forecasted future returns is given by (5). A common theme in all plots is that accounting for estimation risk in the predicitive regression lowers the allocation to equity, regardless of chosen predictor or level of risk aversion. The horizon effects associated with the DY predictor are largely eliminated, suggesting that estimation risk dominates. The horizon effects associated with *cây* are also weakened after allowing for estimation risk. Nonetheless, optimal allocations remain highly sensitive to shocks in both *cây* and DY predictors, especially over shorter holding periods. Even accounting for estimation risk in the predictive regression, a standard deviation shock to the predictors retains an economically substantial effect on optimal allocations.

In summary, the combined effects of correlation between innovations in each predictor and the equity premium and estimation error in predictive regression parameters lead to a similar conclusion for both *cây* and DY over longer horizons. That is, in this simple stylized setting, long-horizon investment weights are quite similar to short-horizon weights at a given level of risk aversion, given equivalent *cây* or DY signals, though for different reasons. The mean predictability associated with DY is largely swamped by estimation risk, whilst the horizon effects associated with *cây* are dampened by the combined effects of estimation risk and the correlation structure of VAR innovations.

4.3. Incorporating the uncertainty surrounding *cây*

The analysis of the economic significance of *cây* as a predictor in Section 4.2 was conditioned on knowledge of *cây*; that is, the parameters of the cointegrating regression used to construct the *cây* predictor are assumed to be known and fixed. In reality, an investor adopting *cây* as a predictor is uncertain about its current value. This section quantifies this additional uncertainty and assesses its impact on evidence of the economic importance of *cây* as a predictor.

Fig. 4 illustrates the uncertainty surrounding *cây* by plotting the time-series of *cây* point estimates utilized in this paper's predictive regression, surrounded by their 90% highest posterior density (HPD) interval. Clearly, there is considerable uncertainty surrounding *cay*. The 90% HPD interval ranges from 0.35 to over 2.95 standardized units.[6] In light of the predictability documented by LL – they suggest that a single (time series) standard deviation shift in *cây* corresponds to a 220 basis point change in quarterly returns on the market index – the dispersion signalled by the 90% HPDs is wide.

To get a sense of how the uncertainty captured in Fig. 4 alters the most basic measure of predictability, we undertake the following exercise. A set of values for the cointegrating regression parameters (α and β) are drawn at random from the posterior density $p(\theta_{\mathrm{c}}|\mathscr{D})$. The time-series of *cây* is constructed using these estimates and a predictive regres-

[6] The estimates of *cay* are standardized to have zero mean and unit standard deviation.

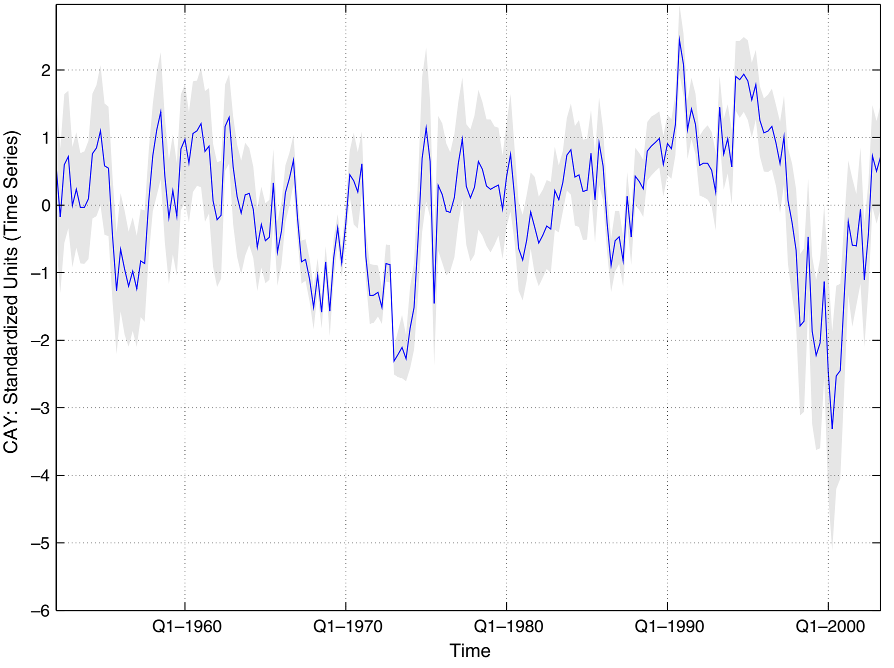


Fig. 4. Estimation risk associated with $c\hat{a}y$. The solid line plots the time-series of $c\hat{a}y$ point estimates over the period 1951 Q4 through 2003 Q1. The shaded region surrounding the point estimates is the 90% HPD of the *cay* posterior. All *cay* series are standardized to have a mean of zero and a standard deviation of one.

