On the Cross-Section of Conditionally Expected Stock Returns[*]

Hui Guo

Federal Reserve Bank of St. Louis

Robert Savickas

George Washington University

October 28, 2005

[*] We thank seminar participants at George Washington University for helpful comments. The views expressed in this paper are those of the authors and do not necessarily reflect the official positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

On the Cross-Section of Conditionally Expected Stock Returns

Abstract

In this paper, we test CAPM using portfolios motivated by Campbell's (1993) ICAPM. That is, we sort stocks equally into ten portfolios according to out-of-sample forecasts formed using predictive variables advocated by recent authors. The average portfolio return increases monotonically from the first decile (stocks with the lowest expected returns) to the tenth decile (stocks with the highest expected returns), and the difference between the tenth and first deciles is a statistically significant 4.8 percent per year. These results are distinct from the momentum anomaly documented by Jegadeesh and Titman (1993). As expected, these portfolio returns pose a challenge to CAPM; however, they are explained by a variant of Campbell's ICAPM, in which risk factors also include the predictive variables, in addition to stock market returns.

I. Introduction

Financial economists have found that the capital asset pricing model (CAPM) developed by Sharpe (1964) and Lintner (1965) fails to explain the cross-section of stock returns.[1] This result should not be a surprise because, as argued by Merton (1973), a hedge demand for investment opportunity changes is also an important determinant of asset returns, in addition to stock market risk. Merton's intertemporal CAPM (ICAPM), however, has not been fully explored; in particular, early authors usually use portfolios constructed according to various ad hoc criteria rather than those implied by ICAPM in their tests of CAPM.[2] Their results do not provide a clearcut ICAPM interpretation because the alternative hypothesis also includes data snooping and irrational pricing.

In this paper, we try to fill this gap by sorting stocks into portfolios according to out-of-sample forecasts formed using predictive variables advocated by recent authors. This portfolio strategy, which is similar to those investigated by Ferson and Harvey (1999), is directly motivated from ICAPM. For example, in a variant of ICAPM developed by Campbell (1993, 1996), the predictive variables are also priced risk factors, in addition to stock market returns. By construction, the cross-section of average returns on our portfolios reflects the cross-sectional variations in loadings on the additional risk factors; therefore, they are likely to pose a challenge to CAPM. Moreover, by imposing ICAPM restrictions, our test is less vulnerable to the criticisms of data snooping and irrational pricing than those adopted by early authors.

We use a new set of predictive variables as predictors for individual stock returns, including the consumption-wealth ratio (e.g., Lettau and Ludvigson 2001), realized stock market

[1] Scruggs (1998) and Guo and Whitelaw (2005), among other, also argue that CAPM does not explain the dynamics of stock market returns across time.

variance, the stochastically detrended risk-free rate, and the past stock market return. These variables not only subsume the information content of other commonly used predictors such as the dividend yield, the term premium, and the default premium, but also have significant out-of-sample forecasting power for stock market returns (e.g., Guo 2006).[3] In this paper, we confirm that they also provide a decent description for the time-series variations of individual stock returns. For example, the cross-sectional average of the adjusted R-squared has a sample mean of 8.7 percent over the period 1954:Q3 to 2002:Q4.

At the end of a quarter, we make a one-quarter-ahead out-of-sample forecast for each stock using an expanding sample and then sort stocks according to this forecast equally into ten portfolios, ranging from the portfolio of stocks with the lowest expected returns (first decile) to the portfolio of stocks with the highest expected returns (tenth decile). The portfolios are held over the next two quarters.[4] We find that the average portfolio return increases monotonically from the first decile to the tenth decile and that the difference between the tenth and first deciles is a significant 4.8 percent per year. Note that this phenomenon is found to be distinct from the momentum anomaly documented by Jegadeesh and Titman (1993). As expected, CAPM fails to explain the portfolio returns at the conventional significance level. In contrast, a variant of Campbell's ICAPM appears to provide a good explanation for the data: (1) It is not rejected at the over-50 percent significance level; (2) most predictive variables are significantly priced and help explain the cross-section of stock returns; (3) its improvement over CAPM is statistically

---

[2] For example, many authors have tested CAPM using portfolios formed according to size (e.g., Banz 1981; Reinganum 1981), the book-to-market value ratio (e.g., Basu 1977; Ball 1978), and the past return (e.g., Jegadeesh and Titman 1993).

[3] Some authors have questioned the predictive power of the consumption-wealth ratio because it might have a look-ahead bias. However, while the look-ahead bias might explain the time-series predictability, it is not clear why it also account for the cross-sectional predictability, as documented in this paper. More importantly, we find essentially the same results by using idiosyncratic volatility instead, which has forecasting power very similar to the consumption-wealth ratio (e.g., see Guo and Savickas 2005).

significant. Our results suggest that time-varying investment opportunities have important effects on asset prices.

We also investigate whether our results are explained by some known CAPM-related anomalies. Indeed, while the portfolios formed on conditionally expected returns pose a challenge to CAPM, they are significantly correlated with and thus explained by the Fama and French (1993) three-factor model augmented by a momentum factor, as adopted by Carhart (1997), among others. This result indicates that, consistent with some recent authors (e.g., Brennan, Wang, and Xia 2004; Campbell and Vuolteenaho 2004; Petkova 2005), these anomalies reflect intertemporal pricing and cannot be fully attributed to data mining or irrational pricing. In particular, Guo (2005) estimates a variant of Campbell's ICAPM using the same predictive variables as those adopted in our paper, and he finds that it helps explain the size premium, the value premium, and the momentum profit.

To be robust, we also investigate various alternative specifications: (1) To address microstructure issues raised by Cooper, Gutierrez, and Hameed (2004), we drop stocks that have prices less than one dollar at the end of the formation period and skip one quarter between the formation and holding periods. (2) As mentioned in footnote 4, we experiment with various holding periods. (3) To address the potential look-ahead bias in the forecasting ability of the consumption-wealth ratio (e.g., Avramov 2002; Brennan and Xia 2005), we replace it with the value-weighted idiosyncratic volatility proposed by Guo and Savickas (2005). (4) We use a rolling sample instead of an expanding sample in the out-of-sample forecast. We obtain essentially the same results using these alternative specifications. Note that the result of using

---

[4] The difference between returns on the tenth and first deciles is two standard deviations above zero for the holding periods from one to five quarters; it becomes statistically insignificant for longer holding periods.

idiosyncratic volatility is particularly interesting because, unlike the consumption-wealth ratio, the idiosyncratic volatility is reliably available to practitioners in real time.

Our paper is closely related to Chordia and Shivakumar (2002; CS, hereafter), who argue that the momentum effect is completely explained by the cross-sectional variations in the expected component of past returns. However, unlike CS, we find that the momentum effect is related to, but not completely explained by, the cross-sectional variations of conditionally expected returns. Similarly, although noticeably attenuated, the return on the strategy of buying expected winners and selling expected losers remains statistically significant after controlling for past raw returns. To summarize, the momentum strategies based on predicted returns and raw returns are two related but distinct phenomena. The difference between CS and our paper mainly reflects the fact that our forecasting variables have better out-of-sample predictive power than those used in CS, including the dividend yield, the term premium, the yield on the three-month Treasury bill, and the default premium.[5]

The remainder of the paper is organized as follows. We briefly discuss theoretical motivations in Section II and explain data in Section III. The empirical results are presented in Section IV, and some concluding remarks are offered in Section V.

II. Some Theories on the Time-Series and Cross-Section of Expected Stock Returns

In this section, we use Campbell's (1996) empirical ICAPM specification to illustrate the relation between the time-series and cross-section of expected stock returns. In Section IV, we also present the estimation results of the Campbell ICAPM using portfolios formed according to conditionally expected returns.

Campbell's empirical ICAPM specification has three blocks. First, suppose that x_t is a *K*-by-1 vector of variables that forecast real stock market return, $r_{m,t+1}$.[6] Also, x_{t+1} and $r_{m,t+1}$ follow a first-order vector autoregressive process:

(1) $$\begin{bmatrix} r_{m,t+1} \\ x_{t+1} \end{bmatrix} = A_0 + A \begin{bmatrix} r_{m,t} \\ x_t \end{bmatrix} + \varepsilon_{t+1},$$

where A_0 is a (*K*+1)-by-1 vector of intercepts, A is a (*K*+1)-by-(*K*+1) matrix of slope parameters, and ε_{t+1} is a (*K*+1)-by-1 vector of shocks. Throughout the paper, variables denoted with lower case letters indicate that they are in logs.

Second, excess return on stock *i*, $r_{i,t+1} - r_{f,t+1}$, follows a stochastic process:

(2) $$r_{i,t+1} - r_{f,t+1} = B_{i0} + B_i \begin{bmatrix} r_{m,t} \\ x_t \end{bmatrix} + \eta_{i,t+1},$$

where B_{i0} is the intercept, B_i is a (*K*+1)-by-1 vector of slope parameters, and $\eta_{i,t+1}$ is the shock to the return on stock *i* at time *t*+1. In equation (2), $B_{i0} + B_i \begin{bmatrix} r_{m,t} \\ x_t \end{bmatrix}$ is the conditional return.

