

A Robustness Test for Cross-Sectional Asset Pricing

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Abstract

In this paper, we follow Fama's (1991) conjecture to investigate whether the cross-sectional stock return predictability is related to the time-series predictability. We find that, when combined with the consumption-wealth ratio or the idiosyncratic volatility, realized stock market variance forecast excess returns on the 25 Fama and French (1993) portfolios. Moreover, the out-of-sample forecast of the portfolio returns is found to be significant in the Fama and MacBeth (1973) regression, and it remains significant after we control for the risk factors of some leading asset pricing models.

Keywords: Stock Return Predictability, Cross Section of Stock Returns, Consumption-Wealth Ratio, Idiosyncratic Volatility, and Realized Stock Market Volatility.

JEL number: G1.

Lo and MacKinlay (1990), among others, have cautioned about the problem of data snooping in the empirical asset pricing literature. For example, while many risk factors have been found to be statistically significant in the Fama and MacBeth (1973) regression, there is no apparent link between the documented factors. Also, Kan and Zhang (1999) argue that it is important to conduct robustness checks in cross-sectional asset pricing tests because some useless factors might appear statistically significant in the cross-sectional regression. One way to address the data-snooping issue, as suggested by Brennan, Wang, and Xia (2003), is to make a distinction between Merton's (1973) intertemporal capital asset pricing model (ICAPM) and Ross' (1976) Arbitrage Pricing Theory. That is, priced "factors" are not just any set of factors that are correlated with returns, but are the innovations in state variables that predict future returns. In the same spirit, we provide a robustness test based on Fama's (1991) conjecture that the cross-sectional return predictability should be related to the time-series return predictability.

In particular, Lettau and Ludvigson (2001a) and Guo (2003a) show that the consumption-wealth ratio (CAY) is a strong predictor of excess stock market returns, especially when combined with realized stock market variance (MV). More importantly, the predictive power of the two variables is consistent with rational expectation models, e.g., Campbell and Cochrane (1999) and Guo (2003b). In this paper, we use the out-of-sample forecast based on CAY and MV as a proxy for the conditional returns on the 25 Fama and French portfolios. Consistent with Fama's conjecture, this proxy is found to be highly significant in the Fama and MacBeth regression and thus helps explain the cross section of the realized portfolio returns. Our result provides a powerful test for asset pricing models, for example, Jagannathan and Wang (1998) show that, under the null hypothesis of a factor model, the proxy should be insignificant in the presence of the proposed risk factors.

For illustration, we use the out-of-sample forecast to test some leading asset pricing theories, including the Fama and French (1993) three-factor model (FF model), the variants of the consumption-based capital asset pricing model (CCAPM) proposed by Lettau and Ludvigson (2001b) and Parker (2003). Of course, it is straightforward to extend our analysis to other asset pricing models. We find that although these models have captured many salient features of the data, they fail to explain the dynamic of stock returns.

There are some issues of using CAY as a forecasting variable: For example, it is not available in real time. However, Guo and Savickas (2003) find that value-weighted idiosyncratic volatility (IV), which is available in real time, has very similar forecasting abilities to CAY. For robustness, we also repeat our analysis by using IV instead of CAY and find essentially the same results.¹

Our approach is very similar to Ferson and Harvey (1999); however, there is an important difference. Ferson and Harvey adopt the forecasting variables commonly used in the earlier literature, which, as shown by Bossaerts and Hillion (1999), among others, do not forecast stock returns out of sample. In contrast, our forecasting variables not only forecast the portfolio returns out of sample, but also are theoretically motivated.

The remainder of the paper is organized as follows. We explain the data in Section I and present evidence of portfolio return predictability in Section II. We then discuss the cross-sectional regression results in Section III and present some robustness tests in Section IV. Some concluding remarks are offered in Section V.

¹ We present the results of using CAY as a forecasting variable for the following reasons. First, while the predictive ability of CAY is directly motivated from theories, e.g., Campbell and Cochrane (1999) and Guo (2003b), IV forecast returns because of its co-movements with CAY. Second, while the data of CAY start from 1952:Q2, IV is

I. Data

In this paper, we focus on the 25 portfolio returns originally constructed by Fama and French (1993) because of their prominent role in the asset pricing literature. We obtain from Kenneth French the monthly portfolio return data spanning from January 1952 to December 2002 and aggregate them into quarterly data. The excess return is the difference between the portfolio return and a risk-free rate obtained from the Center for Research in Security Prices (CRSP). We obtain the Fama and French risk factors, excess stock market returns, SMB, and HML also from Kenneth French. SMB is the return on a portfolio that is long in small stocks and short in big stocks. HML is the return on a portfolio that is long in stocks with the high book-to-market value ratio and short in stocks with the low book-to-market value ratio. Our forecasting variables include CAY obtained from Martin Lettau, and IV and MV constructed using daily CRSP data as in Guo and Savickas (2003) and Merton (1980), respectively. Finally we use per capita consumption to construct the consumption growth used in the modified CCAPM by Lettau and Ludvigson (2001a) and Parker (2003). The consumption series is also obtained from Martin Lettau, who uses it to construct CAY. CAY is available for the period 1952:Q2 to 2002:Q4 and IV is available for the period 1963:Q3 to 2002:Q4.

