Macroeconomic Risk and the Cross-Section of Stock Returns

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JEL classification: G12

Keywords: Asset pricing, macroeconomic variable, stock return predictability, consumption capital asset pricing model, value premium

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Abstract

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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, because risk premiums should reflect macroeconomic risk. Cochrane's 2007 review article suggests the following in 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."

We propose here the "right measure" that captures economic recessions.

It is well-known that time variations in expected returns are related to business cycle (see Fama and French, 1989, and references therein). Expected returns are higher in economic recessions, since investors are less willing to hold risky assets, and lower in economic booms. This evidence suggests that time variations in equity premiums should be accounted for by variables related to business cycle. Previous research focuses mainly 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 return over long horizons, their predictive powers over business cycle frequencies are limited (Lettau and Ludvigson, 2001a).

It is also well documented in the literature that small firms compared to large firms deliver higher returns and value firms compared to growth firms deliver higher returns. These systematic variations in equity premium across stocks of different types of firms are known as the size and value premiums documented by Fama and French (1992). The consumption capital asset pricing model (CCAPM) developed by Breeden (1979) expects that cross-sectional variations in expected returns should be explained by cross-sectional variations in assets' exposure to consumption risk. Empirical works, however, provide strong evidence against this model. Hansen and Singleton (1982, 1983) reject the CCAPM with power utility. The CCAPM fails to explain the cross-section of asset returns (Mankiw and Shapiro, 1986; Breeden, Gibbons, and Litzenberger, 1989). Furthermore, it often performs worse than the CAPM in explaining the cross-section of size and book-to-market sorted portfolio returns (Lustig and Van Nieuwerburgh, 2005).

We study both the variation in risk premium over time and the variation in risk premium across stocks based on the proposed measure which captures business-cycle-related macroeconomic risks. A starting point of this study is to recognize that macroeconomic variables which are used to predict stock returns — dividend yield, term spread, default spread, and short 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.

It is now well documented that predictive variables such as dividend yield, term spread, default spread, and short-rate are very persistent (Torous, Valkanov, and Yan, 2004; Boudoukh, Richardson, and Whitelaw, 2006). There is, however, ongoing debate as to whether these highly persistent variables are indeed non-stationary. For example, Roll (2002) states 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 in Cochrane (2005), dividend yield should be stationary because asset price and dividend are cointegrated. In this study, we do not argue whether these variables are integrated or not; rather, we argue that the use of highly persistent time-series variables in predictive regressions as well as cross-sectional analyses causes some statistical problems, as documented by Ferson, Sarkissian, and Simin (2003). These authors demonstrate that if the expected returns are persistent, these persistent variables can cause spurious regression bias in the predictive regressions. Their simulation results cast some doubt on the existing literature of stock return predictability by showing that many of the regression results are spurious.

In their simulation study, Campbell and Perron (1991) show that although the asymptotic distribution of a time-series is stationary, treating near-integrated stationary data as a unit root variable inferred from unit root and/or cointegration tests may be better modeled in a finite sample.[1] Following Campbell and Perron, we assume that the four variables are non-stationary, since we cannot reject the null hypothesis of non-stationarity in the augmented Dickey-Fuller tests in our sample period. From the conjecture that these predictive variables are closely related to the business cycle, we generate the stationary trend deviation from the Johansen cointegration test. We employ this stationary trend deviation as our conditioning variables, since it is very likely to incorporate information on 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 for not only future stock returns over long horizons but also future asset returns over business cycle frequencies, where financial indicator variables lack forecasting power. Moreover, this variable has significant marginal forecasting power when other 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.[2]

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[1] Lettau and Ludvigson (2001a,b) also follow Campbell and Perron's advice when they construct the consumption-wealth ratio (Lettau and Ludvigson, 2007).

[2] Deviations in common trends among macroeconomic variables can explain a substantial fraction of the variations

Second, when our trend deviations are used as a conditioning variable for the CCAPM, it performs almost as well as Fama and French's (1993) three-factor model and 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. In addition, the proposed conditional CCAPM performs well for other test assets, including 10 earning-to-price sorted portfolios and 10 industry portfolios. Intuitively, the success of pricing size and book-to-market sorted portfolios arises from the fact that small stocks and value stocks have higher consumption betas than big stocks and growth stocks because they are more highly correlated with consumption growth during recessions, when marginal utility rises, which is consistent with Lettau and Ludvigson (2001b). We provide evidence for the intuition. Thus, our results support a risk-based interpretation of size and book-to-market effects.

The most closely related previous studies with our approach include Lettau and Ludvigson (2001a, 2001b), Santos and Veronesi (2006), and Lustig and Van Nieuwerburgh (2005). Lettau and Ludvigson show that the ratio of consumption to wealth forecasts future stock returns and a conditional CCAPM using this variable as a conditioning 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 the ratio of housing wealth to human wealth as a conditioning variable and empirically demonstrate that this housing collateral ratio carries relevant information for predicting asset returns and explaining value-size cross-sectional effects.

This paper adds to the extensive literature on market return predictability and consumption-

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in future returns about as well as the *cay* variable for both long- and short-term future stock returns.

based explanations of the cross-section of stock returns. Our empirical works are related to Campbell and Shiller (1988), Fama and French (1989), Hodrick (1992), Lamont (1998), Lewellen (2004), Ang and Bekaert (2007), and Boudoukh, Michaely, Richardson, and Robert (2007) on the time-series predictability of stock returns and to Chen and Ludvigson (2004), Bansal, Dittmar, and Lundblad (2005), Parker and Julliard (2005), Yogo (2006), and Jagannathan and Wang (2007) on the CCAPM.

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

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. The CAPM had been the most widely used asset pricing model until Fama and French's three-factor model (1993, 1996) drew attention as a challenge to the CAPM. The CAPM implies that the stochastic discount factor, m_{t+1}, is a linear function of the market portfolio return:

$$m_{t+1} = a_t + b_t r_{t+1}^M \tag{1}$$

where a_t and b_t are parameters and r_{t+1}^M is the market portfolio return at time t + 1. In the empirical approach, the CRSP value-weighted portfolio is commonly used as a proxy for the market portfolio.