The last block is the heteroskedastic ICAPM developed by Campbell (1993), in which the expected return on stock *i* is determined by its conditional covariances with the predictive state variables, x_{t+1}, and stock market return, $r_{m,t+1}$:

(3) $$E_t r_{i,t+1} - r_{f,t+1} + E_t \frac{\eta^2_{i,t+1}}{2} = \gamma E_t \eta_{i,t+1} \varepsilon_{m,t+1} + \sum_{j=1}^{K+1} [(\gamma - 1 - \frac{\theta \psi_1}{\sigma})] \lambda_{hj} E_t \eta_{i,t+1} \varepsilon_{j,t+1},$$

---

[5] Cooper, Gutierrez, and Hameed (2004) find that the results of CS are sensitive to microstructure concerns. Also, Chen (2002) and Griffin, Ji, and Martin (2003) show that the forecasting variables in CS do not explain the momentum effect in multifactor models.

[6] Campbell's ICAPM indicates that we should use real stock market returns as a risk factor, while we usually use excess stock market returns in CAPM. However, given that the real risk-free rate is very low and very smooth in the data, this difference has very small effects on asset pricing.

where $E_t \frac{\eta_{i,t+1}^2}{2}$ is the adjustment for Jensen's inequality, γ is the relative risk aversion coefficient, $\frac{\theta\psi_1}{\sigma}$ is the coefficient for the effect of time-varying volatility, and λ_{hj} is a function of slope parameters A in equation (1). In the implementation, we estimate γ and $\frac{\theta\psi_1}{\sigma}$ directly and then use them to back-out the price of risk for each factor.

Campbell (1996) argues that the conditional return defined in equation (3) is the same as that defined in equation (2). In other words, the cross-sectional variations in conditionally expected returns defined in equation (2) reflect the cross-sectional variations in loadings on all risk factors in equation (3). Therefore, the cross-section of average returns on portfolios formed according to conditionally expected returns reflects loadings on the predictive state variables, in addition to stock market risk. In particular, these portfolio returns are likely to pose a challenge to CAPM if the predictive state variables are significantly priced; of course, they should be explained by Campbell's ICAPM, in which the same predictive variables are also risk factors. These are the main implications that we investigate in this paper.

III. Data

We use the consumption-wealth ratio, realized stock market variance, and the stochastically detrended risk-free rate as predictors for individual stock returns. The forecasting ability of the first two variables is consistent with a limited stock market participation model by Guo (2004). Also, Patelis (1997) suggests that variables such as the stochastically detrended risk-free rate forecast stock returns because these variables reflect the stance of monetary policies, which have state-dependent effects on real economic activity through a credit channel (e.g., Bernanke and Gertler 1989). To be consistent with Campbell's (1996) empirical ICAPM specification, we also include lagged excess stock market returns in the forecast equation; however, excluding it does not affect our results in any qualitative manner.

Because the consumption-wealth ratio is reliably measured only on a quarterly basis, we use quarterly data over the period 1952:Q2 to 2002:Q4, the longest sample available to us when this paper was first written. The issue of data availability aside, we believe that quarterly data are more appropriate for the purpose of this paper than monthly data because stock returns exhibit stronger predictability at quarterly frequency. We obtain the consumption-wealth ratio from Martin Lettau at New York University, and Lettau and Ludvigson (2001) provide a thorough description of this variable. Following Merton (1980), among many others, realized stock market variance is the sum of the squared deviation of the daily excess stock return from its quarterly average in a given quarter.[7] We use the daily stock market return data constructed by Schwert (1990) before July 1962 and use the value-weighted daily stock market return data from the Center of Research for Security Prices (CRSP) thereafter. The daily risk-free rate is not directly available, but we assume that it is constant within a given month and the monthly risk-free rate is also obtained from the CRSP. The stochastically detrended risk-free rate is the difference between the risk-free rate and its average over the previous four quarters: The quarterly risk-free rate is approximated by the sum of the monthly risk-free rate in a given quarter. We aggregate the CRSP monthly value-weighted stock market return into quarterly data through compounding, and the excess stock market return is the difference between stock market returns and the risk-free rate. Following Guo and Savickas (2005), we use 500 common stocks of the largest capitalization and use the Fama and French three factors to adjust for systematic risks in the construction of the idiosyncratic volatility, which is available over the period 1963:Q3 to

[7] Following Campbell, Lettau, Malkiel, and Xu (2001), among others, we adjust stock market volatility downward for 1987:Q4 because the 1987 stock market crash has a confounding effect on our volatility measure.

2002:Q4. Last, we obtain the Fama and French three factors as well as the momentum factor from Ken French at Dartmouth College.

Consistent with Lettau and Ludvigson (2001) and Guo (2006), equation (4) shows that the consumption-wealth ratio (CAY), realized stock market variance (MV), and the stochastically detrended risk-free rate (RREL) are strong predictors of excess stock market returns (MKT), with the adjusted R-squared of over 15 percent over the period 1952:Q3 to 2002:Q4.[8] We also confirm that these variables drive out conventional predictive variables, e.g., the dividend yield, the default premium, and the term premium, from the forecasting equation; to conserve space, this result is not reported here but is available upon request.

(4) MKT(t+1) = Constant + CAY(t) + MV(t) + RREL(t) + ER(t) + SHOCK(t+1)

	Constant	CAY(t)	MV(t)	RREL(t)	ER(t)
	-1.387***	2.456***	4.946***	-4.611**	0.009
	(-5.513)	(5.563)	(3.125)	(-2.246)	(0.126)

Sample: 1952:Q3-2002:Q4, Adjusted R-squared: 0.156

Similarly, equation (5) shows that, consistent with Guo and Savickas (2005), the idiosyncratic volatility (IV) is also a strong predictor of stock market returns when combined with stock market variance, with an adjusted R-squared of about 13 percent. It should be noted that, as shown by Guo and Savickas, the idiosyncratic volatility has forecasting power very similar to that of the consumption-wealth ratio. CAY and IV have opposite signs in the forecasting equations because the two variables are negatively correlated.

[8] Heteroskedasticity-corrected t-statistics are in parentheses. *** and ** denote significant at the 1 and 5 percent levels, respectively. It should be noted that we replace volatility of 1987:Q4 with the second-largest realized volatility in our sample. Nevertheless, we find similar results by using (1) a dummy variable to control for the 1987 stock market crash or (2) log-transformation for stock market volatility.

(5) MKT(t+1) = Constant + IV(t) + MV(t) + RREL(t) + ER(t) + SHOCK(t+1)

0.030***	-3.614***	9.894***	-5.322**	0.009
(3.492)	(-5.539)	(4.582)	(-2.485)	(0.126)

Sample 1963:Q4-2002:Q4, Adjusted R-squared: 0.133

We follow Jegadeesh and Titman (1993), among many others, in forming portfolios sorted on conditionally expected returns. In particular, we use all common stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) in the CRSP stock files. However, unlike the early authors, who construct the momentum portfolios using monthly returns, we must rely on quarterly returns for the reason mentioned above. We aggregate the CRSP monthly stock returns into quarterly returns through compounding: If a stock has a missing monthly return in a quarter, we set the quarterly return to be a missing value. Therefore, it is important to verify that the momentum effect based on quarterly returns is similar to that based on monthly returns. To investigate this issue, at the end of each quarter, we sort stocks into ten portfolios according to returns over the previous two quarters, ranging from the portfolio of stocks with the lowest past returns (first decile) to the portfolio of stocks with the highest past returns (tenth decile). The portfolios are then held over the next two quarters. These specifications mimic the 6-month formation period and 6-month holding period, which are commonly used in the momentum literature. Table 1 provides summary statistics of the equal-weighted returns on portfolios formed on past returns. Over the period 1954:Q3 to 2002:Q4, the average returns increase monotonically from past losers (column 1) to past winners (column 10) and the difference between the tenth and first deciles (column 10–1) is a significant 9.2 percent per year. This number is very close to the momentum profit of 8.8 percent obtained from monthly return data.[9] We find very similar results in two subsamples as well. Moreover, Figure I shows that the momentum profit constructed from quarterly return data (dashed line) moves very closely with the momentum profit constructed from monthly return data (solid line), and their correlation coefficient is 0.98. Therefore, using quarterly data should not affect our inference about the momentum effect in any qualitative manner.