II. Forecasting Portfolio Returns

Table 1 presents the OLS regression results of the forecasting equation:

$$(1) \quad er_{i,t} = a_i + b_i * CAY_{t-1} + c_i * MV_{t-1} + \varepsilon_{i,t} \quad ,$$

where $er_{i,t}$ is the excess return on portfolio i , CAY_{t-1} is the consumption wealth ratio, MV_{t-1} is realized stock market variance, and $\varepsilon_{i,t}$ is a shock. It should be noted that the portfolios are

not available until 1963:Q3. Third, CAY is also an important conditional variable used in Lettau and Ludvigson

formed according to two independent sorts: size of capitalization (S) and book-to-market value ratio or B/M (B). For example, S1 is the portfolio of the smallest capitalization and S5 is the portfolio of the biggest capitalization and so forth. Similarly, B1 is the portfolio of the lowest B/M and B5 is the portfolio of the highest B/M and so forth.

Both CAY_{t-1} and MV_{t-1} are highly significant in forecasting the one-quarter-ahead excess return on each of the 25 portfolios. Also, both variables always have positive coefficients. The adjusted R-squared ranges from 8 percent to 15 percent, indicating that there is substantial portfolio return predictability. We also compare the out-of-sample forecast of equation (1) with that of a benchmark model of constant returns in Table 1. We use the data from 1952:Q2 to 1963:Q2 to make the initial out-of-sample forecast for 1963:Q3 and then update the forecast recursively using an expanding sample.² The mean-squared-error ratio (MSER) of the forecasting model to the benchmark model is reported in the MSER column. For all 25 portfolios, the MSER is less than one, indicating that our variables have strong out-of-sample forecasting abilities. Another issue is that the consumption-wealth ratio is constructed using macro variables, which are available with about a one-month delay.³ To be robust, we lag it twice or use CAY_{t-2} in the forecasting equation and report the results in Table 2, which are very similar to those of Table 1.

Figures 1 and 2 plot the coefficient estimates reported in Table 1. In each figure, we use a two-digit number on the horizontal axis to denote a portfolio. Similar to Table 1, the first digit refers to size and the second digit refers to B/M. For example, 11 is the portfolio of the smallest capitalization and the lowest B/M. Figure 1 shows that the growth stocks (low B/M) are more

(2001b), which we test in this paper.

² We choose the starting period of the out-of-sample forecast so that we can match the sample analyzed by Lettau and Ludvigson (2001a), which we discuss in the next section. However, our results are not sensitive to this choice.

sensitive to CAY than the value stocks (high B/M), especially for stocks of relatively small capitalization. We find a very similar pattern for MV, as shown in Figures 2. Figure 3 plots the out-of-sample forecast based on CAY_{t-2} and MV_{t-1} . Unless otherwise indicated, we use this specification in the remainder of the paper; however, we obtain very similar results using one-period lagged CAY. Figure 3 shows that, although the conditional returns usually move in the same direction, there are substantial variations across the portfolios. Overall, our results suggest that the out-of-sample forecast is a reasonable proxy for the conditional stock returns and should help explain the cross section of the realized portfolio returns, which we show below.

III. Cross Section of Stock Returns

We use the conventional Fama and MacBeth method to investigate whether the out-of-sample forecast captures the cross-sectional variations of the conditional portfolio returns and how it is related to leading asset pricing models. In particular, we run a cross-sectional regression at every period t

$$(2) \quad er_{i,t} = \gamma_{0,t} + \gamma_t \beta_{i,t} + \gamma_{fit,t} FIT_{i,t} + \varepsilon_{i,t}, i = 1, \dots, 25 \quad ,$$

where $\beta_{i,t}$ is a vector of the factor loadings, $FIT_{i,t}$ is the out-of-sample forecast based on information available by $t-1$, and $\varepsilon_{i,t}$ is a shock. After we get a time series of the estimated risk premium γ , we report its sample mean and the t-statistic of the sample mean. Shanken (1992) proposes a correction for the Fama and MacBeth standard error because of the estimation error in $\beta_{i,t}$ and $FIT_{i,t}$. However, Jagannathan and Wang (1998) show that Shanken's correction is not valid when returns are conditionally heteroskedastic, and, therefore, as in Ferson and Harvey (1999), we report only the t-statistics based on the Fama and MacBeth standard error.

³ Following Lettau and Ludvigson (2001a), we estimate the cointegration parameters using all the available data

Nevertheless, incorporating Shanken's correction does not change our results in any qualitative way.

Jagannathan and Wang (1998) show that we cannot use the t-ratios to select significant factors because they do not converge to a limiting t-distribution if a model is misspecified. However, they also point out that, including additional cross-sectional predictors in the model, the t-ratios for those variables provide a valid test of the null model. These results justify our robustness test, i.e., adding $FIT_{i,t}$ to the Fama and MacBeth regression of equation (2).

We first report the regression results of the FF model in Table 3. Given that we use the data from 1952:Q2 to 1963:Q2 for the initial in-sample regression in the out-of-sample forecast, the Fama and MacBeth regression is based on a sample spanning from 1963:Q3 to 2002:Q4, with a total of 158 cross-sectional regressions. Because of the relatively small sample size, we first assume that betas are constant and are estimated using the full sample from 1963:Q3 to 2002:Q4 and report the results in panel A. Consistent with the early authors, we find that HML is significantly priced, with a t-value of 2.8 (row 1). The out-of-sample forecast, FIT , is also significant with a point estimate of 0.6 and a t-value of 3.0 (row 2). It should be noted that FIT is significantly less than one at the 5 percent level, indicating that the out-of-sample forecast does not fully explain the cross-sectional variations of the realized portfolio returns. Nevertheless, only FIT remains significant at the 5 percent level if we add it to the FF model (row 3).