sion of market returns on $c\hat{a}y$ is conducted. This procedure is repeated 100,000 times. Averaging regression estimates across random draws gives:

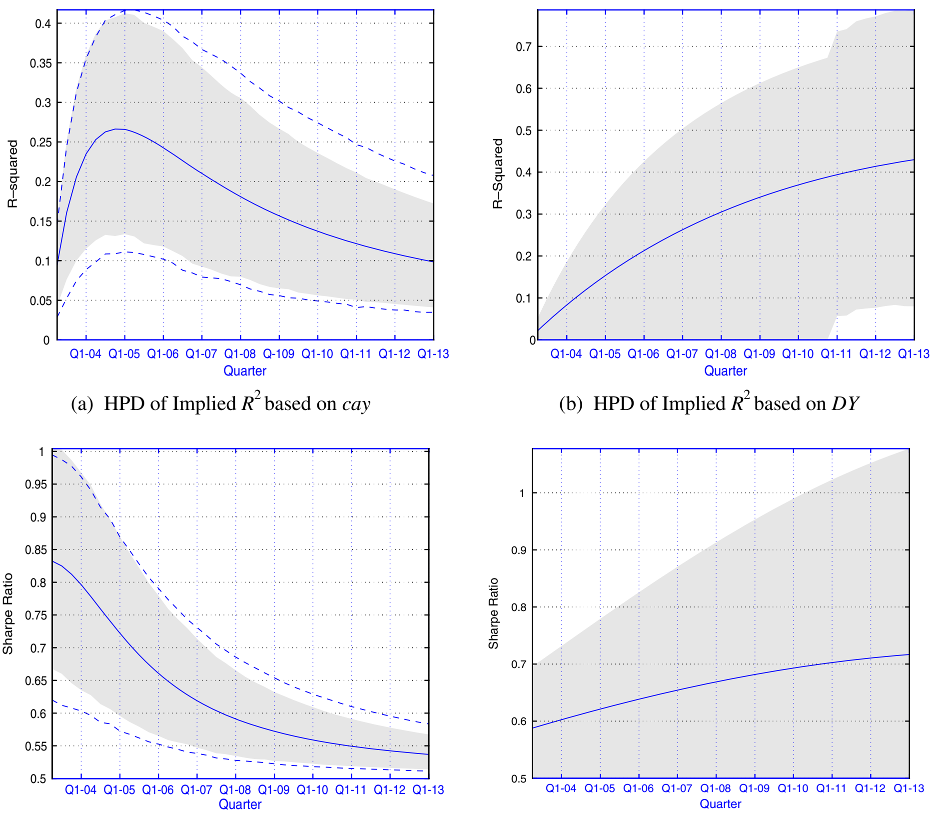
$$r_t = 0.018 + 0.0243c\hat{a}y_{t-1} + e_t, \\ (0.0031) \qquad (R^2 = 0.087, \quad \sigma(R^2) = 0.018), \tag{7}$$

where the point estimates are the mean regression coefficients obtained from 100,000 regressions. The standard deviation of 0.0031 for the slope coefficient on $c\hat{a}y_{t-1}$ and 0.018 for the R^2 reflects the variability attributable to uncertainty in $c\hat{a}y$ parameters. Given the often large dispersion in the posterior values of *cay*, the simple regression estimates of short-horizon predictability are remarkably robust – neither the size of the predictive regression slope coefficient nor the R^2 appear sensitive to the uncertainty surrounding *cay*. The variability of *cay* does not translate to significant variation in the short-horizon predictive regression results. We now examine whether this holds true for long-horizon predictions associated with the vector autoregression.

4.3.1. Unconditional predictability over long horizons: Economic significance

4.3.1.1. Implied long-horizon R^2. One way of better understanding the economic significance of a short- horizon predictive regression is to study its implications for multi-period predictability. Hodrick (1992) suggests a long-horizon R^2 that uses point estimates of VAR parameters to impute the multi-period impact of short-horizon predictability. Note that LL report this implied long-horizon R^2 conditional on the cointegration parameters used to construct $c\hat{a}y$. In this paper, the Bayesian posterior densities enable the imputation of long-horizon R^2 after allowing for the uncertainty associated with both the predictive VAR and the cointegrating regression.

