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Macroeconomic risk and the cross-section of stock returns

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ABSTRACT

We develop a conditional version of the consumption capital asset pricing model (CCAPM) using the conditioning variable from the cointegrating relation among macroeconomic variables (dividend yield, term spread, default spread, and short-term interest rate). Our conditioning variable has a strong power to predict market excess returns in the presence of competing predictive variables. In addition, our conditional CCAPM performs approximately as well as Fama and French's (1993) three-factor model in explaining the cross-section of the Fama and French 25 size and book-to-market sorted portfolios. Our specification shows that value stocks are riskier than growth stocks in bad times, supporting the risk-based story.

1. Introduction

Understanding the time variation and cross-sectional variation in risk premiums has long been a central research question for financial economists. One way to gain an understanding of the nature of risk premiums is to examine the linkage between financial markets and the macroeconomy, since risk premiums should reflect macroeconomic risk. In his review article, Cochrane (2008, p. 238) suggests the following when researching the interaction between macroeconomics and finance:

> The challenge is to find the right measure of "bad times," rises in the marginal value of wealth, so that we can understand high average returns or low prices as compensation for assets' tendency to pay off poorly in "bad times."

Herein, we propose the "right measure" that captures economic recessions.

It is well-known that time variations in expected returns are related with the business cycle (see Fama and French, 1989, and references therein). Expected returns tend to be higher in economic recessions, as investors are less willing to hold risky assets; conversely, expected returns tend to be lower during economic booms. This evidence suggests that time variations in equity premiums should be accounted for by variables associated with the business cycle. Previous research has focused primarily on financial indicator variables such as the dividend-to-price ratio, earning-to-price ratio, and dividend-to-earning ratio as candidates for predictive variables. Although these financial indicators can predict market returns over long horizons, their predictive powers over business cycle frequencies are rather limited (Lettau and Ludvigson, 2001a).

We study the variation in the risk premium both over time and across stocks based on the proposed measure, which captures business-cycle-related macroeconomic risks. The starting point of this study is the recognition that the macroeconomic variables generally used to predict stock returns – dividend yield, term spread, default spread, and short-term interest rate – share a common long-term trend; that is, they are cointegrated. We examine the role of trend deviations in the cointegrated macroeconomic variables in predicting future asset returns and explaining the cross-section of average returns. In an effort to account for the cross-sectional patterns, we focus on the consumption capital asset pricing model (CCAPM) with the proposed measure. Despite its poor performance as an asset pricing model (Mankiw and Shapiro, 1986; Breeden et al., 1989; Cochrane, 1996), the CCAPM continues to draw a great deal of attention, since consumption-based models are quite general and intuitively appealing.[1]

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[1] As documented by Cochrane (2005), consumption-based models are general because any factor model can be regarded as a specialization of consumption-based models. In addition, they are very intuitive in that a simple relation between the consumption growth rate and stock return can describe the implications of complicated intertemporal asset pricing models.

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Moreover, Cochrane (2008, p. 267) emphasizes the importance of consumption-based models this way: "At some level, the consumption-based models must be right if economics is to have any hope of describing stock markets." Therefore, our challenge is to improve the empirical performance of CCAPM rather than to develop alternative asset pricing models.

It has now been well-documented that predictive variables such as dividend yield, term spread, default spread, and short-term interest rate are very persistent (Torous et al., 2004; Boudoukh et al., 2006). There is, however, an ongoing debate as to whether these highly persistent variables are indeed non-stationary. For example, Roll (2002) asserts that predictive variables that are functions of asset prices, such as dividend yield, could be non-stationary under rational expectations. On the other hand, as documented by Cochrane (2005), dividend yield should be stationary because price and dividend are cointegrated. In this study, we do not attempt to determine whether or not these variables are integrated; rather, we argue that the use of highly persistent time-series variables in predictive regressions as well as in cross-sectional analyses induces statistical problems, as documented by Ferson et al. (2003).[2]

In their simulation study, Campbell and Perron (1991) demonstrate that although the asymptotic distribution of a time-series is stationary, treating near-integrated stationary data as unit root variable inferred from unit root and/or cointegration tests may be better modeled in a finite sample.[3] In accordance with the research of Campbell and Perron, we treat the four variables as non-stationary, as we are unable to reject the null hypothesis of non-stationarity in the augmented Dickey-Fuller tests in our sample period. We then generate the stationary trend deviation from the Johansen cointegration test. We employ this stationary trend deviation as our conditioning variables, since it is likely to incorporate information on the business cycle, as indicated by the four predictive variables.

The main findings of this paper are summarized as follows. First, deviations from common long-term trends in macroeconomic variables have strong predictive ability not only for future stock returns over long horizons, but also for future asset returns over business cycle frequencies, where financial indicator variables lack forecasting power. Moreover, our variable has significant marginal forecasting power when popular predictive variables such as payout ratio suggested by Lamont (1998) and consumption-aggregate wealth ratio developed by Lettau and Ludvigson (2001a) are included in the forecasting regression. We also demonstrate that our trend deviations are strongly related to the macroeconomy.

Second, when our trend deviations are employed as a conditioning variable for the CCAPM, it performs almost as well as Fama and French's (1993) three-factor model, and performs better than the CCAPM of Lettau and Ludvigson (2001b) in explaining the cross-section of average returns on Fama and French 25 size and book-to-market sorted portfolios. Intuitively, the success of pricing size and book-to-market sorted portfolios arises from the fact that both small stocks and value stocks have higher consumption betas than large stocks and growth stocks, because they are more highly correlated with consumption growth during recessions, when marginal utility rises, which is consistent with the results reported by Lettau and Ludvigson (2001b). We provide evidence supporting this intuition. Thus, our results support a risk-based interpretation of size and book-to-market effects.

Third, according to Lewellen et al.'s (2010) suggestions for improving empirical tests, we expand the set of test portfolios. The proposed conditional CCAPM performs well for other test assets, including 10 industry portfolios and 25 size and momentum portfolios. The improvement of our model in explaining the cross-section patterns of industry and size and momentum portfolios is quite striking, as it is well-known that describing the cross-section of these portfolios is a challenge for Fama and French's three-factor model. Additionally, based on the emphasis on the theoretical restrictions of slopes imposed on the cross-sectional regressions documented by Lewellen and Nagel (2006), we assess the cross-sectional slopes. Our results do not deviate substantially from the restrictions, although the risk premium still has some skewness to accept our model.

The studies most closely related to our approach include the work of Lettau and Ludvigson (2001a,b), Santos and Veronesi (2006), and Lustig and Van Nieuwerburgh (2005). Lettau and Ludvigson demonstrate that the ratio of consumption to wealth forecasts future stock returns and that a conditional CCAPM using this variable can explain size and value cross-sectional effects. Santos and Veronesi derive a conditional CAPM in which the ratio of labor income to consumption is a conditioning variable. They show that this variable predicts aggregate returns and that the scaled CAPM can account for the cross-section of average returns of the Fama and French size and book-to-market sorted portfolios. Lustig and Van Nieuwerburgh suggest treating the ratio of housing wealth to human wealth as a conditioning variable, and demonstrate empirically that this ratio conveys information relevant to predicting asset returns and explaining value-size cross-sectional effects.

A recent paper by Ludvigson and Ng (2007) also provides empirical evidence of stock return predictability. Using dynamic factor analysis, they summarize the information in a large number of economic time-series in a few factors and use the extracted factors to examine whether the market excess return is forecastable. There is a big difference between our paper and the work of Ludvigson and Ng (2007). While Ludvigson and Ng (2007) do not show that the estimated factors explain the cross-section of stock returns, the present paper documents that the proposed conditioning variable well explains the time-series and cross-section of stock returns. In addition, one disadvantage of dynamic factor analysis is that it is difficult to determine how many factors should be used to effectively summarize the original dataset. As a result, although it uses large dataset, there is possibility that some important information may be still missing, as documented by Brandt and Wang (2010).

This paper adds to the extensive literature on market return predictability and consumption-based explanations of the cross-section of stock returns. Our empirical work on the time-series predictability of stock returns is related to the studies of Campbell and Shiller (1988), Fama and French (1989), Lamont (1998), Ang and Bekaert (2007), Boudoukh et al. (2007), Chen (2009), and Nieto and Rubio (2011), and our empirical study of the CCAPM adds to the body of knowledge compiled by Chen and Ludvigson (2004), Bansal et al. (2005), Parker and Julliard (2005), Yogo (2006), and Jagannathan and Wang (2007).

The remainder of this paper is organized as follows. Section 2 provides the framework of the conditional factor model. Section 3 describes the data and discusses the empirical methodology employed in testing the competing asset pricing models. Section 4 reports empirical evidence on the predictability of stock returns. Section 5 documents the empirical results on the cross-section of average returns. Section 6 reports the results for several robustness tests to reinforce our conclusions. Section 7 summarizes and presents our conclusions.

[2] They demonstrate that if the expected returns are persistent, these persistent variables can cause spurious regression bias in the predictive regressions, thus casting some doubt on the existing literature of stock return predictability.

[3] Lettau and Ludvigson (2001a,b) also follow Campbell and Perron's advice when they construct the consumption-wealth ratio (Lettau and Ludvigson, 2010).

2. The model

2.1. The unconditional and conditional CAPMs

Developed by Sharpe (1964) and Lintner (1965), the CAPM is the first asset pricing model in modern finance, and has been the most widely used model until the development of Fama and French's three-factor model (1993, 1996). The CAPM implies that the stochastic discount factor, m_{t+1}, is a linear function of the market portfolio return:

$$m_{t+1} = a_t + b_t r^M_{t+1} \tag{1}$$

where a_t and b_t are parameters and r^M_{t+1} is the market portfolio return at time $t+1$.

We assume that there exists a risk-free asset, and denote the risk-free rate at time t by r^f_t. The vector of factors in the stochastic discount factor is denoted by f_{t+1} throughout this paper. Under the conditions that the CAPM prices the market portfolio and the risk-free asset exactly, a_t and b_t are expressed by

$$a_t = \frac{1}{1+r^f_t} + b_t E_t(r^M_{t+1}) \tag{2}$$

$$b_t = \frac{E_t(r^M_{t+1}) - r^f_t}{\left(1+r^f_t\right)\sigma^2_t(r^M_{t+1})} \tag{3}$$

where σ^2_t denotes conditional variance. If a_t and b_t are constant over time, the unconditional CAPM is obtained, where $f_{t+1} = r^M_{t+1}$, and the unconditional and conditional CAPM do not create any difference. The beta representation of the unconditional CAPM is given by

$$E[r_{i,t+1}] = E\left[r^f_t\right] + \beta_i \lambda \tag{4}$$

where $\beta = \frac{Cov(f_{t+1}, r_{i,t+1})}{Var(f_{t+1})}$ and λ is the risk premium for the market portfolio.

If a_t and b_t are time-varying, however, the unconditional CAPM does not hold. Rather, the conditional version of CAPM might hold; stocks' expected returns are proportional to their conditional betas. It is very likely that b_t is time-varying, since a variety of empirical asset pricing papers argue that the excess market returns are forecastable. If the parameters are time-varying, the conditional model does not imply the unconditional model.

Following Cochrane (1996) and Lettau and Ludvigson (2001b), we model $a_t = a_0 + a_1 z_t$ and $b_t = b_0 + b_1 z_t$, where z_t is a vector of conditioning variables that help to predict market excess return. Since our conditioning variable, *coin* (defined in Section 3), is a strong forecaster of the market excess return, we utilize it as our conditioning variable. Hence, m_{t+1} can be expressed as

$$m_{t+1} = a_0 + a_1 coin_t + b_0 r^M_{t+1} + b_1 coin_t r^M_{t+1} \tag{5}$$

where a_0, a_1, b_0, and b_1 are constants. Therefore, the conditional CAPM implies the unconditional linear factor pricing model with $f_{t+1} = (coin_t, r^M_{t+1}, coin_t r^M_{t+1})$.