IV. Empirical Results

A. Cross-Section of Conditionally Expected Stock Returns

At the end of quarter *t*, we run an ordinary least-squares (OLS) regression of returns for each stock on four predetermined variables: namely, the consumption-wealth ratio, realized stock market variance, the stochastically detrended risk-free rate, and the past stock market return, as in equation (2). Following CS, we require at least two years of observations in the regression. Given that our regression is intended to capture the systematic movement of individual stock prices, we exclude returns of 100 percent and above from the regression because these returns are driven mainly by idiosyncratic shocks and make parameter estimates unnecessarily noisy. However, we do not exclude these returns for holding periods. We also allow the forecasting sample to increase over time because, as shown by Guo (2006), our forecasting variables have a stable relation with stock returns and the longer sample allows us to obtain more reliable out-of-sample forecasts. Nevertheless, we find qualitatively the same results using a rolling sample of fixed number of observations, as in CS.

Figure II plots the cross-sectional average of the adjusted R-squared through time. It has a sample mean of 8.7 percent over the period 1954:Q3 to 2002:Q4, indicating that our

[9] We use a 6-month formation period and a 6-month holding period in our monthly momentum strategy. The monthly momentum profit is then aggregated into quarterly data through compounding.

forecasting variables capture a substantial portion of predictable variations in individual stock returns. If we use the existing literature as a benchmark, our forecasting variables provide a decent description for conditional stock returns. For example, over the period January 1953 to December 1994, CS report an average adjusted R-squared of 3.5 percent, compared with 9.8 percent in our data for a similar period, 1954:Q3 to 1994:Q4.

We note that the adjusted R-squared tends to decrease over time. For example, its average is 11.1 percent in the first-half sample, 1954:Q3 to 1978:Q4, compared with 6.3 percent in the second-half sample, 1979:Q1 to 2002:Q4. There are two possible explanations for the downward trend in Figure II. First, Guo (2006) shows that stock market returns have become less predictable in recent periods. For example, in the regression of equation (4), the adjusted R-squared is 25.0 percent in the first-half sample, 1954:Q3 to 1978:Q4, compared with 9.1 percent in the second-half sample, 1979:Q1 to 2002:Q4. Second, Campbell, Lettau, Malkiel, and Xu (2001), Goyal and Santa-Clara (2003), and Guo and Savickas (2005), among others, have documented an increasing trend in the idiosyncratic stock volatility, and we find that the idiosyncratic volatility is negatively and significantly correlated with the cross-sectional average of the adjusted R-squared.

We use the fitted value, $\hat{B}_{i,t}\begin{bmatrix} r_{m,t} \\ x_t \end{bmatrix}$, as a proxy for conditionally expected returns at quarter t+1 for stock i. As in CS, the intercept, $\hat{B}_{i0,t}$, is not included in the conditionally expected return because the estimated intercept may capture some of the average returns around the formation period, which might lead to either short-run continuation (e.g., Jegadeesh and Titman 1993) or long-run reversal (e.g., De Bondt and Thaler 1985) and make our results difficult to interpret. Sorting stocks on their sensitivity to predictive variables is also consistent with a factor-based interpretation for the forecasting variables, as argued by Merton (1973) and Campbell (1993), for example. Nevertheless, we find qualitatively the same results by including the intercept.

We then sort stocks equally into ten portfolios according to this forecast, ranging from the portfolio of stocks with the lowest expected returns (first decile) to the portfolio of stocks with the highest expected returns (tenth decile). The portfolios are held over the next two quarters. Table 2 presents the summary statistics for the equal-weighted returns on these portfolios. Over the period 1954:Q3 to 2002:Q4, the average portfolio return increases monotonically from the first decile (column 1) to the tenth decile (column 10) and the difference between the two (column 10–1) is a significant 4.8 percent per year. We document very similar patterns in the two subsamples in Table 2. These results confirm that the cross-sectional variations of stock returns are related to the time-series predictability of stock returns in a plausible way: One stock has a higher return than another stock because its expected return is higher. Interestingly, compared with the momentum sorted on past returns, as reported in Table 1, the difference between expected winners and expected losers has a smaller mean but a higher t-value and thus a higher Sharpe ratio. This is because, as shown in Figure III, the latter (solid line) is much less volatile than the former (dashed line); moreover, the correlation coefficient between the two is only –4 percent. Therefore, in contrast with CS, momentums based on past returns and conditionally expected returns seem to be two related but distinct phenomena, and we will discuss this issue further below.

B. CAPM

In this subsection, we investigate the main issue of this paper: Whether CAPM explains the cross-section of returns on portfolios formed according to conditionally expected returns.

Table 3 presents the results of Jensen's alpha test, in which we run an OLS regression of a portfolio return on a constant and an excess stock market return. Under the null hypothesis that CAPM is the true model, the intercept should not be statistically different from zero.

Table 3 shows that stock market return (MKT) is highly significant in the regressions and accounts for 60-70 percent of variations of portfolio returns. Interestingly, except for the first and second deciles, market beta does increase monotonically—from the third decile to the tenth decile—and it makes a significant and positive contribution to the trading profit from buying expected winners and selling expected losers (column 10–1). This pattern confirms the importance of stock market risk: A stock has a relatively high return because of its relatively large covariance with stock market returns. It also suggests that our results cannot be entirely attributed to spurious regression or data mining because our forecasting variables capture a significant portion of individual stocks' systematic co-movements with stock market returns.

However, CAPM fails dramatically to explain the portfolio returns: Seven of ten portfolios have intercepts that are significantly different from zero at the 5 percent level. Also, the trading profit of buying expected winners and selling expected losers is a significant 3.6 percent per year, after being adjusted for stock market risk. The last row reports the Gibbons, Ross, and Shaken (1989; GRS, hereafter) test that the intercepts of all portfolios are jointly zero, and the null hypothesis is rejected at the 1 percent significance level. Overall, our results provide an overwhelming rejection for CAPM.

C. Fama and French Three-Factor Model

Fama and French's (1993) three-factor model is the most widely used pricing model in academic research because it is quite successful in explaining the cross-section of stock returns.

In particular, Fama and French (1996) advocate an ICAPM interpretation for their model. Recent authors, e.g., Liew and Vassalou (2000), also provide support for the ICAPM interpretation by showing that the value and size premiums forecast GDP growth in many developed countries. Therefore, if the Fama and French three-factor model reflects rational pricing, it should help explain our portfolios sorted on conditionally expected returns. Berk (1995) also provides an explanation for finding such a connection: The capitalization and the book-to-market ratio incorporate information about future returns.

Table 4 presents Jensen's alpha test using the Fama and French three-factor model. We observe some significant improvements in explaining returns on the ten portfolios formed on conditionally expected returns. First, in addition to a stock market return, the other two factors, the value premium (HML) and the size premium (SMB), are also significantly correlated with returns on all decile portfolios. Second, the adjusted R-squared increases substantially from about 70 percent in Table 3 to over 90 percent in Table 4. Third, the intercepts are statistically insignificant except in the first decile, which is significantly negative. Therefore, the size and value premiums help explain the cross-section of conditionally expected returns. Nevertheless, the Fama and French three-factor model does not fully account for the cross-section of the portfolio returns: The difference between the tenth and first deciles is still a significant 4 percent per year in Table 4, and the GRS test rejects the Fama and French three-factor model at the 5 percent significance level.

D. Carhart Four-Factor Model

Table 5 presents Jensen's alpha test using Carhart's (1997) four-factor model, in which we add a momentum factor (WML) to the Fama and French three-factor model. Carhart (1997) and Pastor and Stambaugh (2003), among others, have also used this four-factor model to control for systematic risks. However, unlike the Fama and French three factors, financial economists usually attribute the momentum profit to irrational pricing and do not interpret it as a risk factor. It is included as a factor mainly because these authors need to show whether the newly uncovered "anomalies" are not contaminated by the momentum effect.

Ironically, unlike many other anomalies, the momentum strategy has remained highly profitable in the past decade since it was published in academic journals (e.g., Schwert 2003; Jegadeesh and Titman 2001). The fact that the momentum profit appears to be a robust phenomenon leads some researchers, e.g., Berk, Green, and Naik (1999) and Johnson (2002), to argue for a rational pricing explanation for it. Consistent with these theoretical works, CS find that the momentum profit is related to the cross-sectional variations in the expected component of past returns. Moreover, Guo (2005) estimates a variant of Campbell's ICAPM using the same forecasting variables as those adopted in our paper and finds that it explains momentum profit. Therefore, we cannot entirely rule out momentum as a risk factor.

The four-factor model is indeed quite successful: Intercepts for all portfolios, including the trading strategy of buying expected winners and selling expected losers, are very small and statistically insignificant in Table 5. Similarly, the GRS test does not reject the four-factor model at the 10 percent significance level. Consistent with the ICAPM interpretation, loadings on all risk factors usually increase from deciles with low expected returns to deciles with high expected returns. In particular, all factors make positive contributions to the difference between the tenth and first deciles (column 10–1), and the contribution is significant for the momentum profit (WML) and the size premium (SMB) and is marginally significant for stock market returns (MKT). However, if we include only WML as the risk factor, the intercept is a significant 0.9%, while the loading on WML is statistically insignificant, with an adjusted R-squared of only 1%. We find very similar results by using the momentum profit reported in Table 1. Therefore, although related, the strategy based on predicted returns (as documented here) is distinct from the momentum strategy based on past returns (as documented by Jegadeesh and Titman 1993). We will address this issue further below.