To ensure robustness, in panel B we estimate betas recursively using the past returns of an expanding sample. For example, we use the sample from 1952:Q2 to 1962:Q2 to estimate betas of 1963:Q3 and use the sample from 1952:Q2 to 1962:Q3 for betas of 1963:Q4 and so forth. In panel C we estimate betas recursively using the past returns in a rolling sample of fixed length. For example, we use the sample from 1952:Q2 to 1962:Q2 to estimate betas of 1963:Q3

rather than the data available at the time of the forecast.

and use the sample from 1952:Q3 to 1962:Q3 for betas of 1963:Q4 and so forth. In both panels, *FIT* again drives out the Fama and French factors at the 5 percent significance level.

It is possible that the results of Table 3 are driven mainly by large measurement errors in betas. Alternatively, we use the sample averages of the portfolios' SIZE and B/M, which are more precisely measured than betas, and report the results in Table 4.⁴ Again, we find that *FIT* drives out these characteristic factors as well as the market beta. We also obtain very similar results using the time series of SIZE and B/M, which are not reported here. Our results thus confirm Berk's (1995) critique that size-related measures such as SIZE and B/M explain the cross section of stock returns because they are proxies for the conditional portfolio returns. However, *FIT* appears to be a better measure of the conditional returns than the characteristic factors and thus has more power in rejecting a misspecified model.

Table 5 investigates the conditional CCAPM proposed by Lettau and Ludvigson (2001b), who argue that the risk factors include consumption growth Δc_t , the lagged consumption-wealth ratio CAY_{t-1} , and an interaction term $CAY_{t-1} \cdot \Delta c_t$. For comparison, we use the exactly same data and the exactly same sample period—1963:Q3 to 1998:Q3—and estimate betas using the full sample, as in Lettau and Ludvigson. Also, we consider two specifications as in Lettau and Ludvigson: Row 1 reports the Fama-MacBeth regression results of the full model, and we exclude CAY_{t-1} in row 2. Consistent with their results, the interaction term $cay_{t-1} \cdot \Delta c_t$ is highly significant in both cases. Row 3 shows that *FIT* is also highly significant in this sample. If we add *FIT* to the conditional CCAPM, the interaction term becomes insignificant in row 4 and becomes less significant in row 5, while *FIT* remains highly significant.

⁴ We obtain the time series of SIZE and B/M from Kenneth French.

In the last example, we examine the CCAPM proposed by Parker (2003), who argues that we should measure the risk of a portfolio by its “ultimate” consumption risk defined as the covariance of its return with consumption growth over the quarter of the return and many following quarters. In particular, to measure the ultimate risk, the pricing kernel is $(\frac{C_{t-1}}{C_{t-k}})^{-\alpha}$ rather than $(\frac{C_t}{C_{t-1}})^{-\alpha}$, as in the standard CCAPM, where α is the relative risk aversion coefficient and k is the relevant consumption horizon. Following Parker, we set α to be 5 and k to be 11 and report the regression results for the period 1963:Q3 to 2002:Q4 in Table 6. Consistent with Parker, the ultimate consumption risk is highly significant with a t-value of about 3.8. However, it becomes less significant after we add *FIT* to the regression equation (row 3). Interestingly, it becomes insignificant at the 5 percent level if we add both *FIT* and *SIZE* (row 4). In contrast, *FIT* is always significant in Table 6.⁵

IV. Robustness

As mentioned above, there are some issues of using *CAY* as a forecasting variable, for example, it is not available in real time. In this section, we repeat the analysis above by using *IV* instead *CAY*. *IV* is available over the period 1963:Q3 to 2002:Q4. Table 7 provides both in-sample and out-of-sample forecasting results, as in Table 1. In the out-of-sample forecast, we use the sample 1963:Q3 to 1969:Q4 to make the initial forecast for 1970:Q1 and update the forecast recursively using an expanding sample. We find that while *MV* is statistically significant at the 5

⁵ Similarly, the interaction term $CAY_{t-1} \cdot \Delta C_t$ becomes insignificant at the 5 percent level in Table 5 if we also add the characteristic factor *SIZE* in the regression, in addition to *FIT*. We note that *FIT* usually becomes more significant if we also add *SIZE* in the Fama and MacBeth regression. It is possible that our results may be explained by the useless factors emphasized by Kan and Zhang (1999). Nevertheless, as mentioned above, including additional cross-sectional predictors in the model, the t-ratios for those variables provide a valid test of the null model.

percent level in all cases, IV is significant or marginally significant in most cases. While the adjusted R-squared is noticeably smaller than those in Table 1, MSER is always smaller than one. Therefore, IV and MV are also strong predictors of portfolio returns. Interestingly, consistent with the evidence from using CAY, Figures 4 and 5 illustrate that there are clear differences of loadings on IV and MV across B/M: Growth stocks are much more sensitive to the macrovariables than value stocks. Similarly, Figure 6 indicates that there are substantial variations in conditionally expected returns, both through time and across sections.

Table 8 presents the regression results of equation (2) using the FF model for the period 1970:Q1 to 2002:Q4. Again, we find that while the factor HML is significantly priced, it becomes insignificant at the 5 percent level after we add FIT to the cross-sectional regression. We find the same results in Table 9, in which we use the sample average of SIZE and B/M. Table 10 show that FIT remains significant in Lettau and Ludvigson's (2001b) conditional CCAPM. Table 11 shows that FIT is insignificant in Parker's (2003) ultimate CCAPM; however, it becomes significant if we also add the characteristic factor SIZE to the cross-sectional regression.⁶

V. Conclusion

In this paper, we propose a robustness test based on the time-series predictability. As examples, we find that some leading asset pricing models, i.e., the Fama and French (1993) three-factor model, the modified CCAPM by Lettau and Ludvigson (2001a) and Parker (2003), fail to explain the dynamic of portfolio returns. Our results confirm the importance of incorporating time-series stock return predictability into asset pricing models, as emphasized by

Merton (1973), Campbell (1993), Brennan, Wang, and Xia (2003), and Campbell and Vuolteenaho (2003), among others. Our test should have important implications for the empirical asset pricing models.