2.2. The consumption CAPM

The CCAPM states that an asset's risk is determined by the correlation between consumption growth rate and the return on that asset. Investors require a lower return when the asset provides better insurance against consumption risk. In the language of the stochastic discount factor, the CCAPM implies that it can be expressed as $m_{t+1} = \delta\frac{U_c(C_{t+1}, Z_{t+1})}{U_c(C_t, Z_t)}$, in which U_c is the marginal utility of consumption, Z refers to other factors that might affect utility, and δ is the subjective rate of time preference. This equation can be approximated as $m_{t+1} \approx a_t + b_t \Delta c_{t+1}$, where a_t and b_t are parameters and Δc_{t+1} is the log consumption growth rate.

If a_t and b_t are not time-varying, the unconditional CCAPM is obtained with $f_{t+1} = \Delta c_{t+1}$. The beta representation of the unconditional CCAPM is written as follows:

$$E[r_{i,t+1}] = E\left[r^f_t\right] + \beta_i \lambda \tag{6}$$

where $\beta = \frac{Cov(f_{t+1}, r_{i,t+1})}{Var(f_{t+1})}$ and λ is the risk premium for the consumption risk.

As stated in the conditional CAPM, it appears quite likely that a_t and b_t are time-varying. For example, Campbell and Cochrane (1999) develop a consumption-based asset pricing model in which an asset's riskiness is determined by the intertemporal marginal rate of substitution. This depends on the consumption growth rate and the change in investors' relative risk aversion. Hence, under the framework developed by Campbell and Cochrane, the parameters a_t and b_t are not constant over time. As documented by Lettau and Ludvigson (2001b), even though the coefficients a_t and b_t might be functions of unobservable variables, their variations can be well captured by proxies for time-varying risk premiums. If this is indeed the case, the conditional version of CCAPM may hold. As in the conditional CAPM, we model $a_t = a_0 + a_1 coin_t$ and $b_t = b_0 + b_1 coin_t$. Therefore, m_{t+1} can be written as

$$m_{t+1} \approx a_0 + a_1 coin_t + b_0 \Delta c_{t+1} + b_1 coin_t \Delta c_{t+1} \tag{7}$$

where a_0, a_1, b_0, and b_1 are constants. Hence, the conditional CCAPM implies the unconditional linear factor pricing model with $f_{t+1} = (coin_t, \Delta c_{t+1}, coin_t \Delta c_{t+1})$.

3. Methodology

3.1. Data

We use quarterly data for the period from the third quarter of 1963 to the fourth quarter of 2005. We select the Fama and French 25 size and book-to-market sorted portfolios as the main test assets and construct excess returns as the difference between the returns of these portfolios and the returns on a 3-month Treasury bill.[4] In addition, in order to evaluate the robustness of the empirical success of our specification, we use other test assets, namely 10 industry portfolios and 25 size and momentum portfolios because this exercise is helpful to address some of the criticism of the recent asset pricing literature (Lewellen et al. (2010)).[5]

Following the work of Parker and Julliard (2005), we use per capita quarterly real consumption expenditures on nondurable goods from the National Income and Product Accounts tables, which are available from the Bureau of Economic Analysis. We exclude services because they include health care and education, which are not entirely for personal consumption, as well as housing, which is subject to large adjustment costs.

To construct the conditioning variable, we use the cointegrating relation among macroeconomic variables. The macroeconomic variables used and the test of their cointegrating relation are shown in Appendix A. The conditioning variable employed in our study is *coin*, which is defined as

[4] We study these portfolios because (1) they display a large dispersion in average returns such that they represent one of the most challenging sets of portfolios in the asset pricing literature, (2) they have been a standard playground for evaluating asset pricing models, allowing us to compare our specification with other asset pricing models, and (3) they are designed to investigate economically interesting characteristics of portfolios, which are the size effect (firms with small market capitalization, on average, have higher returns) and the value premium (firms with higher book-to-market ratio, on average, have higher returns).

[5] The 25 size and momentum portfolios are obtained from Lu Zhang's website: http://apps.olin.wustl.edu/faculty/chenl/linkfiles/data_equity.html. Other test assets and the Fama and French factors are from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Lu Zhang and Kenneth French for providing the data.

Table 1
Descriptive statistics. The table reports the mean, standard deviation, and first-order autocorrelation of the cointegrating error adopted in this paper (*coin*), log dividend payout ratio (*d–e*), log consumption-wealth ratio (*cay*), log consumption growth rate (Δc), excess market return (R_m), Fama and French factors related to size (SMB) and book-to-market (HML). It also reports the correlation among these variables. All data are quarterly observations. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

Factors	*coin*	*d–e*	*cay*	Δc	R_m	SMB	HML
Mean							
	−0.11	0.62	0.00	0.42	1.35	0.72	1.52
Standard deviation							
	0.57	0.25	0.01	0.70	8.54	5.81	6.03
Autocorrelation							
	0.88	0.63	0.86	0.21	0.02	−0.02	0.04
Correlation coefficient							
coin		0.02	0.18	−0.10	0.22	0.28	−0.16
d–e			0.26	0.05	0.04	0.07	−0.11
cay				−0.13	0.23	0.03	−0.18
Δc					0.14	0.15	0.00
R_m						0.48	−0.44
SMB							−0.18
HML							

$$coin_t = DIV_t - 0.28TERM_t + 0.25DEF_t + 0.49RF_t \tag{8}$$

where $DIV_t, TERM_t, DEF_t$, and RF_t represent the dividend yield, term spread, default spread, and short-term interest rate, respectively, at time t.[6]

To compare our proposed empirical specification for the conditional CCAPM with that of a popular asset pricing model, we adopt Lettau and Ludvigson's (2001b) *cay* variable, which is known to be the most successful scaling variable for the conditional CCAPM. Additionally, in order to compare the time-series forecasting power of our conditioning variable with that of competing predictive variables, the *cay* variable and the payout ratio of Lamont (1998) are employed.[7] Table 1 provides the descriptive statistics of these conditioning variables and the four risk factors considered: log consumption growth rate (Δc), excess market return (R_m), and Fama and French's SMB and HML. The first-order autocorrelation of *coin* is 0.88 and is comparable to that of the payout ratio and the variable *cay*.

3.2. Econometric approach

We employ two econometric approaches herein. First, we employ the Fama and MacBeth cross-sectional regression methodology to test the competing asset pricing models. This choice of methodology is driven by the fact that some factors do not represent portfolio returns and that this regression-based method is broadly used in the testing of asset pricing models. In the first stage of the method, we run multivariate time-series regressions for each of the Fama and French 25 portfolios to estimate the betas:

$$r_{i,t+1} = \alpha_i + \beta_i' f_{t+1} + \varepsilon_{i,t+1}, \quad i = 1, \ldots, 25 \tag{9}$$

in which $r_{i,t+1}$ is the excess return of asset i at time $t+1$ and f_{t+1} is the vector of factors at time $t+1$.[8] The slope coefficient estimates are used as the explanatory variables in a series of cross-sectional regressions. In the second pass of the method, for each time t, we regress the excess returns of all 25 portfolios on a constant and the estimated betas:

$$r_{i,t+1} = \gamma_0 + \gamma' \beta + e_{i,t+1}, \quad t = 1, \ldots, T \tag{10}$$

where γ_0 is the intercept and γ is a vector of risk premiums for the factor f_{t+1}.

Second, we follow the stochastic discount factor methodology using the generalized method of moments (GMM). As our empirical specification and competing models are all linear models, their stochastic discount factors can be represented as a linear combination:

$$m_{t+1} = b_0 + b_1' f_{t+1} \tag{11}$$

where f_{t+1} is a $k \times 1$ vector of factors, b_0 is a constant, and b_1 is a $k \times 1$ vector of coefficients. The testable asset pricing implications of the models are the set of Euler equations

$$E_t[m_{t+1}R_{t+1} - 1_n] = 0_n \tag{12}$$

where R_{t+1} is an $n \times 1$ vector of gross return, 1_n is an $n \times 1$ vector of ones, and 0_n is an $n \times 1$ vector of zeros. We estimate the unknown vector of factor loadings, $\hat{b}$, by making the pricing errors close to zero in the sense of the minimizing quadratic form

$$\hat{b} = \arg\min J_t = g_T(b)' \cdot W \cdot g_T(b) \tag{13}$$

where $g_T(b)$ denotes the vector of sample pricing errors and W is the weighting matrix.

We select two weighting matrices in estimating the objective function represented in (13). First, we adopt the asymptotically optimal weighting matrix to compute Hansen's J-statistic on the overidentifying restrictions of the models. Second, Hansen and Jagannathan (1997)'s weighing matrix, $E[RR']^{-1}$, which is the inverse of the second moments of asset returns, is employed and the Hansen and Jagannathan (HJ) distance and its p-value are computed.[9] Since this prespecified weighting matrix is invariant across models, the HJ distance enables us to compare asset pricing models. Additionally, the HJ distance has interesting economic implications for asset pricing models: it can be interpreted as the maximum pricing error for the set of assets (see Campbell and Cochrane, 2000).

4. Empirical evidence on time-series predictability

Fig. 1 displays the standardized time-series of market excess returns as well as the trend deviations, *coin*, from the second quarter of 1953 to the third quarter of 2005. Note that we use a different sample period in the time-series analysis to match the sample period used in the study of Lettau and Ludvigson (2001a) and Lamont (1998).[10] It appears that our trend deviations have some outstanding patterns: specifically, they are high during recessions and low during booms. More importantly, trend deviations well capture the "bad times", by showing that high positive trend deviations precede high market excess returns.[11]

[6] We demean the conditioning variable as advocated by Ferson et al. (2003).

[7] Following the study of Lamont (1998), we define the log dividends as the natural logarithm of the Standard and Poor's (S&P) Composite Index, and the log earnings as the natural logarithm of a single quarter's earnings per share. These data are from the Security Price Index Record published by S&P's Statistical Service.

[8] We estimate the full-sample betas, as in Lettau and Ludvigson (2001a,b), Petkova (2006), and Kim et al. (2011).

[9] Jagannathan and Wang (1996) derive the distribution of the HJ distance, which is a weighted sum of $n - k$ independent and identically distributed random variables of $\chi^2(1)$ distribution, where n denotes the number of assets and k the number of factors. We simulate 10,000× of the $n - k$ $\chi^2(1)$ variables to compute the p-value of the HJ distance.

[10] The sample period is from the fourth quarter of 1952 to the third quarter of 1998 in Lettau and Ludvigson's study (2001a) and from the first quarter of 1947 to the fourth quarter of 1994 in Lamont's study (1998). Since *coin* is available from the third quarter of 1953, our sample period is from the third quarter of 1953, and we extend it to the fourth quarter of 2005.

[11] We conduct Granger causality test to investigate whether our trend deviation Granger causes the market excess returns. Specifically, we regress the current value of market excess returns on the lagged values of market excess returns and trend deviations with a lag length from one to four. In all cases, we reject the null hypothesis that *coin* does not Granger cause market excess returns with a significance level of 1%.