E. Campbell ICAPM

Our portfolio strategy is directly motivated from ICAPM; however, it does not incorporate the full set of restrictions of ICAPM. To substantiate the ICAPM interpretation, we estimate a variant of Campbell's ICAPM (discussed in Section II) using the decile portfolios formed according to conditionally expected returns. Because of the relatively small number of observations, we follow Campbell (1996) and estimate an unconditional version of it using Hansen's (1982) general method of moments (GMM), in which we use only a constant as an instrumental variable for equations (2) and (3). Equations (1) and (2) are exact-identified; equation (3) has ten identifying restrictions to estimate two parameters, γ and $\frac{\theta\psi_1}{\sigma}$, and thus is over-identified with eight degrees of freedom. Therefore, we can use Hansen's (1982) over-identifying restriction (OIR) test to evaluate the model performance. For comparison, we also consider CAPM, in which the risk prices of the predictive state variables are constrained to be 0. For the CAPM specification, equation (3) has ten identifying restrictions to estimate only one parameter, γ, and thus is over-identified with nine degrees of freedom. We also test the restrictions imposed by CAPM relative to ICAPM using the D-test proposed by Newey and West (1987), which has a chi-squared distribution with one degree of freedom. See Campbell (1996) and Guo (2005) for details on model specifications.

We present the estimation results in Table 6; overall, consistent with Guo (2005), they are very supportive of Campbell's ICAPM. First, it is not rejected by the over-identifying restriction test at the over-50 percent significance level. Second, stock market returns (MKT) are not the only significantly priced risk factor: Realized stock market variance (MV) and the consumption-wealth ratio (CAY) are significant at the 5 and 10 percent levels, respectively. RREL is also close to being significant at the 10 percent level. Last, in contrast, CAPM is rejected at the 5 percent significance level, and the D-test indicates that ICAPM is a statistically significant improvement over CAPM.

To further illustrate the success of ICAPM, we present factor contributions to the average portfolio return in Table 7. Consistent with Table 3, loadings on stock market risk (MKT) make a positive contribution of 0.44 percent to the difference between the tenth and first deciles (row 10–1). Contributions from the other factors are also positive and sizable: 0.48 percent from realized stock market variance (MV), 0.16 percent from the consumption-wealth ratio (CAY), and 0.06 percent from the stochastically detrended risk-free rate (RREL). Overall, only 0.01 percent of the average difference between the tenth and first deciles is left unexplained. These results indicate that time-varying investment opportunities have important effects on asset prices.

F. *Robustness Checks*

In Table 8, we investigate whether our results are sensitive to microstructure issues raised by Cooper, Gutierrez, and Hameed (2004) and others. In particular, we drop stocks that have prices less than one dollar at the end of the formation period and skip one quarter between formation and holding periods. The second specification also reflects the fact that the macrovariables used to construct the consumption-wealth ratio are available with a one-month delay. Table 8 shows that our results are essentially unchanged after we take into account these microstructure concerns.

In Table 9, we use a rolling sample of ten-year observations instead of the expanding sample. Again, we find that the portfolio return increases monotonically from the first decile (stocks with the lowest expected returns) to the tenth decile (stocks with the highest expected returns). Also, the decile portfolios provide a serious challenge to CAPM: Jensen's alpha is significant in 7 of 11 cases and the GRS test rejects the null hypothesis that the intercepts are jointly insignificant at the 5 percent level. The trading profit from buying expected winners and selling expected losers remains significantly positive after we control for Fama and French's three factors, while it becomes insignificant for Carhart's (1997) four-factor model. However, the GRS test indicates that the Fama and French three-factor model explains the cross-section of stock returns better than the Carhart four-factor model does.

In Table 10, we use the idiosyncratic volatility constructed by Guo and Savickas (2005) instead of the consumption-wealth ratio to forecast individual stock returns. Again, the results are essentially the same as those reported in the preceding subsections, in which we use the consumption-wealth ratio as a forecasting variable. This result should not be a surprise because, as shown in equations (4) and (5), the two variables have very similar forecasting abilities. This result is also particularly interesting because, unlike the consumption-wealth ratio, the idiosyncratic volatility is reliably available to practitioners in real time.

Last, Figure IV shows how the return on the trading strategy of buying stocks with high expected returns and selling stocks with low expected returns varies with holding periods. The square and triangle lines indicate the two-standard-error upper and lower bounds, respectively. The return is significantly positive over the holding periods of one to five quarters; it becomes insignificant for longer holding periods, however. This result is consistent with the fact that stock prices are mean-reverting and that our trading strategy captures temporary variations in conditionally expected returns.

G. *Momentum and Cross-Sectional Variations of Conditionally Expected Returns*

CS show that the momentum profit vanishes if we control for the expected component of past returns and thus argue that the momentum profit is explained by the cross-sectional variations in conditionally expected returns. As mentioned in footnote 3, however, their analysis has several difficulties. One possible explanation for the conflicting results is that, as pointed out by Bossaerts and Hillion (1999) and Goyal and Welch (2003), among others, the forecasting variables used by CS have poor out-of-sample predictive power for stock returns. To investigate this issue, we try to replicate the results in CS using the forecasting variables adopted in this paper. This investigation is interesting also because, in contrast with Chen (2002) and Griffin, Ji, and Martin (2003), Guo (2005) shows that the predictive variables adopted in this paper explain the momentum profit in a variant of Campbell's (1993) ICAPM.

We perform two independent sorts into quintiles by (1) returns over the past two quarters and (2) the one-quarter-ahead forecast. It should be noted that our approach differs from that in CS in two dimensions. First, we use a one-quarter-ahead forecast as a proxy for conditionally expected returns, while CS use the conditionally expected component of past returns. Our specification, which is also advocated by Cooper, Gutierrez, and Hameed (2004), is appropriate because it is directly motivated from recent theoretical works, e.g., Berk, Green, and Naik (1999) and Johnson (2002), among others. Second, we use independent sorts rather than the sequential sorts in CS, e.g., first by expected returns and then by raw returns. However, we find qualitatively the same results using the sequential sorts.

Table 11 reports returns on the 25 portfolios, which are the intersections of two independent sorts according to past returns and expected returns. Portfolios sorted according to past returns are in columns, ranging from the portfolio of stocks with the lowest past returns (column 1) to the portfolio of stocks with the highest past returns (column 5). Portfolios sorted according to expected returns are in rows, ranging from the portfolio of stocks with the lowest expected returns (row 1) to the portfolio of stocks with the highest expected returns (row 5). Therefore, portfolios in the same column have similar past returns and portfolios in the same row have similar expected returns. We find that, after controlling for past returns, the average return on the portfolio of stocks with the highest expected returns (row 5) is significantly higher than the average return on the portfolio of stocks with the lowest expected returns (row 1) in columns 3, 4, and 5. Similarly, in rows 4 and 5, after we control for expected returns, the average return on the portfolio of stocks with the highest past returns (column 5) is significantly higher than the average return on the portfolio of stocks with the lowest past returns (column 1). Therefore, consistent with the results in Table 5, the portfolios sorted according to expected returns are related to the portfolios sorted according to past returns. However, in contrast with CS, Table 11 shows that the momentum is not completely explained by the cross-sectional variations in expected returns and vice versa.[10]

Of course, our results do not imply that our forecasting variables are not related to the momentum profit: Table 12 shows that the consumption-wealth ratio and realized stock market

[10] We confirm the results by Cooper, Gutierrez, and Hameed (2004) that the momentum profit becomes more significant in the double sorts if we (1) exclude the stocks that have prices less than one dollar at the end of the formation period and/or (2) skip one quarter between the formation and holding periods.

volatility are strong predictors of the momentum profit reported in Table 1.[11] Rather, they reflect the fact that, as shown in Table 5, the momentum is only one of the priced risk factors and thus does not fully explain the cross-sectional variations in conditionally expected returns, which also reflect loadings on other risk factors in ICAPM. In other words, although the exercise in Table 11 uncovers an interesting link between the momentum and the conditionally expected stock returns, it is not a formal test of such relation and thus should be interpreted with caution.

V. Conclusion

There is a large amount of evidence that CAPM does not explain the cross-section of stock returns. However, the failure of CAPM has not been well understood because it reflects at least two things: (1) irrational pricing or data snooping and (2) ICAPM; financial economists disagree on which explanation is closer to reality. In this paper, we provide new insight in this debate by forming portfolios on conditionally expected returns, which is motivated from ICAPM and thus not as vulnerable to the criticisms of irrational pricing and data snooping as the early tests. We find that, while CAPM fails to account for the cross-section of returns on these portfolios, they are explained by a variant of Campbell's ICAPM, in which risk factors also include the predictive variables. Our results thus provide support for intertemporal pricing.