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

$$a_t = \frac{1}{1+r_t^f} + b_t E_t(r_{t+1}^M) \tag{2}$$

$$b_t = \frac{E_t(r_{t+1}^M) - r_t^f}{(1+r_t^f)\sigma_t^2(r_{t+1}^M)} \tag{3}$$

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

$$E[r_{i,t+1}] = E[r_t^f] + \beta_i \lambda \tag{4}$$

where $\beta = \dfrac{Cov(f_{t+1}, r_{i,t+1})}{Var(f_{t+1})}$ 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. Instead, the conditional version of CAPM could hold; stocks' expected returns are proportional to their conditional betas. Though the risk-free rate and conditional variance of the market portfolio are constant over time, it is very likely that b_t is time varying, since a variety of empirical asset pricing papers argue that the excess market return is forecastable.[3] 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 predict market

[3] See Fama and Schwert (1977), Fama and French (1989), and Lettau and Ludvigson (2001a), among others.

excess return. Since *coin*, which will be defined later, is a strong forecaster of the market excess return, we use it as our conditioning variable. Hence, m_{t+1} can be written as

$$m_{t+1} = a_0 + b_0 r_{t+1}^M + a_1 coin_t + b_1 coin_t r_{t+1}^M \quad (5)$$

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

2.2. The consumption CAPM

Despite its poor performance as an asset pricing model (Mankiw and Shapiro, 1986; Breeden, Gibbons, and Litzenberger, 1989; Cochrane, 1996), the CCAPM still draws a lot of attention because consumption-based models are very general and intuitively appealing. As documented by Cochrane (2005), consumption-based models are general because any factor model can be considered as a specialization of consumption-based models. In addition, they are very intuitive in that a simple relation between consumption growth rate and stock return can describe the implications of complicated intertemporal asset pricing models. Moreover, Cochrane (2007) 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.

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 written as $m_{t+1} = \delta \frac{U_c(C_{t+1}, Z_{t+1})}{U_c(C_t, Z_t)}$, where 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

$$E[r_{i,t+1}] = E[r_t^f] + \beta_i \lambda \tag{6}$$

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 CAPM, it is very likely that a_t and b_t are time varying. For example, Campbell and Cochrane (1999) developed 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 the investors' relative risk aversion. Hence, under Campbell and Cochrane's framework, the parameters, a_t and b_t are not constant over time. As Lettau and Ludvigson (2001b) document, even though the coefficients a_t and b_t can be functions of unobservable variables, their variations can be well captured by proxies for time varying risk premiums. If this is 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

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

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

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 choose the Fama and French (1993) 25 size and book-to-market sorted portfolios as main test assets and construct excess returns as the difference between the returns of these portfolios and the returns on a three-month Treasury bill. 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 so that we can 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/market values, on average, have higher returns). In addition, we examine the ability of our specification to explain the cross-section of average returns of several other test assets, namely, 10 portfolios sorted by size, 10 portfolios sorted by book-to-market, 10 portfolios sorted by earning-to-price ratio, and ten industry portfolios. All test assets, including the Fama and French factors, are taken from Kenneth French's website.[4]

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

To construct the conditioning variable for the conditional CCAPM, we use the cointegrating relation among macroeconomic variables. The macroeconomic variables used and the test of

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[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We thank Kenneth French for providing the data.

their cointegrating relation are presented in Appendix A. The conditional variable used in our study is *coin*, which is defined as

$$coin_t = DIV_t - 0.28TERM_t + 0.25DEF_t + 0.49RF_t - 3.54 \quad (8)$$

where DIV_t, $TERM_t$, DEF_t, and RF_t represent dividend yield, term spread, default spread, and short-term interest rate at time *t*, respectively. [5]

To compare our proposed empirical specification for the conditional CCAPM with that of a popular asset pricing model, we use the *cay* variable constructed by Lettau and Ludvigson (2001b), which is known as the most successful scaling variable for the conditional CCAPM. In addition, 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.[6]

3.2. Econometric approach

Cochrane (1996) argues that conditional factor models can be tested as multifactor models with additional factors equal to the conditioning variable and the interaction term between the original factor and the conditioning variable. Therefore, our conditional CAPM or CCAPM can be represented as unconditional three-factor models, implying that we can employ the econometric approach used in the unconditional models. The performance of Fama and French's three-factor model (1993) with factors $f_{t+1} = (r^M_{t+1}, SMB_{t+1}, HML_{t+1})$ and the conditional CCAPM of Lettau and Ludvigson (2001b) with factors $f_{t+1} = (cay_t, \Delta c_{t+1}, cay_t \Delta c_{t+1})$ are compared with our specification. To this end, we use two econometric approaches.

First, we employ the Fama and Macbeth cross-sectional regression methodology to test the

[5] We demean the conditioning variable as advocated by Ferson, Sarkissian, and Simin (2003).
[6] Following Lamont (1998), the log dividends are the natural logarithm of the Standard and Poor's (S&P) Composite Index and the log earnings are 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.

competing asset pricing models. This choice of methodology in our analysis is driven by the facts that some factors do not represent portfolio returns and this regression-based method is widely used in testing 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:

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

where $r_{i,t+1}$ is the excess return of asset *i* at time *t* + 1 and f_{t+1} is the vector of factors at time *t* + 1. 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 estimated betas:

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

where γ_0 is the estimated risk-free rate and γ is a vector of risk premiums for the factors f_{t+1}.

As documented in Cochrane (2005), Fama and Macbeth's standard errors do not include corrections for the fact that the betas are estimated. Shanken (1992) develops a correction procedure that accounts for the errors-in-variables problem. Hence, we report the traditional Fama and Macbeth t-statistics as well as Shanken's corrected t-statistics.

Second, we follow the stochastic discount factor methodology using the generalized method of moments (GMM). Since 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 choose 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.[7] Since this prespecified weighting matrix is invariant across models, the HJ distance enables us to compare asset pricing models. Also 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

[7] 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.