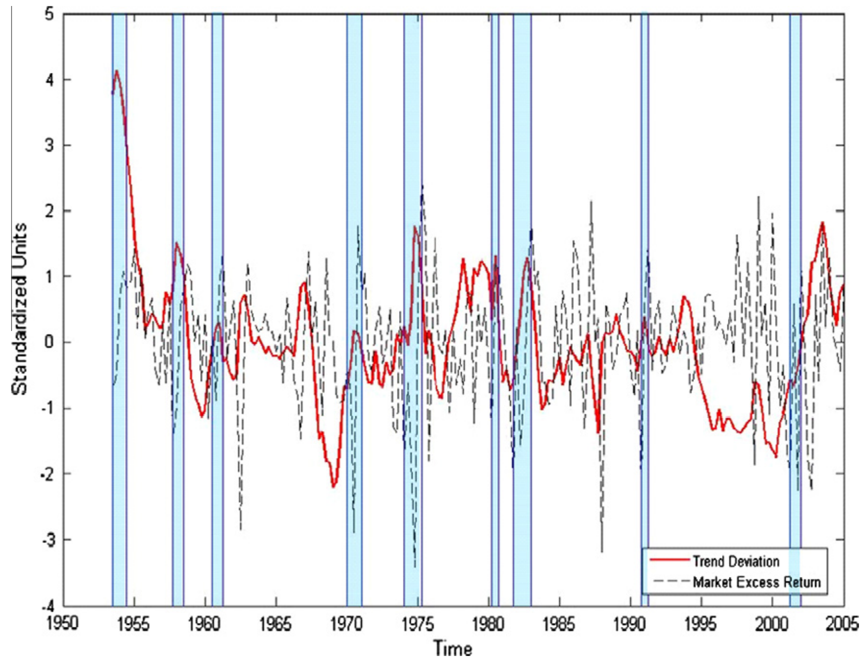

Fig. 1. Excess returns and trend deviations. This figure plots the series of market excess returns and trend deviation from the second quarter of 1953 to the third quarter of 2005. Trend deviation is the estimated cointegration error using the four conditioning variables: dividend yield of the CRSP value-weighted index (computed as the sum of dividends over the last 12 months divided by the level of the index), the difference between the yields of a 10-year and a 1-month government bond, the difference between the yields of Moody's Baa and Aaa corporate bonds, and the 3-month constant maturity Treasury yield. Both series are normalized to standard deviations of unity. The vertical grid lines are the NBER business cycle peaks and troughs.

Next, we evaluate the forecasting ability of our *coin* variable for stock market excess returns. Table 2 shows the results for forecasting regressions using the trend deviation, *coin*, and/or other predictive variables as explanatory variables. The dependent variable of each model is the log excess returns on the CRSP value-weighted returns, while a constant and the predictive variable(s) are employed as the explanatory variables. Table 2 reports the one-quarter-ahead and long-horizon forecasts of excess returns on the CRSP value-weighted index.[12] In all of the regressions shown in Table 2, we report the ordinary least squares (OLS) coefficient estimates in the first row, Newey–West (1987) corrected *t*-statistics with five lags in the second row, and the adjusted R^2 in parentheses.

4.1. One-quarter-ahead forecasts

The first column of Table 2 shows the one-quarter-ahead forecasts of the excess return on the CRSP value-weighted index. Model 1 reports the results for the forecasting regression with our trend deviation. The regression of the log excess returns on the trend deviation generates 6% of the adjusted R^2. Moreover, the corrected *t*-statistic is more than three standard errors from zero. A positive slope estimate is consistent with Fig. 1, indicating that the increase in trend deviation predicts the rise in the expected log excess return. Model 2 shows the regression results using the payout ratio. Unlike the results shown in Lamont's study (1998), the payout ratio explains little of the time variation of the log excess market returns.[13] Lamont (1998) asserts that the high stock prices in the 1990s induces a low forecasting power of the payout ratio in the 1990s. As our sample covers all market excess returns in the 1990s, it appears that the payout ratio has low forecasting power in recent years. Model 3 displays the regression result when the *cay* variable is used as a predictive variable, demonstrating its powerful forecasting ability.

In order to evaluate the additional marginal explanatory power in the presence of competing predictive variables, we regress the log excess market returns on a constant, *coin*, the payout ratio, and the *cay* variable, and the results are shown in Model 4. Even in the presence of the payout ratio and the *cay* variable, *coin* has marginal explanatory power. The three variables together explain 10% of the variation, whereas *cay* and *coin* alone explain 6% and 5% of the variation in the one-quarter-ahead returns, respectively. Therefore, *cay* and *coin* play different roles in predicting log excess market returns.

4.2. Long-horizon forecasts

In this subsection, we study the relative predictive powers of macroeconomic variables for excess returns at longer horizons. Long-horizon regressions of excess stock returns, over horizons spanning 2–24 quarters, on a lagged forecasting variable(s) are presented in the remaining columns of Table 2. The trend deviation, *coin*, has significant forecasting power for future returns at all horizons. The adjusted R^2 increases up to the 2-year horizon (8 quarters), reaching a level of 20%, and then decreases at longer horizons of 3 and 4 years. As one-quarter-ahead regressions, the payout ratio is insignificant and the *cay* variable is statistically

[12] Recent studies document that repurchases have substituted for dividend payments over the last 15–20 years (e.g., Fama and French (2001), Grullon and Michaely (2002)). In addition, Boudoukh et al. (2007) show that the payout yield contains more predictive power for future stock return than the dividend yield does. Based on these evidences, we also construct our state variable, *coin*, using the payout yield which includes share repurchases, and perform the predictive regressions. We also find that *coin*, estimated using the payout yield, contains critical information for predicting risk premiums over short and long horizons. These empirical results are available upon request. We thank the referee for providing this suggestion.

[13] Our results may differ from Lamont's because we use the log excess returns on the CRSP value-weighted index as the dependent variable, whereas Lamont uses the log excess returns on the S&P composite index. Also, the sample periods of the two are different.

Table 2
Forecasting market returns. This table reveals the regression results of current excess market returns on lagged variables *coin*, *d–e*, and *cay*. In each model, the OLS coefficient estimates are presented in the first row, the Newey–West (1987) estimators with five lags are in the second row, and the adjusted R^2 statistics are in parentheses. The dependent variable is the log excess returns on the CRSP value-weighted portfolio. The independent variables are as follows: *coin* denotes the cointegrating error adopted in this paper, *d–e* is the log dividend payout ratio, and *cay* is the log consumption-wealth ratio. H represents the return horizon in quarters. The sample period covers the period from the third quarter of 1953 to the fourth quarter of 2005.

Model	Regressors	Dependent variable: Log excess market return Forecast horizon, *H*							
		1	2	3	4	8	12	16	24
1	*coin*	0.03	0.06	0.08	0.10	0.14	0.15	0.16	0.27
		3.83	4.04	4.50	4.73	3.92	3.27	3.29	4.39
		(0.06)	(0.10)	(0.14)	(0.18)	(0.20)	(0.18)	(0.16)	(0.31)
2	*d–e*	0.03	0.04	0.03	0.03	0.05	0.07	0.03	0.13
		1.04	1.04	0.52	0.41	0.40	0.37	0.14	0.61
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3	*cay*	1.52	2.86	3.97	5.16	8.88	11.70	12.76	14.89
		3.50	3.65	3.64	3.79	4.91	5.23	6.09	6.09
		(0.05)	(0.10)	(0.13)	(0.17)	(0.30)	(0.40)	(0.41)	(0.35)
4	*coin*	0.03	0.05	0.07	0.09	0.12	0.13	0.13	0.24
		3.64	4.03	4.83	5.44	4.99	4.36	4.74	5.58
	d–e	0.00	−0.02	−0.06	−0.08	−0.13	−0.18	−0.25	−0.19
		−0.10	−0.65	−1.32	−1.64	−1.91	−1.90	−2.62	−1.32
	cay	1.34	2.60	3.73	4.89	8.48	11.29	12.58	13.77
		2.92	3.20	3.27	3.48	5.11	5.56	6.31	7.62
		(0.10)	(0.18)	(0.25)	(0.32)	(0.45)	(0.52)	(0.53)	(0.60)

significant for all horizons. Again, *coin* preserves its significant forecasting power when *cay* and the payout ratio are added to the list of independent variables.[14]

4.3. Relation to the macroeconomic conditions

In the forecasting regression, we observe a significant association between the variable, *coin*, and the future stock market returns. In an effort to determine whether our suggested variable captures more fundamental risk, we study the relation between *coin* and the macroeconomy. It is a common practice in the asset pricing literature to ask whether a proposed variable is related to fundamental risk using macroeconomic variables as proxies of state variables (e.g., Liew and Vassalou (2000), Chordia and Shivakumar (2006), and Da and Warachka (2009)). For example, Liew and Vassalou (2000) assess whether the Fama–French factors contain information regarding future investment opportunities. Da and Warachka (2009) investigate whether an earnings beta, defined as the covariance between the cash flow innovations of an asset and those of the market, captures the risk exposure to the macroeconomy. Consistent with this line of research, we study the relationship between the variable *coin* and the macroeconomic variables.

Based on the prior literature, we choose five macroeconomic variables reflecting the real business environment: (i) an indicator variable for economic contraction defined by the National Bureau of Economic Research (Recession), (ii) the growth rate of GDP (GDPG), (iii) the growth rate of consumption (CG), (iv) the growth rate of labor income (LIG), and (v) the inflation (INF).

Table 3 reports the estimation results for the time-series regressions of the (contemporaneous) macroeconomic variables on the conditioning variables, including our variable, *coin*. The NBER indicator variable for a recession is significantly positively correlated with *coin*, which is consistent with the observed pattern in Fig. 1. The growth rate of GDP, consumption, and labor income are all significantly negatively related to *coin*, which indicates that the time variation in *coin* is countercyclical to the business cycle. We find no significant relation between inflation and *coin*. In order to verify the robustness of our results, we repeat the regression analysis including the payout ratio and the *cay* variable as additional explanatory variables. These modifications yield qualitatively similar results. In summary, our evidence indicates that our *coin* variable is related to the macroeconomy, and the negative correlation between *coin* and real business activity (namely, GDPG, CG, and LIG) supports the supposition that *coin* captures the countercyclical risk exposure to the macroeconomy.

5. Empirical evidence on the cross-section of stock returns

5.1. Fama and MacBeth cross-sectional regressions

Table 4 reports the Fama and MacBeth cross-sectional regression results using the Fama and French 25 size and book-to-market sorted portfolios. It also contains the estimated coefficients of the risk premium, uncorrected Fama and MacBeth *t*-statistics, Shanken's (1992) corrected *t*-statistics, and adjusted R^2 statistics.[15] Although the adjusted R^2 statistic is used as a summary statistic for the overall fit of each specification, we also consider the restrictions on the cross-sectional slopes documented by Lewellen and Nagel (2006). Row 1 illustrates the well-known failure of the unconditional CAPM to explain the cross-section of the size and book-to-market sorted portfolios. Row 2 presents the results for Fama and French's three-factor model. The risk premium of the HML factor is both positive and statistically significant, and the adjusted R^2 is 76%. As documented in a variety of papers, Fama and French's three-factor model does a much better job explaining the cross-section of the Fama and French 25 portfolios than the

[14] We do not conduct out-of-sample tests for the following reasons. First, econometric theory indicates that the cointegrating vector should be estimated with all available data. Only when the sufficiently large number of observations is available, the cointegrating vectors are superconsistent and can be regarded as known in subsequent estimation. On the contrary, when a part of the observations is used, it is likely to generate sampling error in the cointegrating vectors. Second, recent studies demonstrate that out-of-sample tests are not as credible as originally advertised. For example, Inoue and Kilian (2004) demonstrate that in-sample tests are more powerful than out-of-sample tests for a variety of out-of-sample procedures. The lower power of the out-of-sample test is likely to underestimate the actual forecasting power, as documented by Lettau and Ludvigson (2005).