⁶ We use the sample 1963:Q3 to 2002:Q4 to calculate the factor loadings in Table 11. However, the ultimate consumption risk becomes insignificant if we use the sample 1970:Q1 to 2002:Q4, even we do not control for FIT and SIZE.

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Table 1. Forecasting One-Quarter-Ahead Portfolio Returns with One-Period Lagged CAY

Portfolios	CAY_{t-1}	$t(CAY_{t-1})$	MV_{t-1}	$t(MV_{t-1})$	\bar{R}^2	MSER
S1/B1	3.29	3.13	9.79	3.61	0.08	0.95
S1/B2	3.16	3.62	10.08	3.95	0.10	0.94
S1/B3	2.75	3.74	9.02	3.94	0.11	0.93
S1/B4	2.68	3.91	8.69	3.92	0.11	0.93
S1/B5	2.87	3.72	8.43	3.42	0.09	0.95
S2/B1	3.49	3.80	10.14	3.94	0.11	0.93
S2/B2	2.75	3.82	9.42	3.70	0.11	0.92
S2/B3	2.53	3.97	7.04	3.52	0.10	0.94
S2/B4	2.80	4.68	7.35	3.56	0.12	0.93
S2/B5	2.48	3.57	6.92	2.94	0.08	0.97
S3/B1	3.16	3.84	8.29	3.36	0.10	0.93
S3/B2	2.86	4.69	7.65	3.86	0.13	0.91
S3/B3	2.57	4.72	7.03	4.04	0.12	0.91
S3/B4	2.52	4.20	6.48	3.42	0.11	0.94
S3/B5	2.29	3.55	6.97	3.34	0.08	0.98
S4/B1	2.96	3.89	7.99	3.65	0.11	0.92
S4/B2	2.75	4.62	8.27	4.77	0.15	0.89
S4/B3	2.45	4.36	6.35	4.44	0.12	0.92
S4/B4	2.29	4.23	6.39	3.85	0.11	0.95
S4/B5	2.65	4.23	7.24	4.06	0.11	0.97
S5/B1	2.60	5.57	5.39	3.18	0.11	0.91
S5/B2	2.49	5.72	5.93	4.52	0.15	0.87
S5/B3	2.29	6.24	5.18	4.08	0.14	0.88
S5/B4	2.30	4.95	6.04	3.65	0.14	0.91
S5/B5	2.49	4.99	5.07	4.29	0.11	0.98

Note: The table reports the OLS regression results of equation (1) using the excess returns on the 25 Fama and French portfolios. The forecasting variables include the consumption-wealth ratio, CAY_{t-1} , and realized stock market variance, MV_{t-1} . The sample of the quarterly observations spans from 1952:Q2 to 2002:Q4. White (1980) corrected standard errors are used to calculate t-statistics. In the out-of-sample forecast, we use the sample from 1952:Q2 to 1963:Q2 to make the initial forecast for 1963:Q3 and update the forecast recursively using an expanding sample. The mean-squared-error ratio of the forecasting model to that of a benchmark of constant returns is reported in the MSER column.

Table 2. Forecasting One-Quarter-Ahead Portfolio Returns with Two-Period Lagged CAY

Portfolios	CAY_{t-1}	$t(CAY_{t-1})$	MV_{t-1}	$t(MV_{t-1})$	\bar{R}^2	MSER
S1/B1	3.11	2.94	9.94	3.58	0.07	0.96
S1/B2	2.84	3.41	10.08	4.03	0.09	0.94
S1/B3	2.50	3.59	9.05	4.02	0.09	0.94
S1/B4	2.33	3.45	8.53	3.95	0.09	0.94
S1/B5	2.30	3.26	8.01	3.29	0.06	0.97
S2/B1	3.33	3.67	10.39	3.96	0.09	0.93
S2/B2	2.61	3.69	9.56	3.81	0.10	0.92
S2/B3	2.17	3.48	6.88	3.51	0.07	0.95
S2/B4	2.52	4.32	7.33	3.69	0.10	0.93
S2/B5	1.98	3.04	6.54	2.87	0.05	0.98
S3/B1	3.13	3.66	8.67	3.51	0.09	0.93
S3/B2	2.53	4.20	7.57	3.84	0.10	0.92
S3/B3	2.25	4.04	6.94	3.98	0.09	0.93
S3/B4	2.17	3.63	6.29	3.41	0.08	0.95
S3/B5	1.84	3.02	6.61	3.27	0.06	0.98
S4/B1	2.58	3.24	7.85	3.54	0.08	0.94
S4/B2	2.40	3.81	8.16	4.69	0.12	0.90
S4/B3	1.85	3.31	5.84	3.85	0.07	0.95
S4/B4	1.94	3.54	6.20	3.78	0.08	0.96
S4/B5	2.04	3.33	6.72	3.68	0.07	0.97
S5/B1	2.30	4.24	5.29	2.98	0.08	0.94
S5/B2	2.08	4.39	5.68	4.01	0.10	0.91
S5/B3	1.76	4.38	4.73	3.73	0.08	0.93
S5/B4	1.89	3.87	5.76	3.48	0.10	0.93
S5/B5	2.18	4.15	4.95	4.06	0.08	0.97

Note: We use two-period-lagged CAY, CAY_{t-2} , as a forecasting variable. The other specifications are the same as Table 1.