Of course, our interpretation crucially depends on the assumption that the uncovered return predictability reflects rational pricing. While this assumption appears to be consistent with economic theories proposed by recent authors, e.g., Campbell and Cochrane (1999) and Guo (2004), we can never rule out the possibility of data mining unless these results persist in the future. Also, it is always arguable that return predictability reflects irrational pricing. In this case, our results indicate that an asset pricing model—either rational or irrational—should provide a

[11] Guo (2005) finds very similar results using the momentum profit constructed in Jegadeesh and Titman (2001).

mechanism to link the time-series and cross-section return predictability. While such a link poses a challenge to behavioral models but not to rational models, again, we can tell which explanation is plausible only by using the out-of-sample test: If the predictability is rational, it should persist in the future; otherwise, it will disappear.

We also find that returns on the decile portfolios sorted according to conditionally expected returns are significantly correlated with the size and value premiums as well as the momentum profit. In particular, they appear to be explained by Carhart's (1997) four-factor model. This result suggests that the CAPM-related anomalies might be consistent with rational pricing models. However, we do not suggest that Carhart's four-factor model is the replacement for CAPM because of its ad hoc nature. A better understanding of the risk-return tradeoff in the stock market can be obtained only by using a fully-fledged ICAPM; and Brennan, Wang, Xia (2004), Campbell and Vuolteenaho (2004), Guo (2005), and our paper have provided some tentative results. We believe that further investigation along these lines is warranted.

Reference:

Avramov, D., 2002, Stock return predictability and model uncertainty, *Journal of Financial Economics* 64, 423-58.

Ball, R., Anomalies in relationships between securities' yields and yield-surrogates, *Journal of Financial Economics* 6, 103-26.

Banz, R., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

Basu, S., 1977, Investment performance of common stocks in relation to their price-earnings ratios: a test of the efficient market hypothesis, *Journal of Finance* 32, 663-82.

Berk, J., 1995, A critique of size related anomalies, *Review of Financial Studies* 8, 275-86.

Berk, J., R. Green, and V. Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553-1608.

Bernanke, B. and M. Gertler, 1989, Agency costs, net worth, and business fluctuations, *American Economic Review* 79, 14-31.

Bossaerts, P. and P. Hillion, 1999, Implementing statistical criteria to select return forecasting models: what do we learn? *Review of Financial Studies* 12, 405-428.

Brennan, M., A. Wang, and Y. Xia, 2004, Estimation and test of a simple model of intertemporal asset pricing, *Journal of Finance* 59, 1743-75.

Brennan, M. and Y. Xia, 2005, tay's as good as cay, *Finance Research Letters* 2, 1-14.

Campbell, J. 1993, Intertemporal asset pricing without consumption data, *American Economic Review* 83, 487-512.

Campbell, J., 1996, Understanding risk and return, *Journal of Political Economy* 104, 298-345.

Campbell, J. and J. Cochrane, 1999, By force of habit: a consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205-251.

Campbell, J., M. Lettau, B. Malkiel, and Y. Xu, 2001, Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk, *Journal of Finance* 56, 1-43.

Campbell, J. and T. Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249-75.

Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chen, J., 2002, Intertemporal CAPM and the cross-section of stock returns, Unpublished Working Paper, University of Southern California.

Chordia, T. and L. Shivakumar, 2002, Momentum, business cycle, and time-varying expected returns, *Journal of Finance* 57, 985-1019.

Cooper, M. J., R. C. Gutierrez, and A. Hameed, 2004, Market states and momentum, *Journal of Finance* 59, 1345-65.

De Bondt, W. F. M. and R. Thaler, 1985, Does the stock market overreact? *Journal of Finance* 40, 793-805.

Fama, E., 1991, Efficient capital markets: II, *Journal of Finance* 46, 1575-1617.

Fama, E., and K. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E., and K. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance* 51, 55-84.

Ferson, W. and C. Harvey, 1999, Conditioning variables and the cross-section of stock returns, *Journal of Finance* 54, 1325-60.

Gibbons, M., S. Ross, and J. Shaken, 1989, A Test of the efficiency of a given portfolio, *Econometrica* 57, 1121-52.

Goyal, A. and P. Santa-Clara, 2003, Idiosyncratic risk matters! *Journal of Finance* 58, 975-1007.

Goyal, A., and I. Welch, 2003, Predicting the equity premium with dividend ratios, *Management Science* 49, 639-54.

Griffin, J., S. Ji, and S. Martin, 2003, Momentum investing and business cycle risk: evidence from pole to pole, *Journal of Finance* 58, 2515-47.

Guo, H., 2004, Limited stock market participation and asset prices in a dynamic economy, *Journal of Financial and Quantitative Analysis* 39, 495-516.

Guo, H., 2005, Time-varying risk premia and the cross-section of stock returns, *Journal of Banking and Finance,* forthcoming.

Guo, H., 2006, On the out-of-sample predictability of stock market returns, *Journal of Business* 79, forthcoming.

Guo, H., and R. Savickas, 2005, Idiosyncratic volatility, stock market volatility, and expected stock returns, *Journal of Business and Economics Statistics*, forthcoming.

Guo, H., and R. Whitelaw, 2005, Uncovering the Risk-Return Relation in the Stock Market, *Journal of Finance*, forthcoming.

Hansen, L., 1982, Large sample properties of generalized method of moments estimators, *Econometrica* 50, 1029-54.

Jegadeesh, N. and S. Titman, 1993, Returns to buying winners and selling losers: implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, N. and S. Titman, 2001, Profitability of momentum strategies: an evaluation of alternative explanations, *Journal of Finance* 56, 699-720.

Johnson, T., 2002, Rational momentum effects, *Journal of Finance* 57, 585-608.

Lettau, M. and S. Ludvigson, 2001, Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815-49.

Liew, J, and M. Vassalou, 2000, Can book-to-market, size and momentum be risk factors that predict economic growth? *Journal of Financial Economics* 57, 221-45.

Lintner, J., 1965, Security prices, risk and maximal gains from diversification, *Journal of Finance* 20, 587-615.

Merton, R., 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 867-87.

Merton, R., 1980, On estimating the expected return on the market: an exploratory investigation, *Journal of Financial Economics* 8, 323-61.

Newey, W. and K. West, 1987, Hypothesis testing with efficient method of moments estimation, *International Economic Review* 28, 777-87.

Pastor, L. and R. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642-85.

Patelis, A., 1997, Stock return predictability and the role of monetary policy, *Journal of Finance* 52, 1951-72.

Petkova, R., 2005, Do the Fama-French Factors Proxy for Innovations in Predictive Variables? *Journal of Finance*, forthcoming.

Reinganum, M. R., 1981, Misspecification of capital asset pricing: empirical anomalies based on earnings yields and market values, *Journal of Financial Economics* 9, 19-46.

Schwert, W. G., 1990, Indexes of stock prices from 1802 to 1987, *Journal of Business* 63, 399-426.

Schwert, W. G., 2003, Anomalies and market efficiency, in: G. Constantinides, M. Harris, and R.

Scruggs, J., 1998, Resolving the Puzzling Intertemporal Relation Between the Market Risk Premium and Conditional Market Variance: A Two Factor Approach, *Journal of Finance*, 53, 575-603.

Stulz, Eds.: Handbook of the Economics of Finance (North-Holland, Amsterdam), 937-72.

Sharpe, W., 1964, Capital asset prices: a theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-42.

Figure Captions

Figure I

For the momentum based on past quarterly returns, we sort stocks into decile portfolios according to their returns over the previous two quarters, and the portfolios are held over the next two quarters. The dashed line is the difference between the tenth (past winners) and first (past losers) deciles. For the momentum based on past monthly returns, we sort stocks into decile portfolios according to their returns in the previous six months, and the portfolios are held over the next six months. Monthly portfolio returns are converted to quarterly returns through compounding. The solid line is the difference between the tenth (past winners) and first (past losers) deciles.

Figure II

We run a regression of individual stock returns on the four predetermined macrovariables, and then average the adjusted R-squared across stocks. We use an expanding sample with the initial sample spanning the period 1952:Q3 to 1954:Q3. The last sample spans the period 1952:Q3 to 2002:Q4. The figure plots the cross-sectional average of the adjusted R-squared over the period 1954:Q3 to 2002:Q4.

Figure III

The dashed line is the momentum based on quarterly raw returns, as in Figure I. For the momentum sorted on conditionally expected returns, we sort stocks into decile portfolios according to out-of-sample forecasts, and the portfolios are held over the next two quarters. The solid line is the difference between the tenth (expected winners) and first (expected losers) deciles.

Figure IV

We sort stocks into decile portfolios according to out-of-sample forecasts and then portfolios are held over 1 to 20 quarters. The figure plots the difference between returns on the tenth (expected winners) and first (expected losers) deciles against various holding periods.