[15] Jagannathan and Wang (1996) use the cross-sectional R^2 measure to evaluate the goodness of fit of the model. The measure is calculated as $R^2 = \frac{\sigma_C^2(\bar{R}) - \sigma_C^2(\bar{e})}{\sigma_C^2(\bar{R})}$, where σ_C^2 is the in-sample cross-sectional variance, $\bar{R}$ is a vector of average excess returns, and $\bar{e}$ is the vector of average residuals.

Table 3
Relation to macroeconomic conditions. This table shows the estimation results of the time-series regression of the contemporaneous macroeconomic variables on the conditioning variables including our variable, *coin*. We choose five macroeconomic variables reflecting the real business environment as dependent variables: (i) an indicator variable for economic contraction defined by the National Bureau of Economic Research (Recession) (ii) the growth rate of GDP (GDPG), (iii) the growth rate of consumption (CG), (iv) the growth rate of labor income (LIG), and (v) the inflation (INF). The independent variables are as follows: *coin* denotes the cointegrating error adopted in this paper, *d–e* is the log dividend payout ratio, and *cay* is the log consumption-wealth ratio. In each specification, the OLS estimates are presented in the first row, *t*-statistics are displayed in the second row, and the adjusted R^2 statistics are in parentheses. The sample period covers the period from the third quarter of 1953 to the fourth quarter of 2005.

	Recession		GDPG		CG		LIG		INF	
INTERCEPT	0.19	0.05	0.79	0.78	0.37	0.29	0.54	0.45	0.95	1.57
	4.23	0.54	9.74	4.40	6.36	2.07	8.43	2.50	8.38	4.28
coin	0.17	0.16	−0.30	−0.30	−0.16	−0.15	−0.22	−0.23	−0.01	0.03
	3.59	3.35	−2.59	−2.58	−2.14	−1.91	−2.65	−2.62	−0.08	0.18
cay		0.16		0.92		−5.67		1.27		−3.92
		0.06		0.17		−1.23		0.25		−0.72
d–e		0.21		0.02		0.12		0.14		−0.95
		1.48		0.07		0.65		0.54		−2.10
Adj. R^2	(0.09)	(0.09)	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.00)	(0.08)

Table 4
Cross-sectional regression. This table shows Fama and MacBeth (1973) cross-sectional regression estimation results using the excess returns on 25 size and book-to-market sorted portfolios created by Fama and French (1993). The full-sample factor loadings, which are used as the independent variables, are computed in one multiple time-series regression. The coefficients are expressed in percentages per quarter. The term R_m is the excess return on the CRSP value-weighted index, Δc is the log consumption growth, and SMB and HML are the Fama and French mimicking portfolios related by size and book-to-market, respectively. The conditioning variables are *cay* as created by Lettau and Ludvigson (2001a,b) and *coin*, as adopted in this paper. The first row of each model reports the coefficient estimates. Fama and MacBeth *t*-statistics are reported in the second row and Shanken's corrected *t*-statistics are in the third row. The adjusted R^2 values from the study of Jagannathan and Wang (1996) are presented in the last column. RMSE is the square root of the average pricing error (in %). The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

Row	Model	Factors				Adj. R^2	RMSE
1	CAPM	Constant	$R_{m,t+1}$				
	Estimate	2.73	−0.47			−0.02	0.75
	t-Value	3.08	−0.43				
	Shanken-*t*	3.07	−0.43				
2	FF3	Constant	$R_{m,t+1}$	SMB	HML		
	Estimate	3.02	−1.63	0.72	1.47	0.76	0.35
	t-Value	2.58	−1.21	1.53	2.90		
	Shanken-*t*	2.43	−1.15	1.52	2.87		
3	Cay CAPM	Constant	cay_t	$R_{m,t+1}$	$cay_t \cdot R_{m,t+1}$		
	Estimate	2.41	−0.02	−0.94	0.06	0.51	0.50
	t-Value	2.87	−2.95	−0.89	2.37		
	Shanken-*t*	1.58	−1.64	−0.57	1.36		
4	Coin CAPM	Constant	$coin_t$	$R_{m,t+1}$	$coin_t \cdot R_{m,t+1}$		
	Estimate	2.11	0.42	−0.74	6.79	0.58	0.46
	t-Value	2.34	1.91	−0.68	3.88		
	Shanken-*t*	1.40	1.15	−0.46	2.36		
5	CCAPM	Constant	Δc_{t+1}				
	Estimate	0.94	0.54			0.21	0.66
	t-Value	1.56	1.73				
	Shanken-*t*	1.23	1.37				
6	Cay CCAPM	Constant	cay_t	Δc_{t+1}	$cay_t \cdot \Delta c_{t+1}$		
	Estimate	3.17	−0.01	0.33	0.00	0.59	0.45
	t-Value	3.04	−1.98	1.06	0.73		
	Shanken-*t*	2.13	−1.40	0.75	0.53		
7	Coin CCAPM	Constant	$coin_t$	Δc_{t+1}	$coin_t \cdot \Delta c_{t+1}$		
	Estimate	1.60	−0.12	0.54	0.46	0.76	0.35
	t-Value	2.57	−0.79	2.67	2.97		
	Shanken-*t*	1.42	−0.45	1.51	1.67		

unconditional CAPM. As shown in the third row, we estimate Lettau and Ludvigson's (2001b) conditional CAPM with an updated *cay* variable. Unlike Lettau and Ludvigson's original results, the cross-term $cay \cdot R_m$ has no power to explain the cross-sectional variation of average returns. We believe that the extended sample period and the use of the updated *cay* data in this paper may give rise to different regression results.[16] Row 4 shows the slope coefficients when the conditioning variable *coin* is included in the regression analysis. The risk premium for the interaction term $coin \cdot R_m$ is positive and both the uncorrected and corrected *t*-statistics are statistically significant. This conditional model performs substantially better than the unconditional CAPM, explaining approximately 58% of the cross-section of the Fama and French 25 portfolios.

We now evaluate the power of consumption-based models. Row 5 shows the results for the unconditional CCAPM. The price of risk related to consumption goes in the right direction and the adjusted R^2 of the unconditional CCAPM is approximately 21%, thereby implying that it explains the cross-sectional patterns better than the unconditional CAPM. Row 6 displays Lettau and Ludvigson's estimates with the *cay* variable, and demonstrates that it explains 59% of the cross-sectional returns. Finally, row 7 reveals

[16] Our sample period spans the third quarter of 1963 to the fourth quarter of 2005, while Lettau and Ludvigson's sample period spans the third quarter of 1963 to the third quarter of 1998. Li et al. (2006) also obtain results that differ from those of Lettau and Ludvigson (2001b).

the results for the conditional CCAPM when *coin* is employed as a conditioning variable. It shows substantial improvement over the unconditional CCAPM results. The risk premium of the consumption risk and the compensation for the interaction term are positive, and the Fama and MacBeth t-statistic is close to three standard errors from zero. Moreover, the adjusted R^2 is 76%, which is comparable to that for Fama and French's three-factor model.

A recent paper by Lewellen and Nagel (2006) emphasizes the theoretical restrictions of slopes imposed on the cross-sectional regressions. The conditional CAPM implies the unconditional model: $E[r_t] = \beta\gamma + \text{cov}(\beta_t, \gamma_t)$, in which β_t and γ_t are the conditional beta and equity premium, and β and γ are their unconditional means. In our specification, $\beta_t = \beta_0 + \delta coin_{t-1}$ where β_0 and δ are estimated in the time-series regression: $r_t = \alpha_0 + \alpha_1 coin_{t-1} + (\beta_0 + \delta coin_{t-1})\Delta c_t = \alpha_0 + \alpha_1 coin_{t-1} + (\beta_0 + \delta coin_{t-1})\Delta c_t + e_t$. Substituting β_t into the unconditional equation yields $E[r_t] = \beta\gamma + \delta\text{cov}(coin_{t-1}, \gamma_t)$. Therefore, the slope on δ in the cross-sectional regression should be $\text{cov}(coin_{t-1}, \gamma_t)$. Since the covariance should be less than the product of the standard deviation of *coin* and equity premium, the standard deviation of the equity premium must be greater than the ratio of covariance to the standard deviation of *coin*. The estimated covariance in Table 4 is 0.0046, and the standard deviation of *coin* is 0.7005, thereby indicating that the standard deviation of the equity premium exceeds 0.66%. However, the estimated average risk premium is 0.54%. Therefore, if our specification does indeed explain the cross-sectional patterns, the risk premium should be 0.54% on average, whereas the volatility exceeds 0.66%. This result does not substantially deviate from the restrictions, though the risk premium still has some skewness to accept our model.[17]

Lettau and Ludvigson (2001b) document that the intercept of the cross-sectional regression is usually large when macroeconomic variables are employed as factors. This is, however, not the case for our model. The estimated intercept of our conditional CCAPM is 1.60% per quarter, which is approximately half of the intercept in Fama and French's three-factor model or the conditional CCAPM of Lettau and Ludvigson (2001b). Moreover, the error-in-variable adjusted Shanken's t-statistic is statistically significant in Fama and French's three-factor model and Lettau and Ludvigson's specification, whereas it is statistically insignificant in our specification. The intercept of the uncorrected Fama and MacBeth t-statistic is, however, statistically significant in our specification. Thus, it appears that our specification could still be missing some important determinants of the cross-section of the Fama and French 25 portfolios.

5.2. Average pricing errors

Fig. 2 illustrates the realized versus the fitted average returns of the unconditional CAPM (Panel A), Fama and French's three-factor model (Panel B), the unconditional CCAPM model (Panel C), and the conditional CCAPM model with *coin* as a conditioning variable (Panel D). Each two-digit number identifies a different portfolio. The first digit represents the size quintiles of the portfolios (1 indicating the smallest and 5 the largest), while the second digit refers to the book-to-market quintiles of the portfolios (1 indicating the lowest and 5 the highest). If the competing model is specified appropriately, all the portfolios should lie on the 45° line through the origin.

As a variety of portfolios lie far away from the 45° line, Panel A shows the well-known failure of the unconditional CAPM. In particular, the fitted average returns of portfolios 11 and 15 are almost the same even though the realized average returns are very different, meaning that the unconditional CAPM does not explain the well-known value premium. As illustrated in Panel B, Fama and French's three-factor model performs substantially better than the unconditional CAPM. It does, however, experience some difficulty in explaining the growth portfolios in the smallest and largest size quantiles (portfolios 11, 41, and 51).

The unconditional CCAPM model performs slightly better than the unconditional CAPM, as is shown in Panel C. This specification, however, does not explain why value stocks earn more than growth stocks throughout our sample period. Panel D provides the results for our specification. In terms of the distance from the 45° line, our conditional CCAPM does a better job in explaining the problematic portfolios 11 and 51 than does Fama and French's three-factor model.[18] The average pricing errors of portfolios 11 and 51 are reduced by 39% and 61%, respectively. Since the linear asset pricing model, such as Fama and French's three-factor model, does not perform well in explaining the return behavior of small growth stocks, the pricing error reduction in portfolio 11 is a performance gain for our model.