Figure 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 our sample period with those of Lettau and Ludvigson (2001a) and Lamont (1998).[8] It appears that our trend deviations have some outstanding patterns, namely, being high during recessions and low in booms.[9] More importantly, trend deviations well capture the "bad times" by showing that high positive trend deviations precede high market excess returns.

To investigate the forecasting ability of our *coin* variable for stock market excess returns, Table 1 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 the explanatory variables.[10] Table 1 reports one-quarter-ahead as well as long-horizon forecasts of excess returns on the CRSP value-weighted Index. In all of the regressions in Table 1, we report the ordinary least squares (OLS) coefficient estimates in the first row, Newey-West 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 1 presents 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. Regression of the log excess returns on the trend deviation produces 6% of the

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[8] The sample period is from the fourth quarter of 1952 to the third quarter of 1998 in Lettau and Ludvigson (2001a) and from the first quarter of 1947 to the fourth quarter of 1994 in Lamont (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.

[9] Business cycle expansions and contractions are taken from the National Bureau of Economic Research (NBER).

[10] Using the log returns (not excess returns) on the CRSP value-weighted returns as the dependent variable does not alter our time-series evidence. The results are available upon request.

adjusted R^2. Moreover, the corrected t-statistic is more than three standard errors from 0. A positive slope estimate is consistent with Figure 1, indicating that the increase in trend deviation predicts the rise in the expected log excess return. Model 2 shows the regression result using the payout ratio. Unlike the original results in Lamont (1998), the payout ratio explains little of the time variation of the log excess market returns. Our results can be different 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 and the sample periods of the two are different. Lamont (1998) states that high stock prices in the 1990s induced a low forecasting power of the payout ratio in 1990s. Since our sample covers all market excess returns in the 1990s, it seems that the payout ratio has low forecasting power in recent years as well. Model 3 displays the regression result when the *cay* variable is used as a predictive variable, showing its powerful forecasting ability.

To investigate 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 reported 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 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 to 24 quarters, on a lagged forecasting variable(s) are presented from column 2 to column 8 of Table 1. The trend deviation, *coin*, has significant forecasting power for future returns at all horizons. The adjusted R^2 increases up to 2 year horizon (8 quarters), reaching at 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 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.

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

5.1. Fama and Macbeth cross-sectional regressions

Table 2 reports the Fama and Macbeth cross-sectional regression results using the Fama and French 25 size and book-to-market sorted portfolios. It contains the estimated coefficients of the risk premium, uncorrected Fama and Macbeth t-statistics, corrected Shanken's (1992) t-statistics, and adjusted R^2 statistics. We use the adjusted R^2 statistic as a summary statistic for the overall fit of each specification.[11] Row 1 shows the well-known failure of the unconditional CAPM to explain the cross-section of the average returns. The compensation for market risk is negative and statistically insignificant. Furthermore, this specification explains little of the cross-section of the Fama and French 25 portfolios. Row 2 presents results for Fama and French's three-factor model. The risk premium of HML factor is 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

[11] 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 $R^2 = \frac{\sigma_C^2(\overline{R}) - \sigma_C^2(\overline{e})}{\sigma_C^2(\overline{R})}$, where σ_C^2 is the in-sample cross-sectional variance, $\overline{R}$ is a vector of average excess returns, and $\overline{e}$ is the vector of average residuals.

much better job explaining the cross-section of the Fama and French 25 portfolios than the 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 $cay \times R_m$ 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.[12] Row 4 shows the slope coefficients when the conditioning variable *coin* is included in the regression analysis. The risk premium for the interaction term $coin \times R_m$ is positive and both the uncorrected and corrected t-statistics are statistically significant. This conditional model performs much better than the unconditional CAPM at explaining about 58% of the cross-section of the Fama and French 25 portfolios. When the CRSP value-weighted return instead of the consumption growth rate is used as the proxy for the market portfolio in our specification, however, it does not perform as well as Fama and French's three-factor model.

We now investigate the power of consumption-based models in explaining the cross-section of average returns. Row 5 gives the results for the unconditional CCAPM. The price of risk related to consumption goes in the right direction and the uncorrected Fama and Macbeth t-statistic is more than two standard errors from 0. The adjusted R^2 of the unconditional CCAPM is about 21%, implying that it performs better than the unconditional CAPM at explaining the cross-section of the Fama and French 25 portfolios. Row 6 displays Lettau and Ludvigson's estimates with the *cay* variable and shows that, contrary to Lettau and Ludvigson's original results, the cross-term $cay \times \Delta c$ is statistically insignificant. Again, we suspect this weak explanatory power comes from the use of different sample periods and the updated *cay*

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[12] Our sample period is from 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. Furthermore, we use expanded time-series of *cay* data from Lettau and Ludvigson.

variable.[13] Finally, row 7 reveals 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 0. Moreover, the adjusted R^2 is 76%, which is comparable to that for Fama and French's three-factor model.

If each specification is correct, the intercept of the cross-sectional regression should be zero, since the dependent variables of the second Fama and Macbeth regression are excess returns. Lettau and Ludvigson (2001b) document that the intercept of the cross-sectional regression is usually large when macroeconomic variables are used 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 about 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

Figure 2 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

[13] Li, Vasslou, and Xing also obtain results that differ from those of Lettau and Ludvigson (2001b).

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 well specified, all the portfolios should lie on the 45-degree line through the origin.

Since a variety of portfolios lie far from the 45-degree line, Panel A shows the well-known failure of the unconditional CAPM to explain the cross-sectional variation of the Fama and French 25 portfolios. 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 much better than the unconditional CAPM. It has, however, some difficulty 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 displayed in Panel C. This specification, however, cannot explain why the value stocks earn more than the growth stocks throughout our sample period. Panel D gives the results for our specification. In terms of the distance from the 45-degree line, our model does about as well as Fama and French's three-factor model. Our conditioning CCAPM does a better job explaining the problematic portfolios 11 and 51 than Fama and French's three-factor model. The average pricing errors of portfolios 11 and 51 are decreased 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. 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. Following 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 from the Fama and Macbeth regressions are given in Tables 3 and 4.