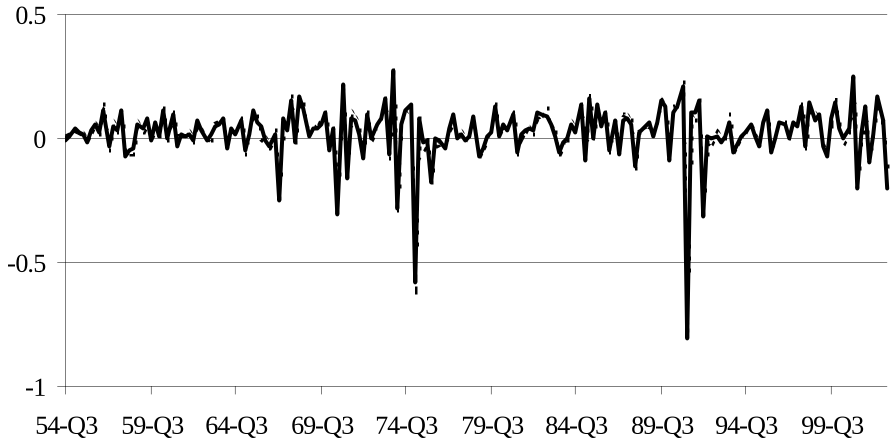

Figure I. Momentum Based on Past Quarterly (Dashed Line) and Monthly Returns (Solid Line)

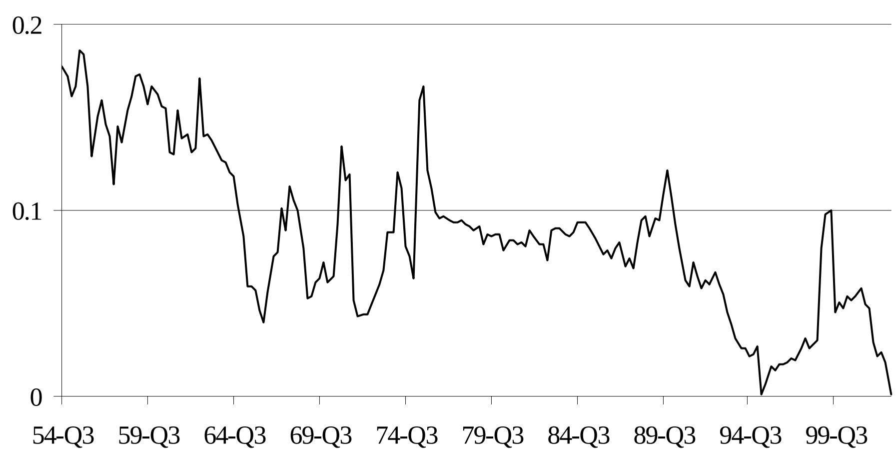

Figure II. Cross-Sectional Average of Adjusted R-Squared

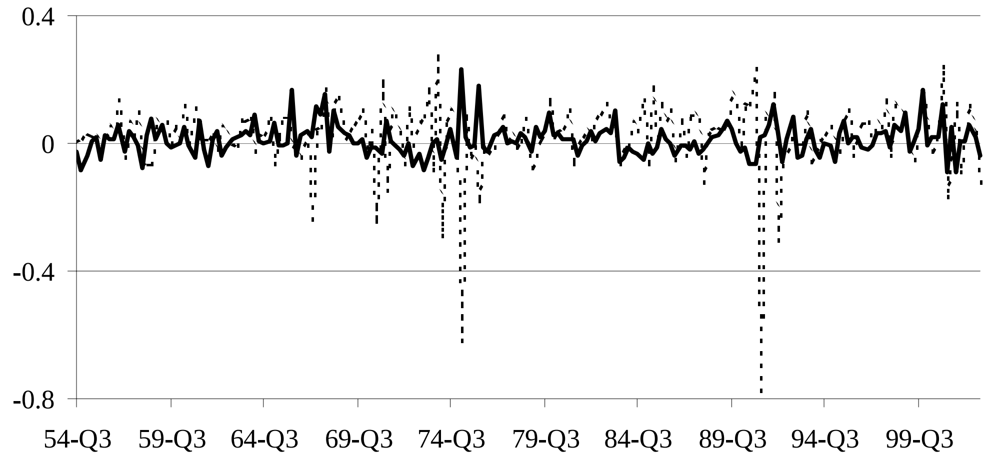

Figure III. Momentum Sorted on Expected Returns (Solid Line) and Past Returns (Dashed Line)

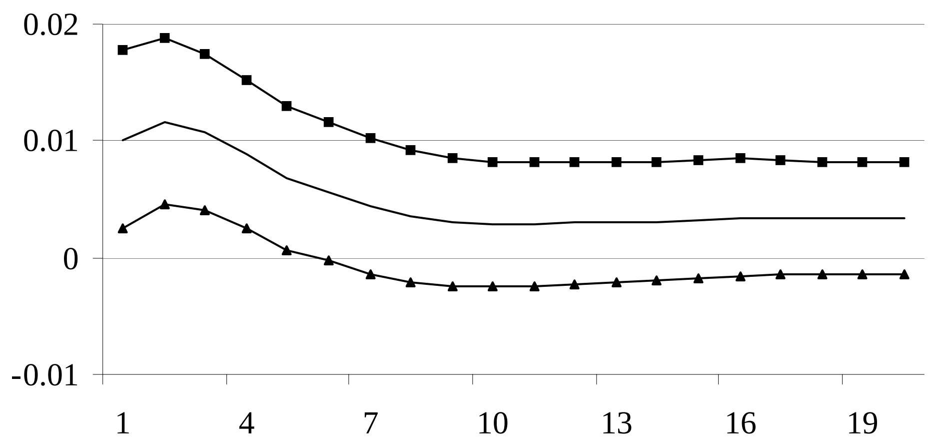

Figure IV. Momentum Profit Based on Expected Returns (Solid Line) with Two-Standard-Error Upper (Square) and Lower (Triangle) Bounds over Various Holding Periods

Table 1. Returns on Portfolios Sorted According to Past Returns

1	2	3	4	5	6	7	8	9	10	10-1
					1954:Q3-2002:Q4					
0.025	0033	0.035	0.035	0.037	0.037	0.038	0.038	0.042	0.047	**0.023**
										(2.858)
					1954:Q3-1978:Q4					
0.029	0.033	0.035	0.034	0.036	0.036	0.037	0.038	0.042	0.046	0.017
										(1.588)
					1979:Q1-2002:Q4					
0.020	0.032	0.036	0.036	0.039	0.039	0.039	0.038	0.041	0.048	**0.029**
										(2.429)

Note: The table reports summary statistics of returns on portfolios formed according to past returns. At the end of each quarter *t*, we sort stocks equally into ten portfolios according to returns in the past two quarters, ranging from the portfolio of stocks with the lowest past returns (first decile) to the portfolio of stocks with the highest past returns (tenth decile). These portfolios are held over the next two quarters. The last column is the momentum profit of buying past winners (column 10) and selling past losers (column 1).

Table 2. Returns on Portfolios Sorted according to Conditionally Expected Returns

1	2	3	4	5	6	7	8	9	10	10-1
					1954:Q3-2002:Q4					
0.033	0.034	0.035	0.036	0.036	0.037	0.039	0.041	0.043	0.044	**0.012**
										(3.297)
					1954:Q3-1978:Q4					
0.034	0.034	0.034	0.034	0.035	0.035	0.037	0.041	0.043	0.047	**0.012**
										(2.341)
					1979:Q1-2002:Q4					
0.031	0.034	0.037	0.038	0.038	0.040	0.040	0.041	0.044	0.042	**0.011**
										(2.336)

Note: The table reports summary statistics of returns on portfolios formed according to conditionally expected returns. At the end of each quarter *t*, we make a one-quarter-ahead forecast for returns on each stock using the consumption-wealth ratio, realized stock market variance, the stochastically detrended risk-free rate, and past stock market returns as predictive variables. We require at least two years of observations and use an expanding sample. We then sort stocks equally into ten portfolios according to this forecast, ranging from the portfolio of stocks with the lowest expected returns (first decile) to the portfolio of stocks with the highest expected returns (tenth decile). These portfolios are held over the next two quarters. The last column is the momentum profit of buying expected winners (column 10) and selling expected losers (column 1).