5.3. Conditional consumption betas

We are now in a position to discuss why our conditional CCAPM performs better than the unconditional CAPM and CCAPM. We argue that one should take a look at the conditional correlation, rather than the unconditional correlation, between the consumption growth rates and asset returns, if the conditional CCAPM holds period-by-period. For instance, in the unconditional CAPM, the unconditional beta of portfolio 11 (small and growth) is 1.67, while the unconditional beta of portfolio 15 (small and value) is 1.19 in our sample period. With these betas, the unconditional CAPM does not explain why value stocks earn more than growth stocks.

To further examine, we calculate the conditional consumption betas for good and bad states. One stylized fact is that the market risk premium is related closely to the business cycle; it is high in business cycle troughs and low in business cycle peaks. Since a high *coin* value forecasts a high market excess return and a low *coin* value forecasts a low market excess return, following Lettau and Ludvigson (2001b), we define a good (bad) state as a quarter during which *coin* is at least one standard deviation below (above) its average. In our analysis, the number of quarters of both bad and good states is 29 among 170 quarters, respectively.

In the first stage of the time-series regression in our model, the regression equation is expressed by

$$r^i_{t+1} = \alpha^i + \beta^i_{coin} coin_t + \beta^i_c \Delta c_{t+1} + \beta^i_{c\times coin} \Delta c_{t+1} coin_t, \quad i = 1, 2, \ldots, 25 \tag{14}$$

where r^i_{t+1} is the excess return on the ith Fama and French portfolio at time $t+1$. The conditional consumption beta, B^i_t, on portfolio i at time t is defined as $B^i_t \equiv \beta^i_c + \beta^i_{c\times coin} coin_t$. Accordingly, we can calculate the average conditional consumption betas in both bad and good states.

Table 5 reports the average conditional consumption betas in all states, good states, and bad states for the Fama and French 25 portfolios. Following the study of Lettau and Ludvigson (2001b), it is helpful to provide a visual comparison of the average consumption betas for value and growth stocks. Fig. 3 illustrates the average consumption betas for portfolios 11, 15, 21, 25, 31, 35, 41, and 45 in bad and good states. In bad states, the average consumption betas for value portfolios (15, 25, 35, 45) are higher than those for

[17] Lewellen and Nagel (2006) document that if the conditional CCAPM with *cay* truly holds, the risk premium must be close to zero on average, whereas the volatility should be greater than 3.2% quarterly.

[18] In order to compare the average pricing errors quantitatively across the models, we compute the root mean square error (RMSE) and report the results in Table 4. The Fama and French three-factor model and the conditional CCAPM with *coin* as a conditioning variable generate the lowest RMSE, which is 0.35.

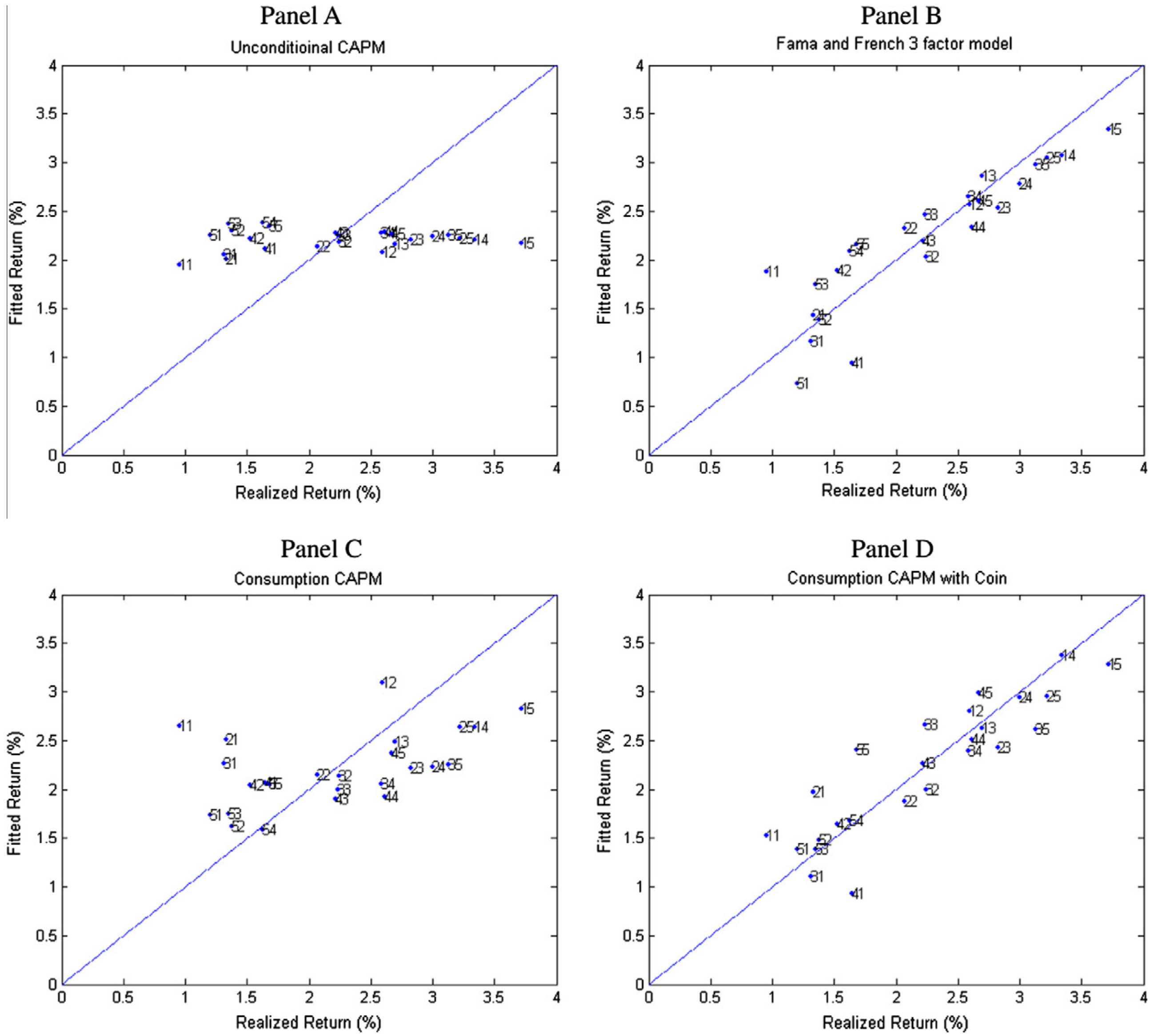

Fig. 2. Realized and fitted excess returns. This figure illustrates the realized versus fitted average returns of the unconditional CAPM (Panel A), Fama and French's three-factor model (Panel B), the unconditional CCAPM model (Panel C), and the conditional CCAPM model with *coin* as a conditioning variable (Panel D). Each two-digit number identifies a different portfolio. The first digit represents the size quintiles of the portfolios (1 indicating the smallest and 5 the largest), while the second digit refers to the book-to-market quintiles of the portfolios (1 indicating the lowest and 5 the highest). The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

growth portfolios (11, 21, 31, 41). For example, the average consumption beta for portfolio 15 in bad states is 4.43 compared to 2.04 for portfolio 11. In contrast, in good states, the average consumption betas for value portfolios are lower than those for growth portfolios. For instance, the average consumption beta for portfolio 15 in good states is 3.48, compared to 5.98 for portfolio 11. These comparisons of average consumption betas imply that value stocks are correlated more highly with consumption risk in bad times than in good times, and that growth stocks are correlated more highly with consumption risk in good times than in bad times. Overall, our specification demonstrates that value stocks are riskier than growth stocks in bad times, when the risk premium is high. Therefore, our model supports the risk-based story behind the value premium.

5.4. GMM estimation

Along with the Fama and MacBeth tests, we also evaluate the performance of competing asset pricing models using the GMM cross-sectional estimator. Table 6 reports the GMM estimation results using the optimal weighting matrix, which are generally consistent with the Fama and MacBeth regression.

Panel A shows the results for the unconditional CCAPM. The coefficient of consumption growth rate (Δc) in the pricing kernel is statistically significant, which implies that the consumption risk factor is useful to price assets. The consumption factor commands a significant positive risk premium. This model, however, delivers the worst fit based on the HJ distance. Hansen's overidentification test (J test) also rejects the model.

Panel B displays the results for Fama and French's three-factor model. The coefficients and risk premiums for SMB and HML are economically significant, but those for MKT (the market excess return) are not significant and produce the wrong sign: its premium is estimated as −0.18% per quarter. The Wald test – Wald (b) – rejects the null hypothesis that the slope coefficients b in the model are jointly equal to zero. Fama and French's three-factor model reduces the average pricing errors over those of the CCAPM, yielding an HJ distance of 0.598, which is smaller than the 0.636

Table 5
Conditional betas in consumption CAPM. This table reports the average consumption betas of all states, good states, and bad states for each Fama and French size and book-to-market sorted portfolio. The average consumption betas for portfolio i are calculated as $B_j^i \equiv \beta_c^i + \beta_{c\times coin}^i \overline{coin}$, where $\overline{coin}$ is the average value in bad states ($j = 1$) and good states ($j = 2$). For each portfolio, the first digit represents the size quintiles of the portfolios (1 indicating the smallest and 5 the largest), while the second digit refers to the book-to-market quintiles of the portfolios (1 indicating the lowest and 5 the highest). Following Lettau and Ludvigson (2001b), we define a good state as a quarter in which the *coin* variable is one standard below its mean value, and a bad state as a quarter in which the *coin* variable is one standard above its mean value.

Portfolio	All states	Good states	Bad states
11	4.0346	5.9752	2.0378
12	4.5827	5.3249	3.8191
13	3.3359	3.4881	3.1793
14	3.4631	2.6925	4.2559
15	3.9497	3.4813	4.4317
21	3.5895	4.6652	2.4825
22	2.7908	3.5895	1.9690
23	2.7540	2.8963	2.6077
24	2.6544	1.9951	3.3329
25	3.5244	3.4779	3.5723
31	3.1973	5.4153	0.9150
32	2.6965	3.3424	2.0319
33	2.2155	1.6854	2.7609
34	2.3861	2.4076	2.3640
35	2.7518	2.7386	2.7654
41	2.7091	5.0732	0.2766
42	2.5318	3.7063	1.3232
43	2.0926	2.0630	2.1232
44	2.0456	1.7247	2.3757
45	2.9096	2.4594	3.3728
51	1.8320	3.1821	0.4428
52	1.6037	2.5108	0.6703
53	1.8402	3.2212	0.4193
54	1.4581	2.1082	0.7891
55	2.2773	2.4876	2.0608

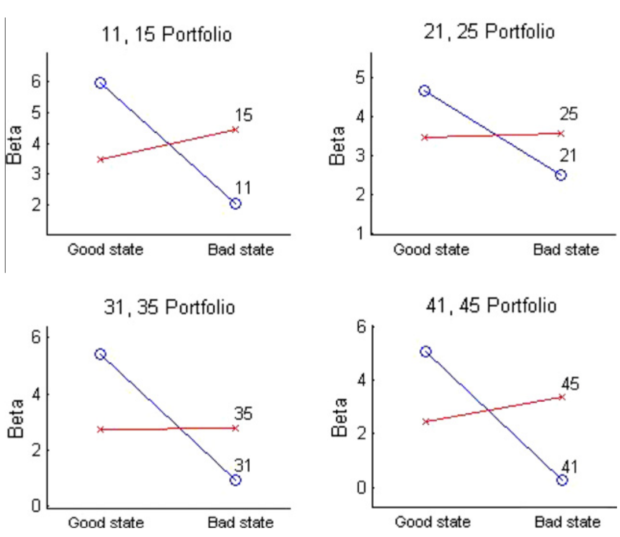

Fig. 3. Conditional consumption beta in good and bad states. This figure displays the average consumption betas for 11, 15, 21, 25, 31, 35, 41, and 45 portfolios in bad and good states. Each two-digit number identifies a different portfolio. The first digit represents the size quintiles of the portfolios (1 indicating the smallest and 5 the largest), while the second digit refers to the book-to-market quintiles of the portfolios (1 indicating the lowest and 5 the highest). A good (bad) state is defined as a quarter during which *coin* is at least one standard deviation below (above) its average. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

estimated from the CCAPM. Nonetheless, the model is still rejected by the data in terms of both the J test and the HJ distance.