Fig. 5a and b display the implied long-horizon R^2 associated with predictive VARs employing $c\hat{a}y$ and DY respectively. The solid line shows the R^2 using VAR point estimates based on the posterior median of $p(\theta_{\rm p}|\theta_{\rm c},\mathscr{D})$, while the surrounding shaded area reflects the 90% HPD intervals from this density. In Panel (a), the 90% HPDs of the long-horizon R^2 implied by the $c\hat{a}y$ VAR are relatively tight. The widest HPD is less than 30%, and it occurs at a horizon of 2 years. After 2 years, the posterior median of the implied R^2 and the associated uncertainty decline in absolute terms. At a horizon of 10 years, the posterior median is 10% and the 90% HPD has a range of only 15%. In contrast, Panel (b) reveals a high degree of uncertainty associated with the predictability implied by



(a) HPD of Implied R^2 based on *cay*

(b) HPD of Implied R^2 based on *DY*

(c) HPD of Maximal Sharpe Ratio based on *cay*

(d) HPD of Maximal Sharpe Ratio based on *DY*

Fig. 5. Implied long-horizon R^2s and maximal sharpe ratios. The solid lines in Panels (a) and (b) plot the posterior median of the long-horizon R^2 computed using draws from $p(\theta_{\rm p}|\mathscr{D})$ when quarterly excess market returns are forecast using $c\hat{a}y$ and DY, respectively. The shaded area denotes the region covered by the 90% HPD interval of the long-horizon R^2 implied by the VAR parameters. Panels (c) and (d) depict the maximal Sharpe ratio and 90% HPDs based on the quarterly regressions employing *cay* and DY, respectively. The dashed lines in (a) and (c) plot the expanded 90% HPDs when one also accounts for estimation risk in $c\hat{a}y$ parameters.

a DY predictive VAR. At a 2-year horizon, the spread of the implied R^2 exceeds 30%, at a 5-year horizon the corresponding dispersion exceeds 50% and at a horizon of 10 years the range of the HPD exceeds 70%.

In light of Brennan and Xia's (2005) criticism over conditioning predictability evidence on knowledge of $\widehat{cay}$, it is instructive to also examine how much additional dispersion in long-horizon R^2 is induced if the uncertainty surrounding the cointegrating regression is acknowledged. The dashed lines in Fig. 5 Panel (a) trace out the expanded 90% HPDs for the long-horizon R^2 implied by the $\widehat{cay}$ VAR after recognizing that wealth shares are not fixed and known. The incremental effect of this uncertainty is modest – the HPDs widen by 2–8%, increasing with horizon. To some extent, therefore, this finding alleviates concerns that have been raised over conditioning evidence of predictability on $\widehat{cay}$.

4.3.1.2. Maximal sharpe ratios. As an alternative measure of the economic significance of predictability, we adopt the approach of Gallant et al. (1990) who show that the R^2 of a predictive regression can be used to infer the maximal Sharpe ratio obtainable from an optimal market timing strategy based on predictive model. As a benchmark, note that the historical Sharpe ratio on a buy-and-hold investment in US equities is around 0.5.

Fig. 5 Panels (c) and (d) plot the maximal Sharpe ratio (by investment horizon) for $\widehat{cay}$ and DY respectively, surrounded by 90% HPDs. In Panel (c), the Sharpe ratio implied by $\widehat{cay}$ predictability is highest at short investment horizons – at around 0.85 for horizons less than one year, the Sharpe ratio is significantly higher than the buy-and-hold market investment. However, the implied Sharpe ratio diminishes rapidly to around 0.55 at the 10-year horizon. Unlike the long-horizon R^2 in Panel (a), the Sharpe ratio based on $\widehat{cay}$ diminishes monotonically, together with the span of the 90% HPD. The longer-horizon risk-return tradeoff implied by $\widehat{cay}$ and DY are strikingly different. These contrasts stem from the combined effects of the differing degrees of persistence of $\widehat{cay}$ and DY, the correlation structure of VAR innovations and estimation risk. However, both the statistical and economic measures of $\widehat{cay}$'s within-sample significance as a predictive variable suggest that there are substantial benefits at short to medium investment horizons. Further, as noted in the case of R^2, the incremental effect of uncertainty associated with the cointegration parameters seems small – as can be seen from the rather modest widening of the 90% HPD in Fig. 5 Panel (c) when we account for this effect.

In Panel (d), the maximal Sharpe ratio based on DY predictability increases monotonically from 0.6 at a 1-year horizon to over 0.7 at a 10-year horizon – in line with the pattern observed in R^2. However, the HPD of the implied Sharpe ratio is extremely wide, reflecting the substantial statistical uncertainty associated with the result.

As noted by Cochrane (1999), unconditional Sharpe ratios can be interpreted as the Sharpe ratio attainable by an investor who follows the best possible market timing strategy over a T-year horizon and evaluates his portfolio based on T-year returns. It does not imply that such Sharpe ratios are attainable by an investor over the next T years using the predictor as a timing signal. To evaluate the latter, one must characterize the return distribution conditional on the current predictive signal. We now consider this perspective in the case of $\widehat{cay}$.