As shown in row 2 of Table 3, the slope coefficient of the log book-to-market ratio is statistically significant under Fama and French's three-factor model, indicating that the book-to-market ratio helps explain the cross-section of the average returns.[14] When the book-to-market ratio is included in the conditioning 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 displayed in row 5, or in the conditional CCAPM with *cay*, as 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 in the presence of factors. Moreover, the book-to-market ratio does not drive out the interaction term $coin_t \Delta c_{t+1}$.

Table 4 reports the Fama and Macbeth cross-sectional regression results when size is added as a variable. In this case, 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.

[14] Jagannathan and Wang (2007) also find that the book-to-market ratio is significant when included as an explanatory variable in the Fama and French three-factor model.

It is, however, also statistically significant under Fama and French's three-factor model.

5.4. Conditional consumption betas

We are now in a position to discuss why our conditional CCAPM performs better than the unconditional CAPM and CCAPM. Since there is growing evidence that the parameters a_t and b_t are time varying in equations (2) and (3), it is natural to think that the unconditional asset pricing model and our conditional CCAPM arrive at very different conclusions. We have shown that the conditioning variable *coin* has strong power to forecast excess returns on the market portfolio, indicating that variations of a_t and b_t are well captured by the conditioning variable *coin*. Hence, we essentially argue that this conditioning substantially improves the performance of the conditional CCAPM.

If the conditional CCAPM holds period by period, we should take a look at the conditional correlation, rather than the unconditional correlation, between the consumption growth rates and asset returns. For instance, in the unconditional CAPM, the unconditional beta of (small and growth) portfolio 11 is 1.67, while the unconditional beta of (small and value) portfolio 15 is 1.19 in our sample period. With these parameter values, the unconditional CAPM does not explain why value stocks earn more than growth stocks.

To examine further, we calculate the conditional consumption betas for good states and bad states. One stylized fact is that the market risk premium is closely related to business cycle; being high in business cycle troughs and low in business cycle peaks.[15] 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 state as a quarter during which *coin* is at least one standard deviation below its average, and a bad state as a quarter during which

[15] See Fama and Schwert (1977), Fama and French (1989), and Lettau and Ludvigson (2001a), among others.

coin is at least one standard deviation above its average. In our analysis, the number of quarters of both bad states 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 given by

$$r_{t+1}^{i} = \alpha^{i} + \beta_{coin}^{i} coin_{t} + \beta_{c}^{i} \Delta c_{t+1} + \beta_{c\times coin}^{i} \Delta c_{t+1} coin_{t}, \quad i = 1, 2, \ldots 25 \tag{14}$$

where r_{t+1}^{i} is the excess return on i th Fama and French portfolio at time t + 1. The conditional consumption beta, B_{t}^{i}, on portfolio i at time t is defined as $B_{t}^{i} \equiv \beta_{c}^{i} + \beta_{c\times coin}^{i} coin_{t}$. Similarly, we can calculate the conditional consumption betas in bad states and good states, $B_{t,j}^{i} \equiv \beta_{c}^{i} + \beta_{c\times coin}^{i} coin_{t,j}$, where j = 1 refers to the bad states and j = 2 refers to the good states.

Table 5 reports the average conditional consumption betas in all states, bad states, and good states for Fama and French 25 portfolios. Following Lettau and Ludvigson (2001b), it is helpful to provide a visual comparison of the average consumption betas for value stocks and growth stocks. Figure 3 illustrates the average consumption betas for portfolios 1, 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 the growth portfolios (11, 21, 31, 41). For example, the average consumption beta for portfolio 15 in bad states is 4.43, which is higher than the 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, which is lower than the 5.98 for portfolio 11. These comparisons of average consumption betas imply that value stocks are more highly correlated with consumption risk in bad times than they are in good times and growth stocks are more highly correlated with consumption risk in good times than they are in bad times. Overall, our specification shows that value stocks are riskier than growth stocks in bad times, when the risk premium is high. Therefore, it appears that our model supports the risk-based story behind the value premium.

5.5. GMM estimation

This section tests competing asset pricing models using the GMM cross-sectional estimator. We report estimation results in Table 6 with the Fama and French 25 portfolios used as test assets.

Panel A reports the results for the unconditional CCAPM. The coefficient of consumption growth rate (Δc) in the pricing kernel is statistically significant, implying 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) rejects the model as well.

Panel B refers to 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 factor) are not significant and produce the wrong sign: Its premium is estimated to be -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 from those of the CCAPM, yielding a 0.598 HJ distance, which is smaller than 0.636 as estimated from the CCAPM. Nonetheless, the model is still rejected by the data in terms of both the J test and 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 consumption risk factor, the model is able to better describe 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 is about 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, which is lowest among the competing models. In spite of demonstrating the best performance, this model is rejected by the data as well.

As a robustness test, we examine whether competing models maintain their pricing abilities by requiring them to price a different set of assets. In particular, Fama and French 25 portfolios and their scaled 25 portfolios by the variable *cay* are chosen as test assets. As Cochrane (1996) discusses, scaled returns have an economically interesting interpretation: They are understood as managed portfolios in which the fund manager adjusts portfolio weights based on the information he receives from the conditioning variable.

Table 7 reports GMM estimation results when managed portfolios are used 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 arises from increased average pricing errors for the managed portfolio used. When we consider, however, the increased dimension of the payoff space to be priced, the increase in pricing errors is not unexpected.

5.6. 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. Petkova (2006) also performs similar regressions to provide empirical evidence that, unlike Fama and French's three-factor model, her model is able to capture the time varying patterns in returns predicted by the conditioning variables. Since this test enables us to examine whether our model is a good conditional model as well as provides the specification test of the competing asset pricing models as documented by Petkova (2006), it is worth revisiting Ferson and Harvey's experiment.