Table 3. Jensen's alpha Test for CAPM: 1954:Q3 – 2002:Q4

	1	2	3	4	5	6	7	8	9	10	10-1
alpha	-0.000	0.005	**0.007**	**0.008**	**0.007**	**0.007**	**0.008**	**0.009**	**0.101**	0.084	**0.009**
	(-0.084)	(1.230)	**(2.137)**	**(2.535)**	**(2.260)**	**(2.113)**	**(2.007)**	**(2.112)**	**(2.042)**	(1.374)	**(2.652)**
MKT	**1.221**	**1.010**	**0.923**	**0.922**	**0.968**	**1.020**	**1.085**	**1.157**	**1.243**	**1.397**	**0.176**
	(14.749)	**(15.319)**	**(14.906)**	**(16.303)**	**(15.943)**	**(15.575)**	**(15.918)**	**(15.975)**	**(15.052)**	**(13.911)**	**(3.383)**
Adj. R-Squared	0.654	0.712	0.724	0.757	0.745	0.737	0.719	0.706	0.676	0.635	0.087
GRS=2.931 (0.002)											

Note: The table reports Jensen's alpha test for CAPM using portfolios formed according to conditionally expected returns, as reported in Table 2. T-statistics are reported in the parentheses and bold denotes significant at the 5 percent level. See note of Table 2 for details about the portfolios. GRS is the Gibbons, Ross, and Shanken (1989) test for the null hypothesis that the intercepts are jointly equal to zero for the decile portfolios and the associated p-value is in parentheses.

Table 4. Jensen's alpha Test for the Fama and French Three-Factor Model: 1954:Q3 – 2002:Q4

	1	2	3	4	5	6	7	8	9	10	10-1
alpha	**-0.007**	-0.002	0.000	0.001	0.000	0.000	0.001	0.002	0.003	0.002	**0.010**
	(-2.521)	(-0.755)	(0.033)	(0.269)	(0.125)	(0.223)	(0.340)	(1.020)	(1.289)	(0.736)	**(3.062)**
MKT	**1.037**	**0.922**	**0.885**	**0.910**	**0.918**	**0.952**	**0.985**	**1.014**	**1.050**	**1.113**	0.076
	(24.539)	**(26.750)**	**(27.126)**	**(30.053)**	**(31.037)**	**(27.081)**	**(28.151)**	**(27.419)**	**(25.539)**	**(19.332)**	(1.232)
HML	**0.520**	**0.460**	**0.490**	**0.496**	**0.487**	**0.487**	**0.509**	**0.501**	**0.508**	**0.488**	-0.031
	(6.330)	**(7.575)**	**(8.506)**	**(8.296)**	**(7.327)**	**(7.246)**	**(7.834)**	**(8.038)**	**(7.100)**	**(5.808)**	(-0.293)
SMB	**1.169**	**0.767**	**0.622**	**0.531**	**0.623**	**0.722**	**0.860**	**1.005**	**1.193**	**1.497**	**0.328**
	(16.643)	**(13.322)**	**(13.979)**	**(14.183)**	**(15.027)**	**(16.000)**	**(18.727)**	**(20.660)**	**(21.681)**	**(18.130)**	**(4.115)**
Adj. R-Squared	0.906	0.910	0.914	0.926	0.927	0.928	0.935	0.940	0.935	0.917	0.186
GRS=1.895 (0.048)											

Note: The table reports Jensen's alpha test for the Fama and French (1993) three-factor model using portfolios formed according to conditionally expected returns, as reported in Table 2. T-statistics are reported in the parentheses and bold denotes significant at the 5 percent level. See note of Table 2 for details about the portfolios. GRS is the Gibbons, Ross, and Shanken (1989) test for the null hypothesis that the intercepts are jointly equal to zero for the decile portfolios and the associated p-value is in parentheses.

Table 5. Jensen’s alpha Test for the Four-Factor Model: 1954:Q3 – 2002:Q4

	1	2	3	4	5	6	7	8	9	10	10-1
alpha	-0.004	0.002	0.002	-0.002	0.002	0.002	0.002	0.002	0.002	-0.002	0.002
	(-1.246)	(0.755)	(0.956)	(0.798)	(0.827)	(0.875)	(1.034)	(0.997)	(0.672)	(-0.468)	(0.707)
MKT	**1.022**	**0.908**	**0.876**	**0.906**	**0.911**	**0.946**	**0.978**	**1.013**	**1.055**	**1.128**	0.105
	(25.332)	**(27.205)**	**(27.755)**	**(30.833)**	**(31.358)**	**(27.511)**	**(28.705)**	**(28.065)**	**(26.254)**	**(20.746)**	(1.920)
HML	**0.487**	**0.428**	**0.472**	**0.486**	**0.473**	**0.427**	**0.494**	**0.499**	**0.520**	**0.520**	0.033
	(6.453)	**(8.132)**	**(9.290)**	**(9.259)**	**(8.041)**	**(7.874)**	**(8.382)**	**(8.407)**	**(7.394)**	**(6.425)**	(0.332)
SMB	**1.136**	**0.734**	**0.603**	**0.521**	**0.609**	**0.707**	**0.844**	**1.002**	**1.206**	**1.530**	**0.394**
	(16.512)	**(13.521)**	**(14.349)**	**(13.219)**	**(14.386)**	**(16.240)**	**(18.883)**	**(21.260)**	**(22.451)**	**(19.156)**	**(5.397)**
WML	-0.111	**-0.110**	-0.063	-0.032	-0.048	-0.048	-0.051	-0.010	0.042	0.109	**0.220**
	(-1.707)	**(-2.115)**	(-1.160)	(-0.622)	(-0.947)	(-0.948)	(-1.073)	(-0.181)	(0.788)	(1.660)	**(3.558)**
Adj. R-Squared	0.909	0.914	0.916	0.926	0.927	0.928	0.936	0.940	0.935	0.919	0.259
GRS=1.483 (0.149)											

Note: The table reports Jensen’s alpha test for the Fama and French (1993) three-factor model augmented by a momentum factor using portfolios formed according to conditionally expected returns, as reported in Table 2. T-statistics are reported in the parentheses and bold denotes significant at the 5 percent level. See note of Table 2 for details about the portfolios. GRS is the Gibbons, Ross, and Shanken (1989) test for the null hypothesis that the intercepts are jointly equal to zero for the decile portfolios and the associated p-value is in parentheses.

Table 6. Unconditional CAPM and Campbell ICAPM

Model	γ	$\frac{\theta\psi_1}{\sigma}$	Risk Prices For MKT	CAY	MV	RREL	OIR
Panel A: Ten Size Portfolios							
CAPM	4.500						$\chi^2(9)$=20.004
	(3.178)						(0.018)
ICAPM	13.386	-5.406	3.752	9.849	8.187	-5.140	$\chi^2(8)$=6.595
	(2.685)	(-1.212)	(2.414)	(1.732)	(2.385)	(-1.638)	(0.581)
D-Test: CAPM vs. ICAPM $\chi^2(1)$=10.891 (0.001)							

Note: The table reports the estimation results of the unconditional Campbell ICAPM using returns on portfolios formed according to conditionally expected returns. We also estimate CAPM, which is a restricted version of ICAPM, in which risk prices of the predictive state variables are constrained to be zero. We estimate structural parameters γ and $\frac{\theta\psi_1}{\sigma}$ directly and then use them to back-out the risk prices of all factors. OIR is the Hansen's (1980) over-identifying restriction test; we also test CAPM vs. ICAPM using D-test proposed by Newey and West (1987). See Subsection IV.E for details.

Table 7. Factor Contributions to Returns on Portfolios Sorted According to Expected Returns

Portfolios	$\overline{er_i}$ (1)	$\overline{er_i} + (V_{ii}/2)$ (2)	MKT (3)	CAY (4)	MV (5)	RREL (6)	Error (7)
Panel A: Ten Size Portfolios							
1(Lowest)	1.08	1.86	2.63	0.41	-1.28	0.20	-0.11
2	1.54	2.04	2.17	0.23	-0.80	0.13	0.30
3	1.74	2.14	1.96	0.19	-0.44	0.14	0.30
4	1.81	2.20	1.97	0.09	-0.34	0.08	0.40
5	1.79	2.21	2.04	0.20	-0.45	0.20	0.21
6	1.86	2.33	2.17	0.24	-0.47	0.21	0.17
7	1.92	2.48	2.33	0.28	-0.55	0.23	0.18
8	2.06	2.69	2.50	0.42	-0.62	0.21	0.18
9	2.18	2.94	2.70	0.49	-0.76	0.24	0.26
10(Highest)	2.00	3.00	3.07	0.57	-0.80	0.27	-0.10
10-1	0.92	1.14	0.44	0.16	0.48	0.06	0.01

Note: The table reports the factor contributions to average returns on portfolios sorted according to conditionally expected returns, based on the estimation of ICAPM reported in Table 6. The first decile is the portfolio of stocks with the lowest expected returns and the tenth decile is the portfolio of stocks with the highest expected returns. "10–1" is the difference between returns on the tenth and first deciles. $\overline{er_i}$ is the average portfolio return in logs; $\overline{er_i} + (V_{ii}/2)$ is the average portfolio return with the adjustment of Jensen's inequality; MKT is the contribution by stock market risk; CAY is the consumption-wealth ratio; MV is realized stock market variance; RREL is the stochastically detrended risk-free rate; and Error is the pricing error. All numbers are reported in percentages at quarterly frequency.