4.3.2. Conditional expectations and out-of-sample significance

Whilst the evidence of in-sample return predictability based on *cay* appears robust to the uncertainty in the cointegration parameters, the dispersion of the *cay* posterior at a given point in time has implications for the usefulness of *cay* as a predictive signal. We conclude this section by returning to the stylized asset-allocation problem and force the investor to account for the estimation risk associated with the cointegration parameters and the attendant uncertainty about any departure from equilibrium. In effect, the distribution of forecasted future returns is conditioned on data only (6) rather than on an assumed fixed and known $\widehat{cay}$.

For the sake of the example, we select actual points in the sample where historical values of c, a and y correspond closely to a one standard deviation shift in $\widehat{cay}$, conditional on the posterior mean of the cointegration parameters. For example, in the third quarter of 1953, an investor would have been confronted with a value of $\widehat{cay}$ approximately one standardized unit above its mean. Similarly, in the third quarter of 2002, an investor would have observed $\widehat{cay}$ one standardized unit below its mean. In each case, the asset-allocation decision uses the predictive distribution conditioned on the observed values of c, a and y at that time.

Fig. 6 presents optimal equity allocations conditional on observations of c, a and y as at Q3 1953 and Q3 2002 to analyze the case where an investor relying on point estimates of the cointegration parameters would consider $\widehat{cay}$ to be "high" and "low" respectively. In strong contrast to the results in Fig. 2, equity allocations now appear relatively insensitive to signals in the data on consumption, asset wealth and income. When the coefficient of risk aversion is low ($A = 5$), the difference between equity allocation given a high signal (solid line) and a low signal (dashed line) is observable, but only a small fraction of that observed in Fig. 2 Panel C. When the coefficient of risk aversion is relatively high ($A = 20$), equity allocation is largely independent of the signal. These results suggest that, even in light of apparently robust historical evidence of short-horizon predictability based on $\widehat{cay}$, data on c, a and y do not necessarily contain economically significant signals once we account for the combined effects of estimation risk in modeling the predictive and cointegrating relations.

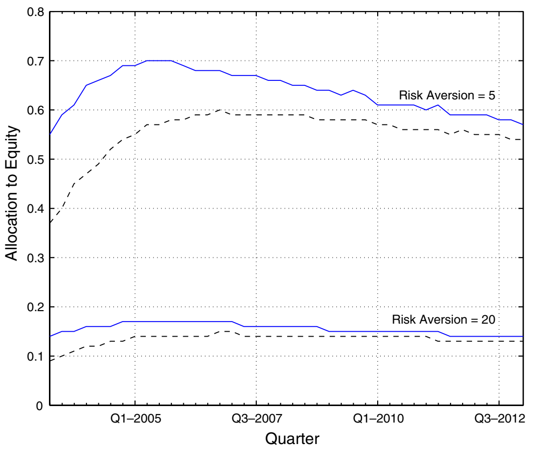


Fig. 6. Equity allocation conditioned on data only. The solid lines plot optimal equity allocation by investment horizon conditional on c, a, and y being set equal to their values observed by an investor in Q3 1953. The dashed lines plot optimal equity allocation by investment horizon conditional on c, a, and y being set equal to their values observed by an investor in Q3 2002. Two levels of investor risk aversion are shown ($A = 5, 20$) in each case.

Conditioning on point estimates of *cay* can thus be seen to ignore substantial uncertainty about point-in-time departures from the long-run equilibrium relation between *c*, *a* and *y* – even after using all available data for estimation. However, the effects of this uncertainty (or ignoring this uncertainty by conditioning predictions on a point estimate of $\widehat{cay}$) do not necessarily generalize in an obvious way and must therefore be evaluated in terms of the particular question or decision problem of interest. Consistent with LL's arguments and results, the estimation error in cointegration parameters has remarkably little impact on regression-based estimates of predictability, whether in-sample R^2 from a simple regression, or long-horizon R^2 imputed from a VAR. Whilst the evidence of strong in-sample predictability is robust, its out-of-sample implications in the context of our simple asset-allocation decision rest on knowledge of the cointegration parameters, uncertainty about the magnitude of departure from equilibrium is sufficient to swamp the impact on an investor's buy and hold investment decision once we account for it. Even robust evidence of in-sample predictability using all available data does not necessarily imply out-of-sample predictive significance from an economic perspective. This result is consistent with the findings of Cochrane (2006), reconciling the apparently conflicting evidence of strong in-sample predictability based on DY, but little apparent out-of-sample predictive value.[7]

4.4. Economic significance of ICS as a predictor

LL note that aggregate consumption, asset wealth, and labour income share a common long-term trend. They show that short-run deviations from this trend predict market returns under a variety of forward-looking models of investor behavior where consumption is a function of aggregate wealth. As such, LL's consumption-to-wealth ratio can be regarded as a behavioral summary of rational agents' expectations about future investment opportunities.