Specifically, we first run the multivariate time-series regressions for the 25 size and book-to-market sorted portfolios 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 test whether 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 and the results are given in Table 8. In Panel A, the estimated slopes of short-term interest rate and dividend are statistically significant, indicating that 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 (2001) 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 shown in Panel B. On the other hand, neither of γ_{DIV}, γ_{TERM}, γ_{DEF}, and γ_{RF} is statistically different from zero in our specification. Therefore, our conditional consumption CAPM serves as a good conditional model and passes the model misspecification test.

5.7. Other portfolios

We have used the Fama and French 25 size and book-to-market sorted portfolios as our test assets throughout this paper since these portfolios have become the common benchmark in testing asset pricing models. In this subsection, we compare the performance of our conditional CCAPM and Fama and French's three-factor model using various test assets, namely, 10 portfolios sorted by size, 10 portfolios sorted by book-to-market ratio, 10 portfolios sorted by earning-to-price ratio, and 10 industry portfolios.

Table 9 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. Our specification is comparable to Fama and French's three-factor model for the portfolios sorted by size (Panel A), book-to-market ratio (Panel B), and earning-to-price ratio (Panel C). First, both our specification and Fama and French's model explain a large fraction of the variation in average returns. Alternative models deliver an R^2 of 93, 91, and 85% for size, book-to-market, and earning-to-price sorted portfolios, respectively. Second, in spite of these models' high explanatory power, in both cases the estimated intercepts are often large and significant. The estimated intercept is larger in our specification for portfolios formed on book-to-market ratio, whereas it is smaller for portfolios based on the earning-to-price ratio.

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 on the same set of characteristics in Fama and French's three-factor model.[16] 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 into portfolios on the basis of industry captures variations in risk factor loadings that are unrelated to book-to-market ratio. Therefore, such an approach should provide power against the characteristic alternative.

Panel D of Table 9 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 other aspects as well. 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. Figure 4 displays the realized versus fitted average returns of Fama and French's three-factor model (Panel A) and the conditional CCAPM model with *coin* as a conditioning variable (Panel B). Each number identifies a different industry portfolio.[17] Our specification performs well except for portfolios 8 and 10. Since portfolio 10 is classified as "other" in its SIC code and includes different business sectors, the failure in explaining the average return of portfolio 10 may not be a big concern.

Fama and French (1997) document that there is a strong variation over time in the Fama and

[16] 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 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.

[17] The industry portfolio data are from Kenneth French's website.

French three-factor risk loadings of industry portfolios. Therefore, if we assume that the factor loadings of Fama and French's three-factor model are constants and estimate the factor loadings using the full-sample data, then the model does a poor job in explaining the cross-section of industry portfolios. This is consistent with our results. Overall, our model performs about as well as Fama and French's three-factor model and is even better at explaining the average return of industry portfolios.

6. 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 show that the 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 study of Campbell and Perron (1991). These authors document simulation 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) also follow the advice of Campbell and Perron when they construct the consumption-wealth ratio (Lettau and Ludvigson, 2007).

We show that the stationary deviation in the common trend among macroeconomic variables picks up fluctuations in 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 has significant marginal forecasting power when other popular predictive variables appear in the forecasting regression.

We also empirically demonstrate 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 expected returns of the size and book-to-market sorted portfolio 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 that passes the book-to-market specification test suggested by Jagannathan and Wang (1998) and that can account for a large portion of the cross-section of average returns for other test assets as well.

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 cycles related to time varying risk premiums. The expected return is high in bad state of the economy when deviations from a shared trend increase. Small stocks and value stocks have greater exposure to consumption risk than big stocks and growth stocks during contractions, when 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 indicating possible model misspecifications. The scaled multifactor version of the CCAPM fails to pass a size specification test. Hence, there could be some residual effects of firm characteristics related to size in the proposed model. In addition, the constant in the Fama and MacBeth cross-sectional regression for our specification is statistically significant, implying that there could be some omitted factors which carry important information for explaining the equity returns in the model. Evidence of possible model misspecifications, however, often appears in previous studies as well (see Hahn and Lee, 2006; 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 to model their cointegrating relationship. 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 ten-year and a one-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 Fama and French, 1989); (4) the three-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 purpose, we perform the cointegration test of Johansen (1988). 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 cannot reject the null hypothesis of non-stationarity 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. We report two cointegration tests of Johansen. The first is "Trace" statistic, providing 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,…,k-1. The second is "L-max" statistic, supplying 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 level data of the conditioning variables might have deterministic trends. However, we allow the cointegrating equations to have only intercepts, since there is no reason that the cointegrating relations have linear trends.

Table A2 presents the cointegration test results among the four conditioning variables. For the trace test, we cannot reject the null hypothesis of one cointegrating relation against the alternative of two or more cointegration relations. The L-max test also indicates that we cannot reject the null hypothesis of one long-run stationary relationship against the alternative of two. Therefore, table A2 shows that there are one cointegrating equation among the four conditioning variables.

Table A1. Augmented Dickey-Fuller (ADF) tests of conditioning variables.

The augmented Dickey-Fuller unit root tests have been performed to the four conditioning variables, DIV, TERM, DEF, and RF. DIV is the dividend yield of 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 ten-year and a one-month government bond, DEF is the difference between the yields of a Moody's Baa and Aaa corporate bonds yields, RF is the three-month constant maturity Treasury yield. The lag length in each test is chosen by Schwarz information criterion (SIC). The sample period covers from second quarter of 1953 to 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 "L-Max" statistic. The four conditioning variables are DIV, TERM, DEF, and RF. DIV is the dividend yield of 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 ten-year and a one-month government bond, DEF is the difference between the yields of a Moody's Baa and Aaa corporate bonds yields, RF is the three-month constant maturity Treasury yield. 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≤1	24.84	29.80	17.48	21.13
r≤2	7.37	15.49	5.36	14.26
r≤3	2.01	3.84	2.01	3.84

Table 1. Forecasting market returns.