Table 8. Portfolios Sorted According to Conditionally Expected Returns with Control for Microstructure

1	2	3	4	5	6	7	8	9	10	10-1
					Mean					
0.032	0.035	0.034	0.035	0.035	0.036	0.037	0.039	0.041	0.043	**0.011**
										(3.170)
					alpha from CAPM					
0.000	0.006	**0.007**	**0.008**	**0.007**	**0.007**	0.007	0.008	0.008	0.008	**0.007**
(0.013)	(1.709)	**(2.096)**	**(2.503)**	**(2.257)**	**(2.006)**	(1.796)	(1.821)	(1.611)	(1.280)	**(2.465)**
GRS=3.244(0.001)										
					alpha from the Fama and French Three-Factor model					
-0.007	-0.000	-0.000	0.001	0.000	0.000	-0.000	0.001	0.001	0.001	**0.008**
(-2.325)	(-.113)	(-.099)	(0.269)	(0.129)	(0.062)	(-.023)	(0.531)	(0.588)	(0.558)	**(2.898)**
GRS=2.328(0.013)										
					alpha from the Four-Factor Model					
-0.003	0.003	0.002	0.00	0.001	0.001	0.001	0.002	0.000	-0.001	0.002
(-.849)	(1.314)	(0.737)	(0.851)	(0.339)	(0.550)	(0.635)	(0.654)	(0.149)	(-.327)	(0.526)
GRS=1.480(0.150)										

Note: The table reports summary statistics of returns to portfolios formed according to conditionally expected returns. The specifications are the same as these in Table 2 except that (1) we exclude stocks with a price less than $1 at the end of the formation period and (2) skip a quarter between formation and holding periods. See notes of Tables 2-5 for other information.

Table 9. Portfolios Sorted According to Conditionally Expected Returns with Rolling Samples

1	2	3	4	5	6	7	8	9	10	10-1
					Mean					
0.033	0.035	0.036	0.036	0.036	0.037	0.038	0.041	0.043	0.044	**0.010**
										(2.824)
					alpha from CAPM					
0.000	0.005	**0.007**	**0.007**	**0.008**	**0.008**	**0.008**	**0.009**	0.009	0.008	**0.008**
(0.031)	(1.317)	**(2.077)**	**(2.198)**	**(2.355)**	**(2.181)**	**(2.075)**	**(2.130)**	(1.887)	(1.300)	**(2.196)**
GRS=2.399 (0.011)										
					alpha from the Fama and French Three-Factor model					
-0.007	-0.001	-0.000	-0.000	0.001	0.000	0.001	0.002	0.003	0.002	**0.008**
(-2.242)	(-.488)	(-.019)	(-.089)	(0.286)	(0.200)	(0.312)	(0.931)	(1.289)	(0.532)	**(2.470)**
GRS=1.549 (0.125)										
					alpha from the Four-Factor Model					
-0.003	0.003	0.003	0.002	0.002	0.001	0.001	0.002	0.002	-0.002	0.001
(-1.059)	(1.308)	(1.374)	(0.748)	(0.894)	(0.495)	(0.503)	(0.842)	(0.654)	(-.667)	(0.284)
GRS=1.981 (0.038)										

Note: The table reports summary statistics of returns on portfolios formed according to conditionally expected returns. The specifications are the same as these in Table 2 except that we use a rolling sample of 10 years. See notes of Tables 2-5 for other information.

Table 10. Portfolios Sorted According to Conditionally Expected Returns Using Idiosyncratic Volatility

1	2	3	4	5	6	7	8	9	10	10-1
					Mean					
0.032	0.036	0.036	0.037	0.036	0.036	0.038	0.040	0.042	0.042	**0.011**
										(2.613)
					alpha from CAPM					
-0.001	0.006	0.007	0.009	**0.009**	**0.009**	**0.010**	**0.012**	**0.013**	0.011	**0.012**
(-.116)	(0.997)	(1.388)	(1.963)	**(1.982)**	**(2.130)**	**(2.479)**	**(2.766)**	**(2.416)**	(1.560)	**(2.800)**
GRS=3.147 (0.001)										
					alpha from the Fama and French Three-Factor model					
-0.011	-0.004	-0.002	0.000	-0.000	0.000	0.002	0.004	0.005	0.003	**0.014**
(-2.770)	(-1.289)	(-.608)	(0.132)	(-.018)	(0.135)	(0.749)	(1.572)	(1.710)	(0.899)	**(3.321)**
GRS=2.005 (0.037)										
					alpha from the Four-Factor Model					
-0.006	-0.001	-0.001	0.001	0.000	0.001	0.003	0.004	0.004	0.002	0.008
(-1.315)	(-.365)	(-.197)	(0.469)	(0.173)	(0.537)	(1.183)	(1.571)	(1.366)	(0.412)	(1.832)
GRS=1.074 (0.387)										

Note: The table reports summary statistics of returns on portfolios formed according to conditionally expected returns. The specifications are the same as these in Table 2 except that we use the idiosyncratic volatility constructed by Guo and Savickas (2003) instead of the consumption-wealth ratio in the forecasting equation. The sample spans from 1965:Q4 to 2002:Q4. See notes of Tables 2-5 for other information.

Table 11. Returns on Portfolios Ranked by Raw Returns and Predicted Returns

	Raw Returns						
Predicted Returns	1 (low)	2	3	4	5 (high)	Difference (5)-(1)	t-stat ((5)-(1))
1(low)	2.83	3.36	3.45	3.43	3.92	1.09	1.65
2	3.47	3.63	3.52	3.64	3.86	0.38	0.59
3	3.13	3.57	3.60	3.80	4.30	1.17	1.87
4	3.25	3.91	4.10	4.04	4.53	**1.28**	2.19
5(high)	3.43	3.85	4.39	4.21	5.03	**1.60**	2.37
Difference (5)-(1)	0.60	0.49	**0.94**	**0.78**	**1.11**		
T-stat ((5)-(1))	1.62	1.32	2.59	2.20	3.08		

Note: The table reports returns on the 25 portfolios, which are the intersections of the two independent sorts according past returns and expected returns. Portfolios sorted according to past returns are in columns, ranging from the portfolio of stocks with the lowest past returns (column 1) to the portfolio of stocks with the highest past returns (column 5). Portfolios sorted according to expected returns are in rows, ranging from the portfolio of stocks with the lowest expected returns (row 1) to the portfolio of stocks with the highest expected returns (row 5). Bold denotes that the difference between returns on two portfolios is significant at the 5 percent level.

Table 12. Forecasting One-Quarter-Ahead Momentum Sorted According to Raw Returns

	Intercept	$r_{m,t-1}$	cay_{t-1}	$\sigma^2_{m,t-1}$	$rrel_{t-1}$	*D1*	$\bar{R}^2$
Panel A. 1952:Q3 – 2002:Q4							
1	**1.141**	-0.026	**-1.914**	**-9.326**	0.034		0.096
	(2.965)	(-0.214)	**(-2.837)**	**(-3.543)**	(0.015)		
2	**1.159**		**-1.948**	**-9.144**			0.105
	(2.817)		**(-2.686)**	**(-4.205)**			
3	**1.035**	0.092	**-1.698**	**-7.245**	1.081	**-0.107**	0.267
	(3.016)	(0.848)	**(-2.835)**	**(-3.222)**	(0.473)	**(-4.977)**	
Panel B. 1952:Q3 – 1977:Q4							
4	0.620	-0.151	-0.971	**-17.443**	6.547		0.225
	(1.422)	(-0.773)	(-1.247)	**(-3.187)**	(1.275)		
5	**1.181**		**-1.984**	**-15.424**			0.211
	(3.423)		**(-3.268)**	**(-3.048)**			
6	0.655	0.043	-1.015	**-13.997**	**9.128**	**-0.103**	0.390
	(1.642)	(0.238)	(-1.423)	**(-2.934)**	**(2.178)**	**(-4.097)**	
Panel C. 1978:Q1 – 2002:Q4							
7	**1.523**	-0.002	**-2.556**	**-9.507**	-1.062		0.065
	(2.162)	(-0.015)	**(-2.091)**	**(-2.928)**	(-0.440)		
8	**1.525**		**-2.560**	**-9.399**			0.083
	(2.159)		**(-2.073)**	**(-3.697)**			
9	**1.231**	0.070	-2.016	**-7.328**	-0.879	**-0.106**	0.220
	(1.982)	(0.531)	(-1.882)	**(-2.732)**	(-0.390)	**(-3.215)**	

Note: The table reports the regression results of the momentum profit (last column of Table 1) on predetermined variables. $r_{m,t-1}$ is lagged stock market return; cay_{t-1} is the consumption-wealth ratio; $\sigma^2_{m,t-1}$ is realized stock market variance; $rrel_{t-1}$ is the stochastically detrended risk-free rate; and *D1* is a dummy variable that is equal to 1 for the first quarter and zero otherwise. Bold denotes significant at the 5 percent level.