Table 3. The FF Model

γ_0	$\gamma_1(MKT)$	$\gamma_2(SMB)$	$\gamma_3(HML)$	$\gamma_4(FIT)$
Panel A. Full-Sample Betas				
0.023 (1.63)	-0.009 (-0.598)	0.007 (1.362)	0.014 (2.826)	
0.005 (0.606)				0.606 (2.954)
0.011 (0.779)	-0.008 (-0.493)	0.003 (0.506)	0.009 (1.714)	0.503 (3.978)
Panel B. Expanding-Sample Betas				
0.035 (2.445)	-0.021 (-1.408)	0.005 (1.079)	0.014 (2.671)	
0.005 (0.606)				0.606 (2.954)
0.016 (1.141)	-0.014 (-0.933)	0.002 (0.319)	0.009 (1.654)	0.598 (4.215)
Panel C. Rolling-Sample Betas				
0.018 (1.761)	-0.005 (-0.465)	0.006 (1.324)	0.014 (2.801)	
0.005 (0.606)				0.606 (2.954)
0.004 (0.384)	0.000 (0.030)	0.004 (0.755)	0.010 (1.935)	0.487 (3.525)

Note: The table reports the results of the Fama and MacBeth regression, as in equation (2). MKT is the market return, SMB and HML are two additional Fama and French risk factors, and *FIT* is the out-of-sample forecast. The quarterly data spans from 1863:Q3 to 2002:Q4, with a total of 158 observations. In panel A, we assume that betas are constant and are estimated using the full sample. In panel B, we estimate betas using the past returns in an expanding sample. In panel C, we estimate betas using the past returns in a rolling sample of fixed length.

Table 4. Characteristic Factors

γ_0	$\gamma_1(MKT)$	$\gamma_2(\ln(SIZE))$	$\gamma_3(\ln(B/M))$	$\gamma_4(FIT)$
Panel A. With in-Sample Betas				
0.044 (2.820)	-0.007 (-0.611)	-0.003 (-2.079)	0.006 (2.190)	
0.005 (0.606)				0.606 (2.954)
0.031 (1.838)	-0.007 (-0.562)	-0.002 (-1.287)	0.004 (1.445)	0.399 (2.823)
Panel B. With Expanding Sample Betas				
0.004 (2.691)	-0.007 (-0.640)	-0.003 (-1.930)	0.006 (2.108)	
0.005 (0.606)				0.606 (2.954)
0.030 (1.715)	-0.006 (-0.510)	-0.002 (-1.281)	0.004 (1.163)	0.441 (3.051)
Panel C. With Rolling Sample Betas				
0.040 (2.978)	-0.006 (-0.712)	-0.002 (-1.804)	0.006 (1.888)	
0.005 (0.606)				0.606 (2.954)
0.030 (1.846)	-0.007 (-0.839)	-0.002 (-1.194)	0.003 (0.813)	0.423 (3.027)

Note: The table reports the results of the Fama and MacBeth regression, as in equation (2). We use the sample average of SIZE and B/M in place of betas associated with SMB and HML, respectively. The other specifications are the same as Table 3.

Table 5. Lettau and Ludvigson's (2001b) Conditional CCAPM

γ_0	$\gamma_1(CAY_{t-1})$	$\gamma_2(\Delta c_t)$	$\gamma_3(CAY_{t-1} \cdot \Delta c_t)$	$\gamma_4(FIT)$
0.030 (4.035)	-0.165 (-0.524)	0.009 (0.068)	0.538 (2.785)	
0.029 (4.495)		-0.062 (-0.296)	0.660 (3.162)	
0.004 (0.422)				0.746 (3.593)
0.017 (2.194)	-0.236 (-0.722)	-0.000 (-0.003)	0.245 (1.330)	0.551 (4.160)
0.012 (1.769)		-0.089 (-0.478)	0.405 (2.077)	0.595 (4.453)

Note: The table reports the results of the Fama and MacBeth regression, as in equation (2). In the conditional CCAPM of Lettau and Ludvigson (2001b), risk factors include lagged consumption-wealth ratio, CAY_{t-1} , the consumption growth, Δc_t , and their product, $CAY_{t-1} \cdot \Delta c_t$, as in row 1. Lettau and Ludvigson also consider a specification without CAY_{t-1} , as in row 2. FIT is the out-of-sample forecast. We use exactly the same data and the exactly sample—1963:Q3 to 1998:Q3— as in Lettau and Ludvigson (2001b). See note of Table 3 for other information.

Table 6. Parker's (2003) Ultimate Consumption Risk

γ_0	$\gamma_1\left(\left(\frac{C_{t-1}}{C_{t-12}}\right)^{-5}\right)$	$\gamma_2(\ln(SIZE))$	$\gamma_3(FIT)$
0.003 (0.271)	0.196 (3.789)		
0.005 (0.606)			0.606 (2.954)
-0.003 (-0.272)	0.147 (3.000)		0.420 (2.060)
0.005 (0.222)	0.097 (1.939)	-0.001 (-0.419)	0.595 (3.129)

Note: The table reports the results of the Fama and MacBeth regression, as in equation (2). $\left(\frac{C_{t-1}}{C_{t-12}}\right)^{-5}$ is the ultimate consumption risk advocated by Parker (2003), *SIZE* is the sample average of market capitalization, and *FIT* is the out-of-sample forecast. The sample spans from 1963:Q3 to 2002:Q4. See note of Table 3 for other information.