Panel C reports the performance of the Lettau and Ludvigson model. The consumption factor and intersection term have economically significant coefficients and risk premiums. The *cay* factor is not statistically significant. The coefficients, however, are jointly significant, as indicated by the Wald (b) test. When *cay* is used to scale the consumption risk factor, the model better describes the cross-sectional differences in expected returns, but it performs worse than Fama and French's three-factor model (HJ distance = 0.611). Again, the model is rejected by the data.

Panel D reports the performance of the conditional CCAPM model with *coin* as the scaling variable. The coefficients are all significant, meaning that all three factors are significant determinants of the cross-section of equity returns. The consumption factor and its scaled factor by the *coin* variable are priced by size and book-to-market portfolios. On the other hand, the *coin* factor does not receive statistically significant risk premiums. The HJ distance for this model is 0.580, the lowest among the competing models. Despite having the best performance, this model is still rejected by the data.

As a robustness test, we examine whether competing models maintain their pricing abilities by requiring them to price a different set of assets. Fama and French 25 portfolios and their 25 portfolios scaled by the variable *cay* are selected as the test assets. As Cochrane (1996) discusses, scaled returns have an economically interesting interpretation: they are understood as managed portfolios in which fund managers adjust portfolio weights on the basis of the information they receive from the conditioning variable.

Table 7 shows the GMM estimation results when managed portfolios are employed as a basis asset. A comparison of Tables 6 and 7 shows that the relative performances of competing models are preserved when they are required to price an alternative set of assets. The difference originates from the increased average pricing errors for the managed portfolio employed. However, when we consider the increased dimension of the payoff space to be priced, the increase in pricing errors is not unexpected.

6. Robustness of the results

6.1. Fama and MacBeth cross-sectional regressions including characteristics

Jagannathan and Wang (1998) suggest that model misspecification can be tested using firm characteristics as additional explanatory variables in the Fama and MacBeth cross-sectional regressions. If the model is well specified, the t-statistics of the firm characteristic variables should be zero. In accordance with Fama and French (1992), for each time t in the second stage of the Fama and MacBeth regressions we include the log value of the book-to-market equity ratio and the log value of firm size. The time-series averages of the estimated slopes, the Fama and MacBeth t-statistics, and the adjusted R^2 are provided in Tables 8 and 9.

As shown in row 2 of Table 8, the slope coefficient of the log book-to-market ratio is statistically significant under Fama and French's three-factor model, indicating that the characteristic, rather than the factor loading, helps explain the cross-section of the average returns. When the book-to-market ratio is included in the conditional CAPM, its coefficients are always statistically significant.

We now examine the residual effects of the CCAPM. The estimated coefficient of the book-to-market ratio is statistically significant in the unconditional CCAPM, as is shown in row 5, or in the conditional CCAPM with *cay*, as is shown in row 6. In our specification of the conditional CCAPM with *coin*, however, the book-to-market ratio does not have statistically significant explanatory power. Moreover, the book-to-market ratio does not drive out the interaction term $coin_t \Delta c_{t+1}$.

Table 6
GMM estimation. This table provides GMM estimation results of the competing models using 25 size and book-to-market sorted portfolios created by Fama and French (1993). The term Δc is the log consumption growth and SMB and HML are the Fama and French mimicking portfolios related to size and book-to-market, respectively. The conditioning variables are *cay* as created by Lettau and Ludvigson (2001a,b) and *coin* as adopted in this paper. The *t*-values of the coefficients in the pricing kernel and the risk premiums of the factors are reported in parentheses. The *J* test is Hansen's (1982) test on the overidentifying restrictions of the model. The Wald (b) test is a joint significance test of the factor loadings in the pricing kernel. The HJ distance is the Hansen–Jagannathan (1997) measure and its *p*-value is obtained from 10,000 simulations. The coefficients in the pricing kernel and the test statistics for *J* and Wald (b) are computed through the GMM estimation, which uses the optimal weighting matrix. The *p*-values of the test statistics for J, Wald (b), and the HJ distance are reported in square brackets. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

	Constant	Δc	*J*	Wald (b)	HJ distance
Panel A: Unconditional CCAPM					
b	1.25	−0.69	104.61	16.21	0.636
t-Value	(14.52)	(−4.03)	[0.000]	[0.000]	[0.000]
Risk premium		0.35			
t-Value		(4.03)			

	Constant	MKT	SMB	HML	*J*	Wald (b)	HJ distance
Panel B: Fama and French's three-factor model							
b	1.10	0.01	−0.05	−0.04	58.07	27.03	0.598
t-Value	(22.56)	(0.35)	(−2.90)	(−3.00)	[0.000]	[0.000]	[0.000]
Risk premium		−0.18	1.23	1.24			
t-Value		(−0.22)	(3.41)	(3.31)			
	Constant	*cay*	Δc	$cay \cdot \Delta c$	*J*	Wald (b)	HJ distance
Panel C: Lettau and Ludvigson model							
b	1.87	0.20	−2.23	−0.92	53.06	33.16	0.611
t-Value	(8.53)	(0.73)	(−4.96)	(−3.27)	[0.000]	[0.000]	[0.003]
Risk premium		−0.18	0.95	0.72			
t-Value		(−0.34)	(4.47)	(2.37)			
	Constant	*coin*	Δc	$coin \cdot \Delta c$	*J*	Wald (b)	HJ distance
Panel D: Alternative model							
b	1.18	0.65	−0.69	−1.32	66.09	17.21	0.580
t-Value	(9.17)	(1.93)	(−3.20)	(−3.07)	[0.000]	[0.001]	[0.037]
Risk premium		−0.05	0.36	0.21			
t-Value		(−0.55)	(3.03)	(2.68)			

Table 7
GMM estimation on the managed portfolios. This table reports GMM estimation results of the competing models using 25 size and book-to-market sorted portfolios created by Fama and French (1993) plus the 25 scaled Fama and French portfolios. The scaled Fama and French portfolios are obtained by multiplying each of the Fama and French 25 portfolios by *cay*, which is the consumption-wealth ratio created by Lettau and Ludvigson (2001a). The term Δc is the log consumption growth and SMB and HML are the Fama and French mimicking portfolios related to size and book-to-market, respectively. The conditioning variables are *cay* and *coin* as adopted in this paper. The *t*-values of the coefficients in the pricing kernel and the risk premiums of the factors are shown in parentheses. The *J* test is Hansen's (1982) test on the overidentifying restrictions of the model. The Wald (b) test is a joint significance test of the factor loadings in the pricing kernel. The HJ distance is the Hansen–Jagannathan (1997) measure and its *p*-value is obtained from 10,000 simulations. The coefficients in the pricing kernel and the test statistics for *J* and Wald (b) are computed through the GMM estimation, which uses the optimal weighting matrix. The *p*-values of the test statistics for *J*, Wald (b), and the HJ distance are reported in square brackets. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

	Constant	Δc	*J*	Wald (b)	HJ distance
Panel A: Consumption CAPM					
b	1.31	−0.60	221.20	61.36	0.796
t-Value	(31.50)	(−7.83)	[0.000]	[0.000]	[0.000]
Risk premium		0.28			
t-Value		(7.83)			

	Constant	MKT	SMB	HML	*J*	Wald (b)	HJ distance
Panel B: Fama and French's three-factor model							
b	1.10	0.03	−0.07	−0.05	133.07	149.04	0.736
t-Value	(35.49)	(2.57)	(−6.61)	(−6.18)	[0.000]	[0.000]	[0.000]
Risk premium		−1.13	1.52	1.73			
t-Value		(−2.46)	(5.80)	(9.10)			
	Constant	*cay*	Δc	$cay \cdot \Delta c$	*J*	Wald (b)	HJ distance
Panel C: Lettau and Ludvigson model							
b	1.73	−0.13	−1.27	−0.53	168.18	110.06	0.790
t-Value	(20.46)	(−1.17)	(−6.55)	(−4.10)	[0.000]	[0.000]	[0.000]
Risk premium		0.31	0.42	0.45			
t-Value		(2.09)	(5.80)	(5.52)			
	Constant	*coin*	Δc	$coin \cdot \Delta c$	*J*	Wald (b)	HJ distance
Panel D: Alternative model							
b	1.48	1.25	−0.92	−2.11	138.94	59.90	0.767
t-Value	(15.45)	(6.48)	(−5.86)	(−6.46)	[0.000]	[0.000]	[0.000]
Risk premium		−0.12	0.39	0.25			
t-Value		(−2.38)	(5.65)	(4.43)			

Table 8
Cross-sectional regression including book-to-market ratio. This table shows the Fama and MacBeth (1973) cross-sectional regression estimation results including the book-to-market ratio (BM) as an additional explanatory variable. The term R_m is the excess return on the CRSP value-weighted index, Δc is the log consumption growth, and SMB and HML are the Fama and French mimicking portfolios related by size and book-to-market, respectively. The conditioning variables are *cay* as created by Lettau and Ludvigson (2001a,b) and *coin*, as adopted in this paper. The first row of each model reports the coefficient estimates. The coefficients are expressed as percentages per quarter. Fama and MacBeth *t*-statistics are reported in the second row. The adjusted R^2 values are presented in the last column. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

Model	Factors					Adj. R^2
CAPM	Constant	R_m			BM	
Estimate	0.54	1.66			1.18	0.70
t-Value	0.55	1.32			3.67	
FF3	Constant	R_m	SMB	HML	BM	
Estimate	3.18	−1.26	0.77	0.32	0.73	0.76
t-Value	2.75	−0.93	1.65	0.41	2.15	
Cay CAPM	Constant	*cay*	R_m	$cay \cdot R_m$	BM	
Estimate	0.22	0.00	1.83	0.03	1.08	0.69
t-Value	0.25	−0.21	1.60	1.19	4.31	
Coin CAPM	Constant	*coin*	R_m	$coin \cdot R_m$	BM	
Estimate	0.51	0.05	1.54	1.73	0.98	0.69
t-Value	0.51	0.24	1.21	1.21	3.49	
CCAPM	Constant	Δc			BM	
Estimate	1.34	0.46			0.76	0.71
t-Value	2.11	1.42			2.63	
Cay CCAPM	Constant	*cay*	Δc	$cay \cdot \Delta c$	BM	
Estimate	1.33	0.00	0.37	0.00	0.74	0.70
t-Value	1.97	0.45	1.24	0.89	2.38	
Coin CCAPM	Constant	*coin*	Δc	$coin \cdot \Delta c$	BM	
Estimate	1.41	0.02	0.33	0.35	0.41	0.78
t-Value	2.21	0.15	1.56	2.59	1.57	

Table 9
Cross-sectional regression including size. This table shows the Fama and MacBeth (1973) cross-sectional regression estimation results including size (SIZE) as an additional explanatory variable. The term R_m is the excess return on the CRSP value-weighted index, Δc is the log consumption growth, and SMB and HML are the Fama and French mimicking portfolios related by size and book-to-market, respectively. The conditioning variables are *cay* as created by Lettau and Ludvigson (2001a,b) and *coin*, as adopted in this paper. The first row of each model reports the coefficient estimates. The coefficients are expressed as percentages per quarter. Fama and MacBeth *t*-statistics are reported in the second row. The adjusted R^2 values are presented in the last column. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