Brennan and Xia (2005) argue that the predictive ability of *cay* hinges on individuals' ability to solve a complex consumption–investment plan.[8] A pragmatic response to this line of questioning is to shift focus from the behavioral implications of the model to a direct measure of the expectations that influences agents' behavior. This motivates our examination of the Index of Consumer Sentiment (ICS) as a potential predictor of returns.

4.4.1. Association and causality

As a preliminary examination, Fig. 1 plots the time-series of ICS versus $\widehat{cay}$ in Panel A, and ICS versus DY in Panel B over the period 1960 Q4 though 2002 Q4.[9] The −27% contemporaneous correlation between ICS and $\widehat{cay}$, and the stronger −67% correlation between ICS and DY evident in Fig. 1 is broadly consistent with what one might expected

[7] Cochrane (2006) attributes the poor out of sample predictive performance of DY to the difficulty of estimating the predictive regression coefficients in short samples when the predictive variable is highly persistent.

[8] Whether the plausibility of this assumption affects the credibility of tests of its implications is an example of a more fundamental debate over whether rationality can be defined in terms of the choices it produces or the process that is used to make the choices. Refer to Curtin (2000) for further discussion on this dichotomous view of rationality in the social sciences.

[9] This slightly truncated version of the data employed in the paper reflects the 1960 start date for University of Michigan's ICS data series.

in a setting where departures from equilibrium consumption rates reflect changes in risk aversion (risk premia). To the extent that the behavioral and survey-based measures are not time aligned, contemporaneous correlation may be a misleading measure of the extent to which they reflect the same expectations. As a practical matter, it is not clear whether fluctuations in *measured* sentiment presage fluctuations in *measured* departures from equilibrium consumption to wealth, or vice versa.

More importantly, whilst evidence of contemporaneous correlation between $\widehat{cay}$ and ICS, or evidence of return predictability based on ICS is consistent with the behavioral foundations of the model, empirical findings must be interpreted with caution. For example, returns may be predicted by shifts in consumer sentiment because the expectations are self-fulfilling if we admit the possibility of *strategic complementarities* or *coordination failures*. In these circumstances, observed economic outcomes can reflect expectations themselves rather than economic fundamentals that give rise to (or presage) such outcomes. At a macro-level, Matsusaka and Sbordone (1995) provide evidence consistent with the existence of strategic complementarities using the ICS as a measure of expectations. Upon controlling for a range of economic conditions (fundamentals), they consistently reject the null hypothesis that consumer sentiment does not Granger cause GNP. This finding motivates our analysis of (Granger) causal linkages between $\widehat{cay}$, ICS and aggregate equity returns.

Table 3 summarizes evidence of Granger causality based on a bivariate VAR of ICS and $\widehat{cay}$. We report model estimates based on 1–4 lags.[10] On the basis of all but the first-order VAR, we find strong evidence to suggest that $\widehat{cay}$ Granger causes ICS. There is no evidence of bi-directional causality. However, given the magnitude of predictive coefficients, it is also worth noting that, whilst statistically significant, the impact of $\widehat{cay}$ on ICS is relatively small, and ICS appears highly persistent.

Augmenting the VAR to also include the market risk premium r (Table 4) eliminates the apparent link between sentiment and lagged $\widehat{cay}$ – $\widehat{cay}$ is no longer significant at any lag length. Again, the magnitude of the regression coefficients and the incremental R^2s suggest that, although statistically significant, the economic impact is relatively small. The ICS explains most of its own variation. Adding the lagged market risk premium increases the adjusted R^2 from 80% to 85%. Inclusion of the market risk premium also reveals some weak (lag-dependent) evidence of bi-directional causality between r and $\widehat{cay}$. Consistent with previous work, $\widehat{cay}$ forecasts the quarterly return premium.

Table 4 also provides a first look at the link between ICS and the market premium. Based on the VAR in Table 4, the ICS appears to have no incremental ability to forecast the quarterly market premium on a stand-alone basis, but as we discuss in the following section, it is premature to conclude that the sentiment index contains no predictive information.

4.4.2. Univariate predictive regressions

We now compare the predictive properties of $\widehat{cay}$, DY and ICS in a univariate regression framework typical of the approach commonly employed in predictability studies. Whilst the VAR reported in Table 4 suggests that ICS does not forecast the quarterly

[10] As can be seen in Table 3, and shortly in Table 4, the AIC and SBIC do not provide a clear winner in terms of lag length specification, hence, we report results based on the first four lags.