Table 7. Forecasting One-Quarter-Ahead Portfolio Returns with IV

Portfolios	IV_{t-1}	$t(IV_{t-1})$	MV_{t-1}	$t(MV_{t-1})$	\bar{R}^2	MSER
S1/B1	-4.75	-2.58	16.09	3.35	0.06	0.94
S1/B2	-2.93	-2.33	12.75	3.25	0.05	0.91
S1/B3	-1.76	-1.65	9.97	2.75	0.05	0.91
S1/B4	-1.49	-1.42	8.93	2.62	0.04	0.90
S1/B5	-2.16	-1.87	9.70	2.60	0.03	0.92
S2/B1	-5.01	-3.93	16.34	4.04	0.08	0.91
S2/B2	-2.86	-2.67	12.56	3.06	0.07	0.91
S2/B3	-2.15	-2.45	8.59	2.80	0.03	0.91
S2/B4	-1.76	-2.01	7.95	2.55	0.03	0.91
S2/B5	-1.69	-1.82	7.76	2.20	0.02	0.95
S3/B1	-4.95	-3.98	15.00	3.97	0.08	0.92
S3/B2	-2.91	-3.35	10.59	3.45	0.06	0.89
S3/B3	-2.35	-2.59	8.91	3.12	0.05	0.90
S3/B4	-2.04	-1.95	8.04	2.68	0.04	0.91
S3/B5	-1.18	-1.32	6.80	2.17	0.03	0.95
S4/B1	-4.00	-3.14	12.72	3.79	0.07	0.92
S4/B2	-2.31	-2.38	10.07	3.41	0.07	0.88
S4/B3	-2.01	-1.95	7.98	3.11	0.05	0.92
S4/B4	-1.86	-2.04	7.74	2.95	0.04	0.93
S4/B5	-2.62	-2.58	9.93	3.38	0.06	0.94
S5/B1	-3.92	-4.80	10.38	4.13	0.09	0.90
S5/B2	-2.68	-4.21	8.59	4.22	0.07	0.88
S5/B3	-2.21	-3.67	7.56	4.00	0.07	0.89
S5/B4	-2.27	-2.80	8.52	3.33	0.08	0.90
S5/B5	-1.73	-2.11	5.98	3.20	0.03	0.97

Note: In this table, we use the idiosyncratic volatility, IV_{t-1} , instead of the consumption-wealth ratio, CAY_{t-1} as a forecasting variable. IV is available over the period 1963:Q3 to 2002:Q4. In the out-of-sample forecast, we use the sample from 1963:Q3 to 1969:Q4 to make the initial forecast for 1970:Q4 and then update the forecast recursively using an expanding sample. The other specifications are the same as those of Table 1.

Table 8. The FF Model: Using IV as a Forecasting Variable

γ_0	$\gamma_1(MKT)$	$\gamma_2(SMB)$	$\gamma_3(HML)$	$\gamma_4(FIT)$
Panel A. Full-Sample Betas				
0.029 (1.933)	-0.015 (-0.890)	0.004 (0.739)	0.015 (2.606)	
-0.004 (-0.367)				0.587 (2.474)
0.013 (0.851)	-0.014 (-0.812)	-0.000 (-0.082)	0.009 (1.627)	0.432 (3.298)
Panel B. Expanding-Sample Betas				
0.039 (2.330)	-0.024 (-1.377)	0.002 (0.448)	0.015 (2.470)	
-0.004 (-0.367)				0.587 (2.474)
0.0157 (0.944)	-0.022 (-1.322)	-0.003 (-0.561)	0.008 (1.353)	0.650 (4.005)
Panel C. Rolling-Sample Betas				
0.019 (1.620)	-0.005 (-0.441)	0.004 (0.710)	0.015 (2.584)	
-0.004 (-0.367)				0.587 (2.474)
0.004 (0.342)	-0.006 (-0.457)	0.001 (0.099)	0.010 (1.675)	0.447 (2.837)

Note: The specifications are the same as Table 3 except that we use IV instead of CAY as a forecasting variable. Also, the sample spans from 1970:Q1 to 2002:Q4. See note of Table 3 for other information.

Table 9. Characteristic Factors: Using IV as a Forecasting Variable

γ_0	$\gamma_1(MKT)$	$\gamma_2(\ln(SIZE))$	$\gamma_3(\ln(B/M))$	$\gamma_4(FIT)$
Panel A. With in-Sample Betas				
0.033 (1.946)	-0.004 (-0.211)	-0.001 (-0.648)	0.009 (2.467)	
-0.004 (-0.367)				0.587 (2.474)
0.014 (0.721)	-0.009 (-0.467)	0.000 (0.125)	0.006 (1.578)	0.461 (3.014)
Panel B. With Expanding Sample Betas				
0.046 (2.466)	-0.017 (-0.921)	-0.001 (-0.634)	0.009 (2.463)	
-0.004 (-0.367)				0.587 (2.474)
0.021 (1.049)	-0.023 (-1.235)	0.000 (0.251)	0.006 (1.640)	0.510 (2.938)
Panel C. With Rolling Sample Betas				
0.026 (1.593)	0.003 (0.255)	-0.001 (-0.708)	0.009 (2.380)	
-0.004 (-0.367)				0.587 (2.474)
0.009 (0.494)	-0.001 (-0.078)	-0.000 (-0.121)	0.006 (1.599)	0.387 (2.469)

Note: The specifications are the same as Table 4 except that we use IV instead of CAY as a forecasting variable. Also, the sample spans from 1970:Q1 to 2002:Q4. See note of Table 4 for other information.