Model	Factors					Adj. R^2
CAPM	Constant	R_m			SIZE	
Estimate	8.35	−2.94			−0.47	0.79
t-Value	4.73	−2.51			−3.99	
FF3	Constant	R_m	SMB	HML	SIZE	
Estimate	5.07	−1.26	−0.25	1.32	−0.27	0.79
t-Value	3.04	−0.95	−0.35	2.57	−1.96	
Cay CAPM	Constant	*cay*	R_m	$cay \cdot R_m$	SIZE	
Estimate	7.43	0.00	−2.43	0.03	−0.42	0.78
t-Value	5.18	−0.65	−2.23	1.24	−4.48	
Coin CAPM	Constant	*coin*	R_m	$coin \cdot R_m$	SIZE	
Estimate	6.79	−0.26	−1.65	1.93	−0.44	0.82
t-Value	5.17	−1.62	−1.50	1.43	−4.79	
CCAPM	Constant	Δc			SIZE	
Estimate	3.45	0.04			−0.23	0.26
t-Value	2.74	0.14			−2.29	
Cay CCAPM	Constant	*cay*	Δc	$cay \cdot \Delta c$	SIZE	
Estimate	4.55	−0.01	0.08	0.00	−0.13	0.61
t-Value	3.45	−2.24	0.35	0.39	−1.21	
Coin CCAPM	Constant	*coin*	Δc	$coin \cdot \Delta c$	SIZE	
Estimate	5.32	−0.40	0.41	0.09	−0.32	0.84
t-Value	4.51	−2.85	1.97	0.77	−3.62	

Table 9 reports the Fama and MacBeth cross-sectional regression results when size is added as an explanatory variable. The slope coefficient of size is statistically insignificant only in the conditional CCAPM of Lettau and Ludvigson (2001b). The slope coefficient of size is statistically significant under our specification, indicating that our model might be misspecified. It is, however, also statistically significant under Fama and French's three-factor model.

6.2. Cross-sectional regression including conditioning information

Ferson and Harvey (1999) document that Fama and French's three-factor model does not account for the time-varying patterns in stock returns, by showing that the sensitivity of the fitted conditional expected return is statistically significant when included in the cross-sectional regressions. Performing similar regressions, Petkova (2006) provides empirical evidence to suggest that her model, unlike Fama and French's three-factor model, is capable of capturing the time-varying patterns in returns predicted by the conditioning variables. As this test allows us to examine whether our model is a good conditional model, and also enables the specification test of the competing asset pricing models as documented by Petkova (2006), it is worthwhile to revisit Ferson and Harvey's experiment.

Specifically, we first run the multivariate time-series regressions for the 25 size and book-to-market sorted portfolios in order to estimate the betas of lagged conditioning variables:

$$r_{i,t+1} = \alpha + \beta_{i,DIV}DIV_t + \beta_{i,TERM}TERM_t + \beta_{i,DEF}DEF_t + \beta_{i,RF}RF_t + \varepsilon_{i,t+1} \tag{15}$$

where $r_{i,t+1}$ is the excess return of portfolio i at time $t+1$ and $DIV_t, TERM_t, DEF_t$, and RF_t represent the dividend yield, term spread, default spread, and short-term interest rate at time t, respectively. We then add these estimated betas in our cross-sectional regressions of 25 size and book-to-market sorted portfolios to assess whether or not γ_{DIV}, γ_{TERM}, γ_{DEF}, and γ_{RF} are equal to zero:

$$\begin{aligned} r_{i,t+1} = {} & \gamma_0 + \gamma_{\Delta c}\beta_{i,\Delta c} + \gamma_{coin}\beta_{i,coin} + \gamma_{coin\Delta c}\beta_{i,coin\Delta c} + \gamma_{DIV}\beta_{i,DIV} \\ & + \gamma_{TERM}\beta_{i,TERM} + \gamma_{DEF}\beta_{i,DEF} + \gamma_{RF}\beta_{i,RF} + u_{i,t+1} \end{aligned} \tag{16}$$

To compare competing asset pricing models, we also report the results for Fama and French's three-factor model as well as Lettau and Ludvigson's (2001a,b) model; the results are shown in Table 10. In Panel A, the estimated slopes of short-term interest rate and dividend are statistically significant, thereby indicating that the short-term interest rate and dividend yields are determinants of the cross-section of stock returns in the presence of Fama and French's three factors. Lettau and Ludvigson's (2001a,b) model fails to capture the time-varying patterns of expected returns related to the cross-sectional differences in sensitivity with respect to the default spread as shown in Panel B. On the other hand, neither $\gamma_{DIV}, \gamma_{TERM}, \gamma_{DEF}$, nor γ_{RF} differs statistically from zero in our specification. Therefore, our conditional CCAPM serves as a good conditional model, and passes the model misspecification test.

6.3. Other portfolios

One natural way to improve empirical tests is to expand the set of test portfolios, as suggested by Lewellen et al. (2010). In this subsection, we compare the performance of our conditional CCAPM and Fama and French's three-factor model using different test assets: namely, 10 industry portfolios, and 25 size and momentum portfolios. Table 11 reveals the slope coefficients, Fama and MacBeth *t*-statistics, Shanken's corrected *t*-statistics, and adjusted R^2 for our specification and Fama and French's three-factor model.

Table 10
Ferson and Harvey (1999) test. This table shows the Fama and MacBeth (1973) cross-sectional regression estimation results using the excess return on 25 size and book-to-market sorted portfolios as created by Fama and French (1993). We first run the multivariate time-series regressions for each portfolio to estimate the betas of the lagged conditioning variables. We then add these estimated betas to the cross-sectional regressions. Panels A and B reveal the results for Fama and French's three-factor model and Lettau and Ludvigson's (2001a,b) model. Panel C shows the results for our specification. The coefficients are expressed as percentages per quarter. The first row of each panel reports the coefficient estimates. Fama and MacBeth t-statistics are reported in the second row. The adjusted R^2 values are presented in the last column. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

	Constant	R_m	SMB	HML	*DIV*	*TERM*	*DEF*	*RF*	Adj. R^2
Panel A: Fama and French's three-factor model									
Estimate	−0.09	1.81	1.74	0.75	−0.83	−0.24	0.01	−1.25	0.86
t-Value	−0.07	1.13	2.83	1.42	−3.08	−0.43	0.08	−2.02	
	Constant	*cay*	Δc	$cay \cdot \Delta c$	*DIV*	*TERM*	*DEF*	*RF*	Adj. R^2
Panel B: Lettau and Ludvigson model									
Estimate	1.59	−0.02	0.47	0.00	0.06	1.25	0.40	−0.20	0.74
t-Value	2.00	−2.48	2.39	−1.56	0.19	1.80	2.88	−0.29	
	Constant	*coin*	Δc	$coin \cdot \Delta c$	*DIV*	*TERM*	*DEF*	*RF*	Adj. R^2
Panel C: Alternative model									
Estimate	0.69	−0.02	0.46	0.39	−0.26	0.30	0.17	−0.58	0.79
t-Value	1.16	−0.07	2.18	1.83	−0.87	0.58	1.37	−0.86	

Table 11
Cross-sectional regression of other portfolios. This table shows the Fama and MacBeth (1973) cross-sectional regression estimation results using the return on other portfolios. Test portfolios are 10 industry portfolios, and 25 size and momentum portfolios. The full-sample factor loadings, which are used as the independent variables, are computed in one multiple time-series regression. The coefficients are expressed as percentages per quarter. The first row reports the coefficient estimates. Fama and MacBeth t-statistics are reported in the second row and Shanken's corrected t-statistics are in the third row. The adjusted R^2, which is followed by Jagannathan and Wang (1996), are presented in the last column. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

	Alternative model					Fama and French's three-factor model				
	Constant	*coin*	Δc	$coin \cdot \Delta c$	Adj. R^2	Constant	R_m	SMB	HML	Adj. R^2
Panel A: 10 Industry portfolios										
Estimate	0.46	0.47	−0.38	−0.01	0.75	4.55	−3.01	1.75	−0.94	0.24
t-Value	0.75	1.31	−0.88	−0.02		2.00	−1.25	1.37	−1.35	
Shanken t	0.51	0.89	−0.60	−0.02		1.61	−1.02	1.13	−1.18	
Panel B: 25 Size and momentum portfolios										
Estimate	4.23	0.34	−1.34	1.10	0.79	16.44	−15.35	4.08	−12.22	0.27
t-Value	6.45	1.79	−3.92	4.44		6.33	−5.63	5.12	−5.31	
Shanken t	2.04	0.58	−1.25	1.41		1.50	−1.37	1.44	−1.28	

Some argue that it is not surprising that Fama and French's three-factor model can explain the cross-section of the 25 size and book-to-market portfolios, because factors and test portfolios are formed using the same set of characteristics in Fama and French's three-factor model.[19] Since industry portfolios are not based on price variables, explaining the cross-section of the industry portfolios may be a challenge for Fama and French's three-factor model. Daniel and Titman (2006) emphasize that sorting portfolios on the basis of industry captures variations in risk factor loadings that are unrelated to the book-to-market ratios. Therefore, such an approach should provide some power against the characteristic alternative.

Panel A of Table 11 shows that our model performs better than Fama and French's three-factor model in explaining the cross-sectional variation of the 10 industry portfolios. Our specification performs better in several aspects. First, it has a smaller estimated intercept of 0.46% per quarter and is not statistically significant, whereas Fama and French's three-factor model has an estimated intercept of 4.55% per quarter, which is marginally significant. Second, Fama and French's three-factor model can explain 24% of the cross-sectional variation in average returns. In sharp contrast, our specification explains 75% of the cross-sectional variation of industry portfolios.[20] Fama and French (1997) demonstrate a strong variation over time in the Fama and French three-factor risk loadings of industry portfolios. Therefore, if we assume that the factor loadings of Fama and French's model are constants and estimate the factor loadings using the full-sample data, then the model may does a poor job in explaining the cross-section of industry portfolios. This is consistent with our results.

It is well-known that Fama and French's three-factor model cannot explain the momentum profits (Fama and French, 1996). Thus, it is interesting to examine whether our specification accounts for momentum portfolios. Panel B of Table 11 reveals the results for 25 size and momentum portfolios. First, Fama and French's three-factor model accounts for 27% of the cross-sectional patterns, whereas our model explains 79% of the cross-sectional variation of size and momentum portfolios. Second, the interaction term of our specification goes in the right direction and is statistically positive, whereas the loading on HML goes in the wrong direction. Overall, our model performs better than Fama and French's three-factor model in explaining the average returns of industry and momentum portfolios.

[19] Berk (1995) states that firm size measured by market equity and the ratio of book equity to market equity can account for the cross-section of average returns, regardless of whether or not they are related to rationally priced economic risks. He emphasizes that ratios with a price in the denominator are related to returns by construction and if book equity can be used as a control for the cross-section variation, the book-to-market ratio is a good measure of expected returns.

[20] Our specification performs well except for portfolios 8 and 10. Since portfolio 10 is classified as "other" in SIC code and includes different business sectors, the failure in explaining the average return of portfolio 10 may not be a substantial concern.

7. Conclusion

This paper contributes to the evidence on the linkage between financial markets and the macroeconomy. We construct a conditioning variable from a set of macroeconomic variables and address one of the most compelling issues in finance, the time and cross-sectional variations in risk premium based on the suggested variable. We demonstrate that our proposed measure contains important information for predicting future stock returns and explaining the cross-section of average equity returns.