This table reveals the regression results of current excess market returns on lagged variables $coin_t$, d_t-e_t, and cay_t. In each model, the OLS coefficient estimates are presented in the first row, the Newey-West estimators with five lags are in the second row, and 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: $coin_t$ denotes the cointegrating error adopted in this paper, d_t-e_t is the log dividend payout ratio, and cay_t is the log consumption-wealth ratio. Here H represents the return horizon in quarters. The sample period is from the third quarter of 1953 to the fourth quarter of 2005.

Dependent Variable: Log Excess Market Return									
		Forecast Horizon H							
Model	Regressors	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)

Table 2. Cross-sectional regression.

This table shows the Fama and MacBeth (1973) cross-sectional regression estimation results using the excess returns on 25 size/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 reports the coefficient estimates. Fama and MacBeth t-statistics are reported in the second row and Shanken corrected t-statistics are in the third row. The adjusted R^2 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.

Model	Factors				Adj. R^2
CAPM	**Constant**	**R_m**			
Estimate	2.73	-0.47			-0.02
t value	3.08	-0.43			
Shanken t	3.07	-0.43			
Fama French	**Constant**	**R_m**	**SMB**	**HML**	
Estimate	3.02	-1.63	0.72	1.47	0.76
t value	2.58	-1.21	1.53	2.90	
Shanken t	2.43	-1.15	1.52	2.87	
Cay CAPM	**Constant**	**cay**	**R_m**	**cay $\cdot$ R_m**	
Estimate	2.41	-0.02	-0.94	0.06	0.51
t value	2.87	-2.95	-0.89	2.37	
Shanken t	1.58	-1.64	-0.57	1.36	
Coin CAPM	**Constant**	**coin**	**R_m**	**coin $\cdot$ R_m**	
Estimate	2.11	0.42	-0.74	6.79	0.58
t value	2.34	1.91	-0.68	3.88	
Shanken t	1.40	1.15	-0.46	2.36	
CCAPM	**Constant**	**Δc**			
Estimate	0.94	0.54			0.21
t value	1.56	1.73			
Shanken t	1.23	1.37			
Cay CCAPM	**Constant**	**cay**	**Δc**	**cay $\cdot$ Δc**	
Estimate	3.17	-0.01	0.33	0.00	0.59
t value	3.04	-1.98	1.06	0.73	
Shanken t	2.13	-1.40	0.75	0.53	
Coin CCAPM	**Constant**	**coin**	**Δc**	**coin $\cdot$ Δc**	
Estimate	1.60	-0.12	0.54	0.46	0.76
t value	2.57	-0.79	2.67	2.97	
Shanken t	1.42	-0.45	1.51	1.67	

Table 3. Cross-sectional regression including nook-to-market ratio.

This table shows the Fama and MacBeth (1973) cross-sectional regression estimation results using the excess return on 25 size/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 as percentages per quarter. This table examines whether book-to-market (BM) has incremental explanatory power in each of the models. The first row reports the coefficient estimates. Fama and MacBeth t-statistics are reported in the second row and Shanken corrected t-statistics are in the third row. The time-series averages of the quarterly adjusted R^2 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 · 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 · 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 · Δc**	**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 · Δc**	**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 4. Cross-sectional regression including size.

This table shows the Fama and MacBeth (1973) cross-sectional regression estimation results using excess returns on 25 size/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 as percentages per quarter. This table examines whether size has incremental explanatory power in each of the models. The first row reports the coefficient estimates. Fama and MacBeth t-statistics are reported in the second row and Shanken corrected t-statistics are in the third row. The time-series averages of the quarterly adjusted R^2 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 · 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 · 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 · Δc**	**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 · Δc**	**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 5. Conditional betas in consumption CAPM.

This table reports 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). 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
S1B1	4.0346	5.9752	2.0378
S1B2	4.5827	5.3249	3.8191
S1B3	3.3359	3.4881	3.1793
S1B4	3.4631	2.6925	4.2559
S1B5	3.9497	3.4813	4.4317
S2B1	3.5895	4.6652	2.4825
S2B2	2.7908	3.5895	1.9690
S2B3	2.7540	2.8963	2.6077
S2B4	2.6544	1.9951	3.3329
S2B5	3.5244	3.4779	3.5723
S3B1	3.1973	5.4153	0.9150
S3B2	2.6965	3.3424	2.0319
S3B3	2.2155	1.6854	2.7609
S3B4	2.3861	2.4076	2.3640
S3B5	2.7518	2.7386	2.7654
S4B1	2.7091	5.0732	0.2766
S4B2	2.5318	3.7063	1.3232
S4B3	2.0926	2.0630	2.1232
S4B4	2.0456	1.7247	2.3757
S4B5	2.9096	2.4594	3.3728
S5B1	1.8320	3.1821	0.4428
S5B2	1.6037	2.5108	0.6703
S5B3	1.8402	3.2212	0.4193
S5B4	1.4581	2.1082	0.7891
S5B5	2.2773	2.4876	2.0608

Table 6. GMM Estimation.

This table reports GMM estimation results of the competing models by using 25 size/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 by size and book-to-market, respectively. The conditioning variables are *cay* as created by Lettau and Ludvigson (2001) 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 that 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.

Panel A: Unconditional CCAPM							
	Constant	**Δc**			*J*	Wald (b)	HJ distance
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)					
Panel B: Fama and French's Three-Factor Model							
	Constant	**MKT**	**SMB**	**HML**	*J*	Wald (b)	HJ distance
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)			
Panel C: Lettau and Ludvigson Model							
	Constant	**cay**	**Δc**	**cay · Δc**	*J*	Wald (b)	HJ distance
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)			
Panel D: Alternative Model							
	Constant	**coin**	**Δc**	**coin · Δc**	*J*	Wald (b)	HJ distance
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 by using 25 size/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 by 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 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 that 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.