Table 10. Lettau and Ludvigson's (2001b) Conditional CCAPM: Using IV as a Forecasting Variable

γ_0	$\gamma_1(cay_{t-1})$	$\gamma_2(\Delta c_t)$	$\gamma_3(cay_{t-1} \cdot \Delta c_t)$	$\gamma_4(FIT)$
0.037 (4.408)	-0.305 (-0.840)	-0.103 (-0.753)	0.521 (2.308)	
0.034 (4.720)		-0.235 (-1.015)	0.747 (3.038)	
-0.010 (-0.787)				0.550 (2.454)
0.018 (2.166)	-0.546 (-1.439)	-0.157 (-1.124)	0.189 (0.905)	0.503 (3.258)
0.013 (1.549)		-0.383 (-1.793)	0.641 (2.726)	0.447 (3.026)

Note: The specifications are the same as Table 5 except that we use IV instead of CAY as a forecasting variable. Also, the sample spans from 1970:Q1 to 1998:Q3. See note of Table 5 for other information.

Table 11. Parker's (2003) Ultimate Consumption Risk: Using IV as a Forecasting Variable

γ_0	$\gamma_1\left(\left(\frac{C_{t-1}}{C_{t-12}}\right)^{-5}\right)$	$\gamma_2(\ln(SIZE))$	$\gamma_3(FIT)$
0.000	0.213		
(0.011)	(3.555)		
-0.004			0.587
(-0.367)			(2.474)
-0.010	0.170		0.335
(-0.840)	(3.037)		(1.458)
-0.017	0.133	0.000	0.609
(-0.669)	(2.424)	(0.369)	(2.707)

Note: The specifications are the same as Table 6 except that we use IV instead of CAY as a forecasting variable. Also, the sample spans from 1970:Q1 to 2002:Q4. See note of Table 6 for other information.

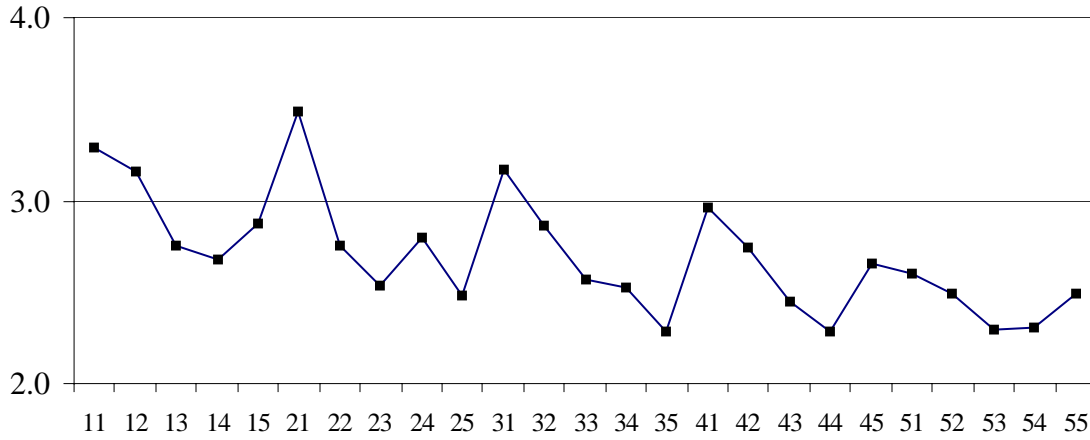


Figure 1. Coefficients of CAY (Table 1)

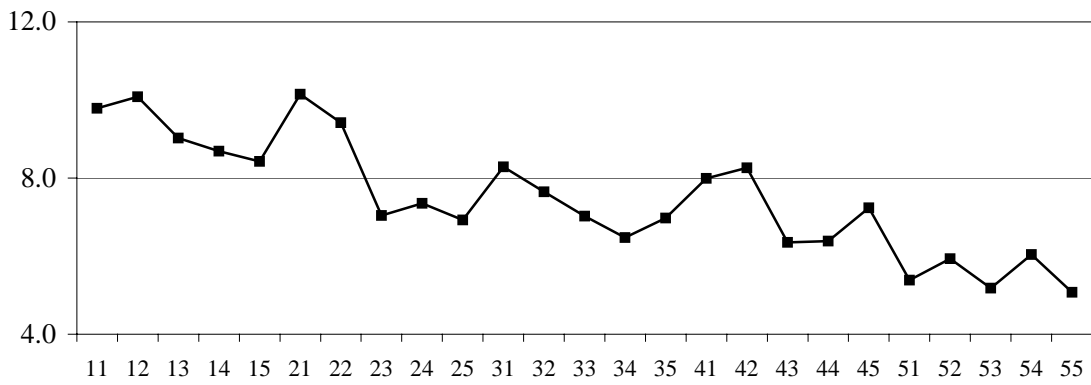


Figure 2. Coefficients of MV (Table 1)

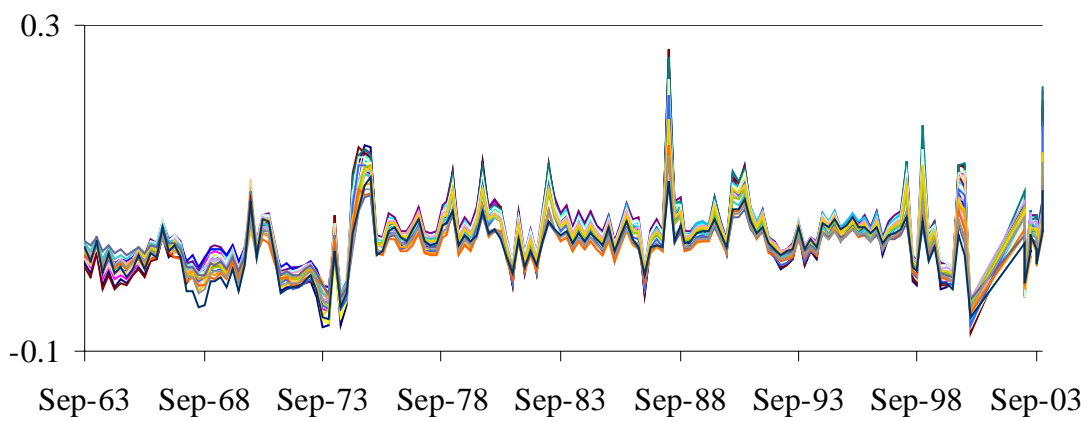


Figure 3. Time Series of Out-of-Sample Forecast (Table 1)