We empirically find that the macroeconomic variables known to forecast stock returns are cointegrated in finite samples, and propose deviations from this shared trend as a conditioning variable. This approach is built on the work of Campbell and Perron (1991), who document simulation-based evidence that although the asymptotic distribution of a time-series is stationary, treating a near-integrated stationary data inferred from unit root and/or cointegration tests as unit root variable may be better modeled in a finite sample. Lettau and Ludvigson (2001a,b) follow this advice when they construct the consumption-wealth ratio (Lettau and Ludvigson, 2010).

We demonstrate that the stationary deviation in the common trend among macroeconomic variables captures fluctuations in the equity premium over time and has strong forecasting power for future stock returns over short and long horizons. In contrast to the lack of predictive power of financial indicators at shorter horizons, the proposed variable strongly forecasts movements in excess stock returns at business cycle frequencies. Furthermore, this variable exhibits significant marginal forecasting power when other popular predictive variables appear in the forecasting regression.

We also demonstrate empirically that the marginal utility of consumption is the relevant measure of risk when the suggested conditioning variable is used to scale the parameters in the discount factor. The suggested conditional version of the CCAPM can account for the cross-section of the expected returns of the size and book-to-market sorted portfolios nearly as well as Fama and French's (1993) three-factor model, and better than the Lettau and Ludvigson (2001b) model. Moreover, this scaled CCAPM is the only model which passes the book-to-market specification test suggested by Jagannathan and Wang (1998), and can also account for a large portion of the cross-section of average returns for other test assets.

A key component of the empirical success of deviations from the common trend among macroeconomic variables as a forecasting variable and a scaling variable for the CCAPM is the ability of this variable to track the business-cycle-related time-varying risk premiums. The expected return is high under bad economic conditions, during which time deviations from a shared trend increase. Small stocks and value stocks have greater exposure to consumption risk than large stocks and growth stocks during contractions, during which time deviations from the common trend are higher relative to their average values.

Although fluctuations in the proposed variable contain relevant information for forecasting excess stock returns and explaining the cross-section of expected returns, we also find evidence for possible model misspecifications. The scaled multifactor version of the CCAPM fails to pass a size specification test. Hence, there may be some residual effects of firm characteristics related to size in the proposed model. Additionally, the constant in the Fama and MacBeth cross-sectional regression for our specification is statistically significant, thus implying the possible existence of some omitted factors that carry information relevant to explaining the equity returns in the model. Evidence of possible model misspecifications, however, frequently appears in previous studies as well (see Hahn and Lee, 2006a; Jagannathan and Wang, 1996, 2007; Lettau and Ludvigson, 2001b; Lustig and Van Nieuwerburgh, 2005; Santos and Veronesi, 2006). Possible sources of model misspecifications are left for future research.

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Appendix A. Johansen cointegration tests for conditioning variables

We use the most widely used macroeconomic variables for forecasting the future returns on the market portfolio from the previous studies. These conditioning variables are: (1) the dividend yield of the CRSP value-weighted portfolio (computed as the sum of dividends over the last 12 months, divided by the level of the index, see Fama and French, 1988); (2) the difference between the yields of a 10-year and a 1-month government bond (term spread, see Fama and French, 1989); (3) the difference between the yields of a Moody's Baa and Aaa corporate bonds yields (default spread, see Abhyankar and Gonzalez, 2009); (4) the 3-month T-bill yield (see Ferson, 1989). Data on bond yields are from the FRED® database of the Federal Reserve Bank of St. Louis.

In this paper, we are interested in the long-run equilibrium relation among four conditioning variables. For this objective, we perform the cointegration test of Johansen (1991). Before applying the Johansen test, we implement the augumented Dickey-Fuller (ADF) test of unit roots in the four conditioning variables. For all variables, we are unable to reject the null hypothesis of non-stationarity with a significance level of 1% as shown in Table A1.

The Johansen method applies the maximum likelihood procedure to determine the presence of cointegrating vectors. In addition, it provides the number of cointegrating equations. This method assumes a k-dimensional vector autoregressive (VAR) model with order p, where k is the total number of non-stationary variables. Consider the following VAR model:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + \varepsilon_t \tag{17}$$

where y_t is a k-vector of non-stationary variables, x_t is a d-vector of deterministic variables, and ε_t is a vector of innovations. In our

Table A1
Augmented Dickey-Fuller (ADF) tests of conditioning variables. The augmented Dickey-Fuller unit root tests are performed with the four conditioning variables, *DIV*, *TERM*, *DEF*, and *RF*. *DIV* is the dividend yield of the value-weighted portfolio CRSP index (computed as the sum of dividends over the last 12 months, divided by the level of the index), *TERM* is the difference between the yields of a 10-year and a 1-month government bond, *DEF* is the difference between the yields of a Moody's Baa and Aaa corporate bonds yields, and *RF* is the 3-month constant maturity Treasury yield. The lag length in each test is selected by the Schwarz information criterion (SIC). The sample period covers the second quarter of 1953 to the third quarter of 2005.

Variables	ADF t-statistic	Critical values	
		5% Critical level	1% Critical level
DIV	−2.584	−2.875	−3.462
TERM	−1.772	−2.875	−3.462
DEF	−2.949	−2.875	−3.462
RF	−1.284	−2.875	−3.462

Table A2
Johansen cointegration tests. This table presents the results of Johansen cointegration tests among the four conditioning variables using "Trace" statistic, and the "*L*-max" statistic. The four conditioning variables are *DIV*, *TERM*, *DEF*, and *RF*. *DIV* is the dividend yield of the value-weighted CRSP index (computed as the sum of dividends over the last 12 months, divided by the level of the index), *TERM* is the difference between the yields of a 10-year and a 1-month government bond, *DEF* is the difference between the yields of Moody's Baa and Aaa corporate bonds yields, *RF* is the 3-month constant maturity Treasury yield. A linear trend in each conditioning variable is allowed, and a constant is only included in the cointegration relation. The Akaike Information Criterion (AIC) is employed to select the number of lags required in the cointegration test.

Null hypothesis	Trace		*L*-max	
	Test statistic	95% Critical value	Test statistic	95% Critical value
$r = 0$	58.80	47.86	33.96	27.58
$r \leqslant 1$	24.84	29.80	17.48	21.13
$r \leqslant 2$	7.37	15.49	5.36	14.26
$r \leqslant 3$	2.01	3.84	2.01	3.84

Table A3
Estimates from the VAR estimation. Panel A of this table shows the estimated cointegrating vector, and *t*-values of each coefficient are revealed in parentheses. The *t*-value of *DIV* is not available since the coefficient of *DIV* is restricted to 1. Panel B of this table presents the estimated coefficients from cointegrating VAR of the column variable on the row variable. The *t*-statistics are shown in parentheses, and the adjusted R^2 values are provided in the final row. The four conditioning variables are *DIV*, *TERM*, *DEF*, and *RF*. *DIV* is the dividend yield of the value-weighted CRSP index (computed as the sum of dividends over the last 12 months, divided by the level of the index), *TERM* is the difference between the yields of a 10-year and a 1-month government bond, *DEF* is the difference between the yields of Moody's Baa and Aaa corporate bonds yields, *RF* is the 3-month constant maturity Treasury yield. ΔDIV_t is the difference of *DIV* between $t-1$ and t, $\Delta TERM_t$ is the difference of *TERM* between $t-1$ and t, ΔDEF_t is the difference of *DEF* between $t-1$ and t, ΔRF_t is the difference of *RF* between $t-1$ and t, and $Coin_{t-1}$ is the cointegration error at time $t-1$. The lag length of one is selected using the Akaike Information Criterion (AIC). The sample period covers the third quarter of 1953 to the third quarter of 2005.

	DIV	*TERM*	*DEF*	*RF*
Panel A: Estimation of cointegrating vector				
Cointegrating coefficient	1.00	−0.28	0.25	0.49
t-Value		(−3.69)	(0.52)	(6.36)
	Dependent variable			
	ΔDIV_t	$\Delta TERM_t$	ΔDEF_t	ΔRF_t
Panel B: VAR estimation				
ΔDIV_{t-1}	0.27	−0.25	0.22	−0.04
	(4.06)	(−1.84)	(5.10)	(−0.58)
$\Delta TERM_{t-1}$	0.08	0.24	0.11	−0.02
	(2.15)	(3.29)	(4.56)	(−0.49)
ΔDEF_{t-1}	−0.11	−0.03	0.08	−0.00
	(−1.15)	(−0.13)	(1.24)	(−0.03)
ΔRF_{t-1}	−0.01	0.10	0.01	0.37
	(−0.20)	(0.78)	(0.14)	(5.90)
$Coin_{t-1}$	−0.09	0.02	0.01	−0.08
	(−3.85)	(0.42)	(0.74)	(−3.55)
Adj. R^2	0.18	0.04	0.24	0.18

model, $y_t = [DIV\ TERM\ DEF\ RF]'$, and x_t is a vector of constants. The Eq. (17) can be written as

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + B x_t + \varepsilon_t \tag{18}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$, $\Gamma_i = -\sum_{j=i+1}^{p} A_j$, and I represents an identity matrix. The Granger representation theorem states that if the matrix Π has a reduced rank of r ($r < k$), then there exist k by r matrices α and β such that $\Pi = \alpha\beta'$ and $\beta' y_t$ is stationary. In this case, r is the number of cointegrating relations and each column of β is the cointegrating vector.

We report Johansen's two cointegration tests. The first is the "Trace" statistic, which provides a likelihood ratio test of the null hypothesis of r cointegrating relations against the alternative of k cointegrating relations, where k is the number of endogenous variables, for $r = 0, 1, \ldots, k-1$. The second is the statistic "*L*-max", which supplies the maximum eigenvalue statistic that tests the null hypothesis of r cointegrating relations against the alternative of $r + 1$ cointegrating relations.

The critical values from the Johansen method depend on the number of lags as well as the deterministic trend specifications. The Akaike Information Criterion (AIC) is employed to select the number of lags required in the cointegration test. For the cointegration test specification, we assume that the cointegrating equation has only an intercept, as there is no reason that the cointegrating relations should have linear trends.[21]

Table A2 presents the cointegration test results among the four conditioning variables. For the trace test, we are unable to reject the null hypothesis of one cointegrating relation against the alternative of two or more cointegration relations. The *L*-max test also shows that we cannot reject the null hypothesis of one long-run stationary relationship against the alternative of two. Therefore, Table A2 demonstrates the existence of one cointegrating equation among the four conditioning variables. Panel A of Table A3 shows the estimated cointegrating vector, and *t*-values of each coefficient are revealed in parentheses. Panel B presents estimated coefficients from the cointegrating VAR of the column variable on the row variable. The *t*-statistics appear in parentheses, and the adjusted R^2 are provided in the final row.

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[21] Hahn and Lee (2006b) document that the *cay* variable has a deterministic trend in the cointegration relation and find that a highly persistent biased component derives *cay*'s predictive power. Since this critique may prove applicable to the present paper, we re-estimate the cointegrating vector by allowing the cointegration relation to have a deterministic trend. The estimated trend coefficient is very small and statistically insignificant. To investigate further, we also reconstruct Tables 2 and 3 using the cointegrating vector estimated by allowing the cointegration relation to have a deterministic trend. The forecasting power of the *coin* variable remains the same, and its relation with macroeconomic variables does indeed exist. These empirical results are available upon request. We thank the referee for providing this insight.

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