Panel A: Consumption CAPM							
	Constant	**Δc**			J	Wald (b)	HJ distance
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)					
Panel B: Fama and French's Three-Factor Model							
	Constant	**MKT**	**SMB**	**HML**	J	Wald (b)	HJ distance
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)			
Panel C: Lettau and Ludvigson Model							
	Constant	**cay**	**Δc**	**cay · Δc**	*J*	Wald (b)	HJ distance
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)			
Panel D: Alternative Model							
	Constant	**coin**	**Δc**	**coin · Δc**	*J*	Wald (b)	HJ distance
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. 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 created by Fama and French (1993). We first run the multivariate time-series regressions for each portfolio to estimate the betas of 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 (2001) 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 time-series averages of the quarterly adjusted R^2 are presented in the last column. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.

Panel A: Fama and French's Three Factor Model with Loadings on Lagged Values of DIV, TERM, DEF, and RF									
	Constant	**R_m**	**SMB**	**HML**	**DIV**	**TERM**	**DEF**	**RF**	Adj. R^2
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	
Panel B: Lettau-Ludvigson Model with Loadings on Lagged Values of DIV, TERM, DEF, and RF									
	Constant	**cay**	**Δc**	**cay · Δc**	**DIV**	**TERM**	**DEF**	**RF**	Adj. R^2
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	
Panel C: Alternative Model with Loadings on Lagged Values of DIV, TERM, DEF, and RF									
	Constant	**coin**	**Δc**	**coin · Δc**	**DIV**	**TERM**	**DEF**	**RF**	Adj. R^2
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 9. 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 size sorted portfolios, 10 book-to-market sorted portfolios, and 10 earning-to-price sorted 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 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 . Δc**	Adj. R^2	**Constant**	R_m	**SMB**	**HML**	Adj. R^2
Panel A: 10 Size Portfolios										
Estimate	-0.03	0.32	0.08	-0.04	0.93	-1.42	2.88	0.74	0.42	0.94
t value	-0.04	1.60	0.27	-0.36		-0.66	1.27	1.56	0.37	
Shanken t	-0.04	1.29	0.22	-0.29		-0.61	1.18	1.54	0.35	
Panel B: 10 Book-to-Market Portfolios										
Estimate	2.69	-0.23	0.16	0.48	0.91	1.54	-0.04	1.90	0.54	0.95
t value	2.83	-1.18	0.64	1.76		0.82	-0.02	1.50	0.80	
Shanken t	1.57	-0.66	0.36	0.98		0.76	-0.02	1.41	0.77	
Panel C: 10 Earning-to-Price Portfolios										
Estimate	1.35	-0.11	0.54	0.33	0.85	3.03	-1.53	2.38	0.68	0.93
t value	1.98	-0.60	2.27	1.71		2.00	-0.93	2.26	1.01	
Shanken t	1.25	-0.38	1.45	1.09		1.72	-0.81	1.99	0.93	
Panel D: 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	

Figure 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 ten-year and a one-month government bond, the difference between the yields of a Moody's Baa and Aaa corporate bond, the three-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.

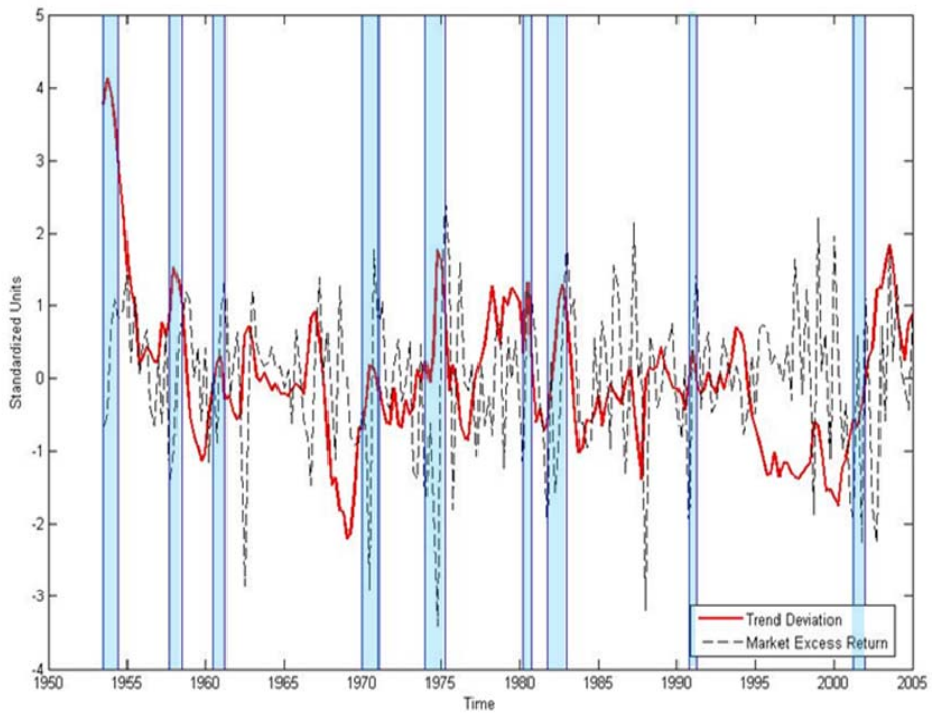

Figure 2. Realized and fitted excess returns.

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.