Table 3
Vector autoregression based on $c\hat{a}y$ and ICS

	1 Lag		2 Lags		3 Lags		4 Lags	
	Dependent variables							
	ICS_t	$c\hat{a}y_t$	ICS_t	$c\hat{a}y_t$	ICS_t	$c\hat{a}y_t$	ICS_t	$c\hat{a}y_t$
ICS_{t-j}								
F-Probability	0.00	0.85	0.00	0.16	0.00	0.36	0.00	0.43
Sum of coefficients	**0.91**	−0.01	**0.92**	−0.03	**0.91**	−0.04	**0.91**	−0.031
Standard error	0.03	0.04	0.03	0.04	0.03	0.05	0.03	0.05
$c\hat{a}y_{t-j}$								
F-Probability	0.97	0.00	0.00	0.00	0.00	0.00	0.01	0.00
Sum of coefficients	0.00	**0.84**	**0.04**	**0.84**	**0.04**	**0.85**	**0.04**	**0.84**
Standard error	0.03	0.04	0.03	0.04	0.03	0.05	0.04	0.05
$\bar{R}^2$	0.82	0.70	0.84	0.70	0.84	0.70	0.84	0.71
AIC		−11.58		**−11.64**		−11.61		−11.57
SBIC		**−11.5**		−11.47		−11.35		−11.24

This table reports estimates of the system $Y_t = \phi(L)Y_t + \epsilon_t$ where $Y_t \equiv [c\hat{a}y_t\ \text{ICS}_t]'$ using data from Q1 1960 to Q1 2003. Each column reports an OLS regression. The rows of the table report the sum of the coefficients on sets of (lagged) independent variables, the standard error of the summed coefficients and the probability of the null hypothesis that the coefficients are jointly equal to zero (*F* probability). Sets of coefficients that are jointly significant at levels $\leqslant 5\%$ are in bold. The bottom row of the table is the adjusted R^2 of each regression. In each model, $c\hat{a}y = c - 0.2769a - 0.6116y$; that is, the posterior mean of the cointegrating vector from the sampler. AIC refers to the Akaike Information Criteria, and SBIC is the Schwartz Bayes Information Criteria. Bold denotes the optimal lag length specification based on each selection criteria.

return premium on a stand alone basis, we extend the analysis to consider interaction effects.

Table 5 reports predictive regressions estimated over the period 1960 Q1 to 2003 Q1. As noted earlier, $c\hat{a}y$ is a highly significant predictor of returns with a raw regression R^2 of 8.5% (model 1) and DY is a marginally significant predictor of return with a regression R^2 of 1.78% (model 2). As a stand-alone predictor of the quarterly equity return premium, the ICS appears useless – a regression R^2 indistinguishable from zero (model 3). Similarly, there is no value in adding the ICS to a predictive regression containing $c\hat{a}y$ (model 5).

Whilst ICS does not have any stand-alone predictive value, there is a significant interaction with $c\hat{a}y$ (model 8). The ratio of consumption to wealth scaled by measured consumer sentiment is statistically significant when added to $c\hat{a}y$. In addition, the adjusted R^2 of the predictive regression jumps from 7.87% to 10.8%. In economic terms, point estimates of the (standardized) raw regression coefficients imply that the predictive implications of $c\hat{a}y$ are heavily influenced by the level of measured sentiment.

Ignoring consumer sentiment, based on the shorter estimation interval for the predictive regression, a standard deviation shift in $c\hat{a}y$ implies a 261 basis point change in the expected quarterly return premium (model 1). If consumer sentiment is neutral, the same standard deviation shift in $c\hat{a}y$ implies a 329 basis point change in the expected quarterly return premium (model 8). If the ICS is a standard deviation above its historical mean, the standard deviation change in $c\hat{a}y$ implies a 169 basis point change in the quarterly return premium. Clearly, the regression results imply that the level of $c\hat{a}y$ should be interpreted in

Table 4
Vector Autoregressions based on $\hat{cay}$, ICS and r_t

	1 Lag			2 Lags			3 Lags			4 Lags		
	Dependent variables											
	ICS_t	$\hat{cay}_t$	r_t	ICS_t	$\hat{cay}_t$	r_t	ICS_t	$\hat{cay}_t$	r_t	ICS_t	$\hat{cay}_t$	r_t
ICS_{t-j}												
F-Probability	0.00	0.86	0.85	0.00	0.1	0.33	0	0.15	0.33	0.00	0.25	0.45
Sum of coefficients	**0.91**	−0.01	0.00	**0.92**	−0.03	0.00	**0.91**	−0.03	0.00	**0.91**	−0.03	0.00
Standard error	0.03	0.04	0.01	0.03	0.04	0.01	0.03	0.04	0.01	0.03	0.05	0.01
$\hat{cay}_{t-j}$												
F-Probability	0.77	0.00	0.00	0.90	0.00	0.00	0.84	0.00	0.00	0.92	0.00	0.00
Sum of coefficients	0.01	**0.83**	**0.03**	0.01	**0.86**	**0.03**	0.00	**0.87**	**0.02**	0.01	**0.86**	**0.03**
Standard error	0.03	0.04	0.01	0.03	0.04	0.01	0.03	0.05	0.01	0.03	0.05	0.01
r_{t-j}												
F-Probability	0.00	0.18	0.42	0.00	0.05	0.47	0.00	0.06	0.62	0.00	0.15	0.49
Sum of coefficients	**1.93**	−0.65	0.06	**2.81**	**−1.57**	0.05	**3.20**	−2.60	0.03	**3.45**	−2.10	−0.14
Standard error	0.34	0.48	0.07	0.59	0.84	0.13	0.83	1.18	0.18	1.06	1.52	0.23
$\bar{R}^2$	0.85	0.70	0.08	0.86	0.71	0.08	0.86	0.71	0.08	0.86	0.70	0.07
AIC		**−12.21**			−12.2			−12.1			−12	
SBIC		**−12.02**			−11.83			−11.56			−11.3	