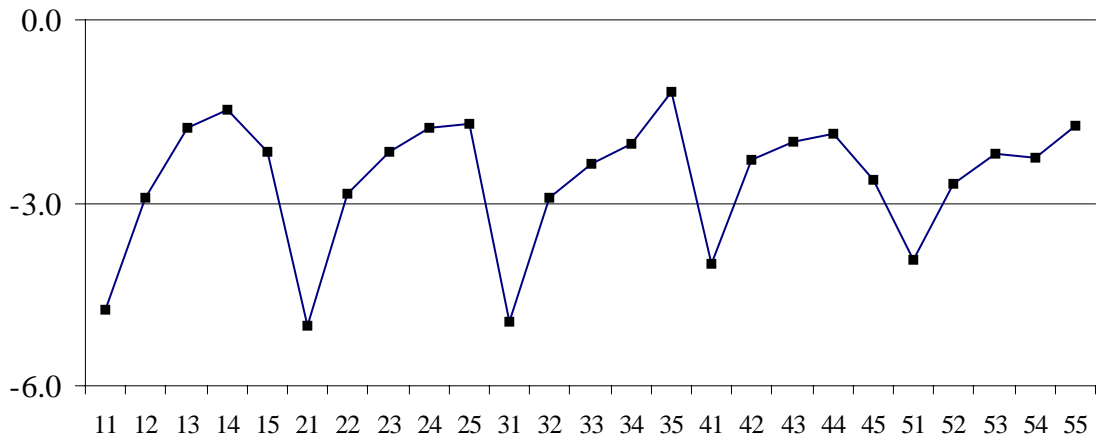


Figure 4. Coefficients of IV (Table 7)

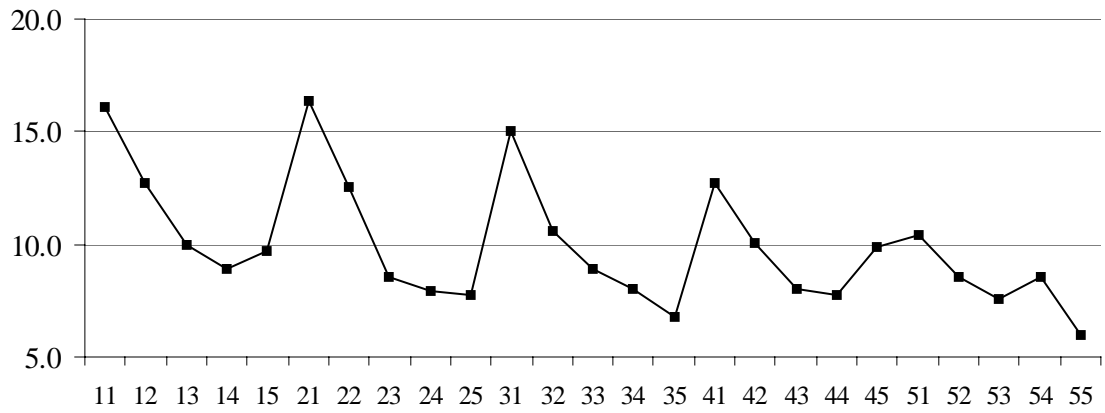


Figure 5. Coefficients of MV (Table 7)

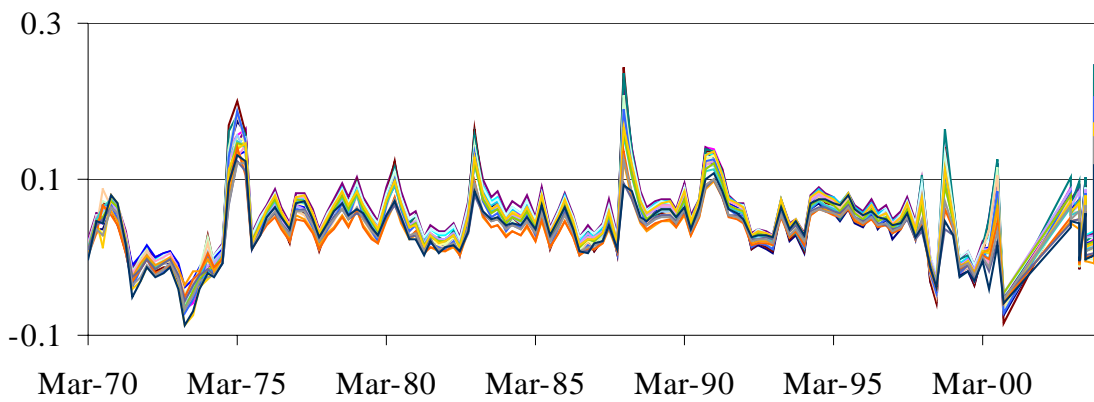


Figure 8. Time Series of Out-of-Sample Forecast (Table 7)