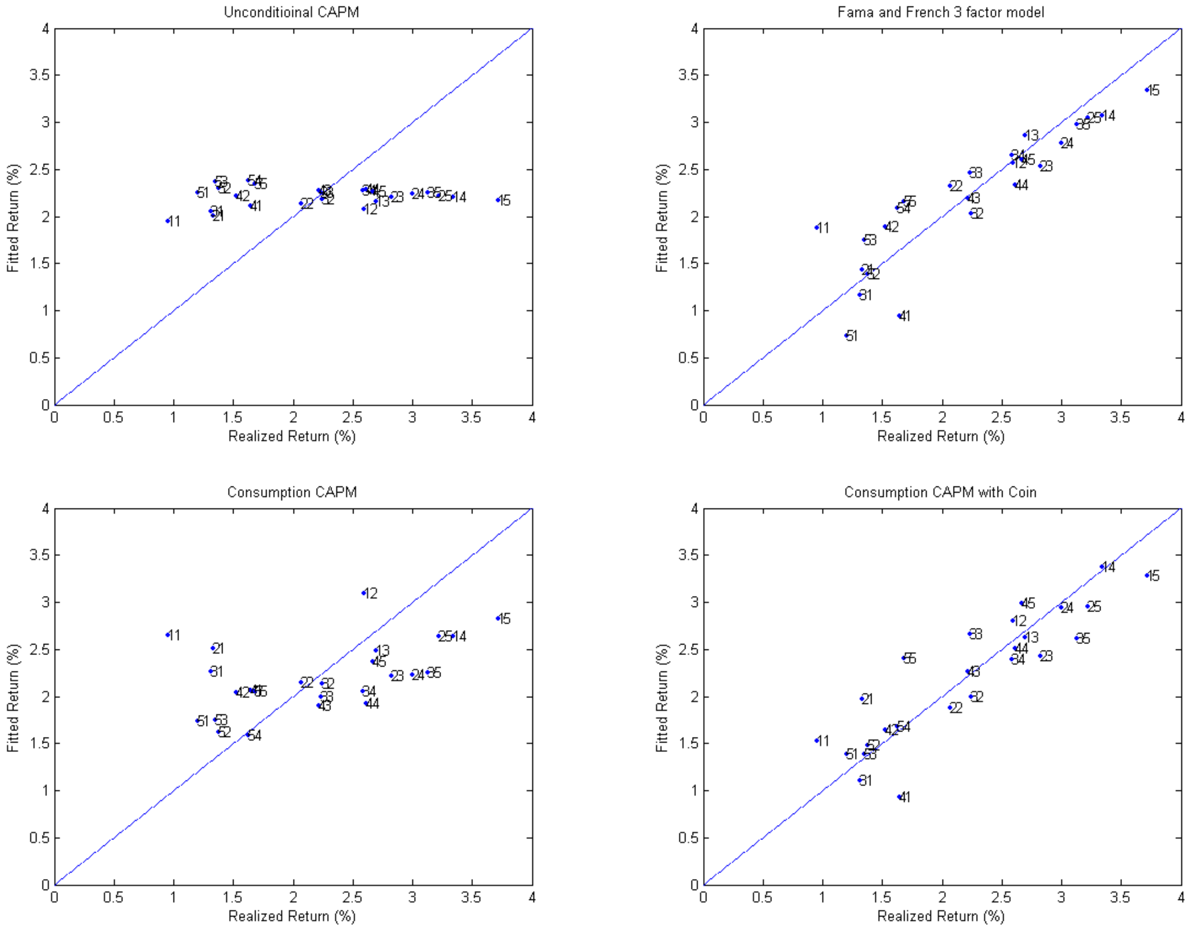

Figure 3. Conditional consumption beta in good and bad states.

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.

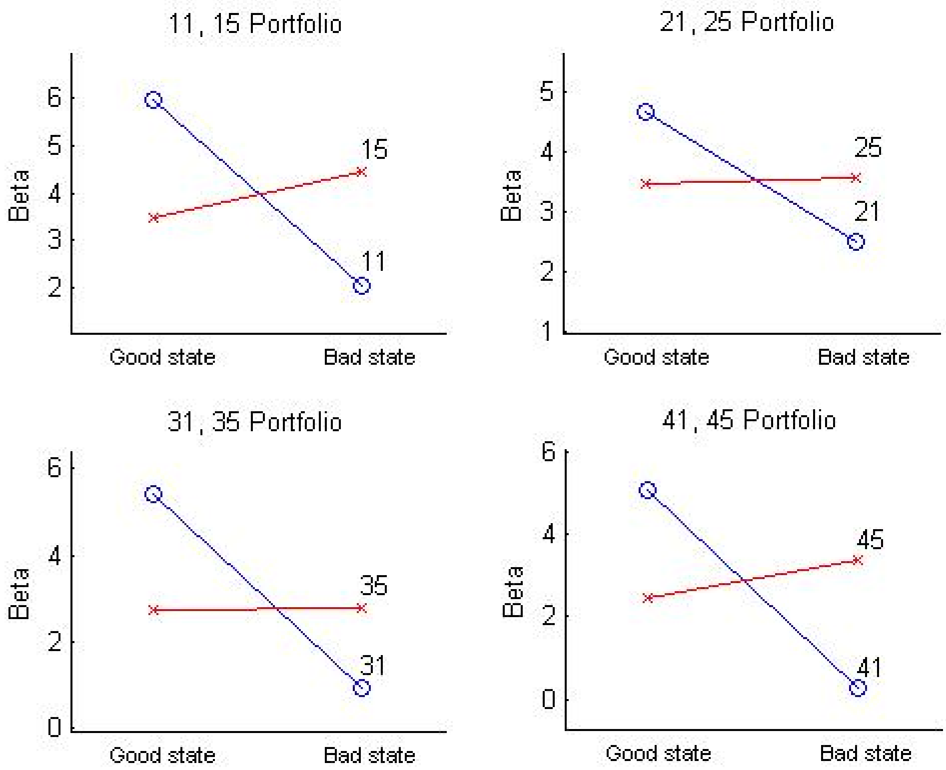

Figure 4. Realized and fitted excess return of 10 industry portfolios.

This figure illustrates the realized versus fitted average returns of Fama and French's three-factor model (Panel A) and the conditional CCAPM model with *coin* as a conditioning variable (Panel B). Each digit number identifies a different portfolio: 1 is consumer nondurables, 2 is consumer durables, 3 is manufacturing, 4 is oil, gas, and coal extraction and products, 5 is business equipment, 6 is telephone and television transmission, 7 is wholesale, retail, and services, 8 is health care, medical equipment, and drugs, 9 is utilities, and 10 is other sectors, including mines, hotels, entertainment, and finance. The sample period is from the third quarter of 1963 to the fourth quarter of 2005.