This table reports estimates of the system $Y_t = \phi(L)Y_t + \epsilon_t$ where $Y_t \equiv [\hat{cay}_t\ \mathrm{ICS}_t\ r_t]'$ using data from Q1 1960 to Q1 2003. Each column reports an OLS regression. The rows of the table report the sum of the coefficients on sets of (lagged) independent variables, the standard error of the summed coefficients and the probability of the null hypothesis that the coefficients are jointly equal to zero (*F* probability). Sets of coefficients that are jointly significant at levels $\leqslant 5\%$ are in bold. The bottom row of the table is the adjusted R^2 of each regression. In each model, $\hat{cay} = c - 0.2769a - 0.6116y$; that is, the posterior mean of the cointegrating vector from the sampler. AIC refers to the Akaike Information Criteria, and SBIC is the Schwartz Bayes Information Criteria. Bold denotes the optimal lag length specification based on each selection criteria.

light of the ICS during the same period. In contrast, the regression evidence in Table 5 shows no corresponding interaction between sentiment and the dividend yield.[11]

4.4.3. Economic impact of sentiment

The regression estimates in Table 5 suggest a statistically and economically significant interaction between sentiment and $\hat{cay}$. To better understand the importance of this result, we consider the joint dynamics of the return premium, $\hat{cay}$ and the interaction between $\hat{cay}$ and sentiment modeled as a first-order VAR. Fig. 7 illustrates the impact of sentiment in the context of the asset-allocation decision considered earlier.

A shock to $\hat{cay}$ has very different implications for short to medium term asset allocation when we allow for effect of sentiment. Defining optimism (pessimism) as a positive (negative) standard deviation from mean sentiment, a pessimistic investor's short term

[11] Estimates of the predictive regressions (not reported) using real returns on the S&P500 are not qualitatively different from those reported in Table 5.

Table 5
Univariate predictive regressions

Model	Predictor(s)	$\hat{\lambda}_0$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	R^2	$(\bar{R}^2)$
1	$\hat{cay}$	0.0132	0.0261			0.085	(0.0787)
		(1.85)	(3.67***)				
2	DY	−0.019	0.012			0.0178	(0.011)
		(−0.89)	(1.62)				
3	ICS	0.0132	−0.008			0.0086	(0.0017)
		(1.78)	(−1.12)				
4	$\hat{cay}$, DY	0.005	0.025	0.0031		0.086	(0.0734)
		(0.231)	(3.28***)	(0.4)			
5	$\hat{cay}$, ICS	0.0222	0.0258	0.0013		0.085	(0.0725)
		(0.417)	(3.47)	(−0.171)			
6	$\hat{cay}$, ICS, ICS × $\hat{cay}$	0.0087	0.032	−0.0043	−0.0167	0.1167	(0.104)
		(1.197)	(4.144***)	(−0.58)	(−2.46**)		
7	DY, ICS, ICS × DY	−0.025	0.0125	0.0196	−0.0066	0.025	(0.0049)
		(−0.8599)	(1.223)	(0.919)	(−1.05)		
8	$\hat{cay}$, ICS × $\hat{cay}$	0.0088	0.0329	−0.016		0.12	(0.108)
		(1.22)	(4.36***)	(−2.4**)			
9	DY, ICS × DY	−0.0118	0.0089	−0.0015		0.0196	(0.006)
		(−0.4687)	(0.9443)	(−0.5105)			

This table reports predictive regressions of the form $r_t = \hat{\lambda}_0 + \hat{\lambda}_1\,\mathrm{pred}_{1,t-1} + \cdots + \hat{\lambda}_k\,\mathrm{pred}_{k,t-1}$, where $\mathrm{pred}_{j,t-1}$ are lagged predictors. In the $\hat{cay}$ regression: $\hat{cay} = c - 0.2769a - 0.6116y$. Point estimates are based on the posterior mean of the cointegrating vector. A single asterisk indicates significance of t-statistic at the 5% level, two asterisk indicate significance at the 2% level, three asterisk indicate significance at 1%.

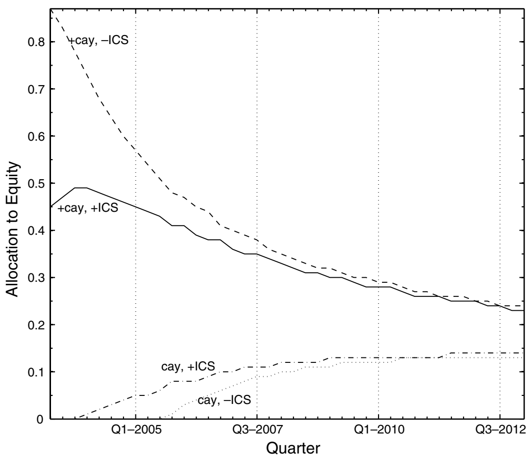


Fig. 7. Optimal allocations using $\hat{cay}$ and ICS predictors. The solid line plots optimal equity allocation when the current level of $\hat{cay}$ is one standard deviation above its historical mean, and the ICS is one standard deviation above its historical mean. The dashed line plots optimal allocations when the current value of $\hat{cay}$ is one standard deviation above its historical mean, and the ICS is one standard deviation below its historical mean. The dotted line plots equity allocation when the current value of both $\hat{cay}$ and the ICS are set to one standard deviation below historical means. Dash-dots plot equity allocation when the current value of $\hat{cay}$ is a standard deviation down and ICS is a standard deviation up. The results in this figure condition on the posterior mean of the cointegrating parameters but account for estimation risk in the (tri-variate) VAR parameters.

allocation to equity is almost double that of an optimistic investor's in response to a positive standard deviation shock to $\widehat{cay}$. Negative shocks to $\widehat{cay}$ have a slightly larger effect on the asset allocation of a pessimistic investor than the corresponding optimistic investor. These results suggest that the findings of significant interaction between the ICS and $\widehat{cay}$ are robust. Shifts in $\widehat{cay}$ should be considered in light of sentiment, as measured by the ICS. These findings are conditional on a point estimate of $\widehat{cay}$ and must of course be interpreted in light of the results in Section 4.3.[12]

5. Conclusions

Campbell and Cochrane (1999) suggest an explicit link between consumption behavior and asset returns through time variation in risk aversion. During economic booms, consumption rises above habit and risk aversion declines, leading to a greater demand for risky assets and a decline in expected returns (risk premia). Hence, booms are times of rising consumption, but declining ratios of consumption to wealth. As such, Lettau and Ludvigson (2001) argue that fluctuations in the equilibrium ratio of consumption to wealth ($\widehat{cay}$) reflect changing expectations of returns on asset wealth. LL show that the residual from the cointegrating relationship between consumption, asset returns and labour income – $\widehat{cay}$ – is a significant short-horizon predictor of excess market returns.

This paper provides further evidence supporting short-horizon predictive ability of $\widehat{cay}$. While considerable estimation risk surrounds the parameters of the cointegrating regression used to construct $\widehat{cay}$, the regression-based evidence of strong short-horizon predictability is remarkably robust to this uncertainty. However, our findings suggest that the regression-based evidence should be interpreted with caution, as uncertainty associated with the parameters of the budget constraint gives rise to substantial uncertainty about a given departure from equilibrium. Within a simple optimal asset-allocation framework, point-in-time allocations to equity are relatively insensitive to signals provided by shifts in c, a and y. These results accord with the findings of Cochrane (2006), reconciling the evidence of in-sample predictability associated with DY with findings that the same variable is of little use in out of sample forecast applications.

LL's interpretation of $\widehat{cay}$ as a behavioral summary of investor expectations of future investment opportunities can also been questioned on the grounds that it assumes investors are capable of formulating consumption–investment plans as optimal solutions to difficult intertemporal optimization problems. The current paper moves the focus away from the behavioral implications of LL's model to a more-direct measure of expectations – the Index of Consumer Sentiment. Specifically, we explore whether ICS can augment or even supplant $\widehat{cay}$ as a predictor of equity returns. The results suggest that, while ICS has no stand-alone ability to forecast returns, it does have an economically-important interaction with $\widehat{cay}$. The survey-based measure of expectations (ICS) complements the behavioral measure ($\widehat{cay}$) suggesting that the predictive signals provided by $\widehat{cay}$ should be interpreted in light of measured consumer sentiment. Since we have not attempted to optimize our usage of the ICS, our results may be viewed as a conservative measure of its ability forecast returns on equity. Whether these findings are attributable to what is measured by the

[12] We have estimated the analog of (7) and confirmed that the finding of predictability is not particular to the point estimate $\widehat{cay}$.

Michigan Index or a more fundamental shortcoming of the posited link between consumer expectations, behavior and asset returns, are questions left for future research.

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