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Do the Fama–French Factors Proxy for Innovations in Predictive Variables?

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ABSTRACT

The Fama–French factors HML and SMB are correlated with innovations in variables that describe investment opportunities. A model that includes shocks to the aggregate dividend yield and term spread, default spread, and one-month Treasury-bill yield explains the cross section of average returns better than the Fama–French model. When loadings on the innovations in the predictive variables are present in the model, loadings on HML and SMB lose their explanatory power for the cross section of returns. The results are consistent with an ICAPM explanation for the empirical success of the Fama–French portfolios.

IN A SERIES OF PAPERS, Fama and French (1993, 1995, 1996) (FF hereafter) show that a three-factor model explains most of the cross-sectional variation in average returns of portfolios sorted by size and book-to-market. The three factors are the excess return of the market portfolio (R_M), the return of a portfolio long in high book-to-market stocks and short in low book-to-market stocks (R_{HML}), and the return of a portfolio long in small stocks and short in big stocks (R_{SMB}).

The impressive performance of the FF three-factor model has spurred an enthusiastic debate in the finance literature over the economic interpretation of the HML and SMB factors. Among the many competing explanations behind the success of the FF model is the one based on time-varying investment opportunities. Specifically, FF (1993) suggest that HML and SMB might proxy for state variables that describe time variation in the investment opportunity set. This risk-based explanation is in the context of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM).[1]

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[1] There exist other explanations for the success of the HML and SMB factors. Some of these include data snooping and other biases in the data (Lo and MacKinlay (1990) and Kothari, Shanken, and Sloan (1995)). Berk, Green, and Naik (1999) and Gomes, Kogan, and Zhang (2003) suggest that problems in the measurement of beta may explain the FF results. Ferson, Sarkissian, and Simin (1999) state that attribute-sorted portfolios may appear to be risk factors even when the

Is the FF model a good candidate for an intertemporal asset pricing model? Recent empirical research provides support for the risk-based explanation behind the HML and SMB factors. For the most part, this is done by relating the FF factors to macroeconomic variables and business cycle fluctuations. Liew and Vassalou (2000), for instance, show that HML and SMB help forecast future rates of economic growth, and both Lettau and Ludvigson (2001) and Vassalou (2003) show that accounting for macroeconomic risk reduces the information content of HML and SMB. The relation between the FF factors and GDP growth is consistent with an ICAPM explanation behind the three-factor model. According to this explanation, changes in the investment opportunity set are summarized by changes in future GDP growth.

However, changes in financial investment opportunities are not necessarily exclusively related to news about future GDP growth. Furthermore, Campbell (1996) points out that empirical implementations of the ICAPM model should not rely on choosing important macroeconomic variables. Instead, the factors in the model should be related to innovations in state variables that forecast future investment opportunities.

The goal of this paper is twofold. First, I examine an empirical implementation of the ICAPM in which the factors are innovations in state variables that forecast future investment opportunities. Second, I relate the FF factors to innovations in state variables to show that the FF model is consistent with an ICAPM explanation behind the size and book-to-market effects. This paper differs from the studies mentioned above since it does not rely on important macroeconomic variables such as GDP or consumption growth. In particular, I choose a set of relevant state variables including the short-term T-bill, term spread, aggregate dividend yield, and default spread. These state variables are chosen to model two aspects of the investment opportunity set, namely, the yield curve and the conditional distribution of asset returns.

By choosing variables that have forecasting power for future investment opportunities, this paper responds to Fama's (1991) and Cochrane's (2001) criticism that the ICAPM should not be used as a "fishing license" for choosing multiple factors. Only factors that forecast future investment opportunities should be admitted in the model. Furthermore, Cochrane (2001, p. 444) points out that "... though Merton's ... theory says that variables which predict market returns should show up as factors which explain cross-sectional variation in average returns, surprisingly few papers have actually tried to see whether this is true ... ." More recently, Brennan, Wang, and Xia (2004) use an ICAPM model in which the relevant state variables are the real interest rate and the Sharpe ratio. They test the pricing abilities of their model and have some success at explaining the book-to-market and size effects. In this paper, I consider a larger set of state variables, and in particular, I show that both the level and

attributes are unrelated to risk. Lakonishok, Shleifer, and Vishny (1994) argue that the book-to-market effect arises since investors overvalue companies that have performed well in the past. Daniel and Titman (1997) suggest that stocks' characteristics, rather than risks, are priced in the cross section of average returns.

the slope of the yield curve have important pricing implications. Chen (2003) models not only changes in future market returns, but also changes in future market volatility. He argues that if HML and SMB are to be explained in the context of his model, then they should forecast the market return and its volatility. He finds no empirical support for such forecasting ability of the FF factors. In this paper, I do not assume that HML and SMB have predictive abilities for the excess market return. Rather, I argue that they proxy for innovations in variables that possess such ability.

There are three main contributions in this study. First, I show that HML and SMB proxy for innovations in state variables that predict the excess market return and the yield curve. Second, I show that a model in which the factors are both the excess market return and innovations in the aggregate dividend yield, term spread, default spread, and one-month T-bill yield has a higher explanatory power than the FF three-factor model. In addition, the FF factors are not significant explanatory variables for the cross section of average returns in the presence of these innovations factors.

Third, I show that the model based on innovations in the dividend yield, term spread, default spread, and short-term T-bill is able to account for common time-varying patterns in returns. Namely, the model captures cross-sectional differences in sensitivities with respect to conditioning information. The FF model, however, is not successful at capturing the effect of conditioning information, as shown in Ferson and Harvey (1999). Therefore, the ICAPM specification that I consider is a good candidate for a conditional asset pricing model.

The rest of the paper is organized as follows. Section I presents the ICAPM framework of this study and the methods used to construct shocks in state variables. Section II presents the data and examines the relation between the FF factors and the innovations in the state variables. Section III runs different sets of cross-sectional regressions for 25 portfolios sorted by size and book-to-market, and also contains several robustness tests. Section IV summarizes and concludes.

I. The Determinants of Average Returns

A. The ICAPM Framework

The analysis in this paper assumes that asset returns are governed by the discrete-time version of the ICAPM of Merton (1973). According to the ICAPM, if investment opportunities change over time, then assets' exposures to these changes are important determinants of average returns in addition to the market beta. I follow the framework adopted by Campbell (1996) to model changes in the investment opportunity set. More precisely, I look at the innovations in state variables that capture uncertainty about investment opportunities in the future.

I assume the following general model for the unconditional expected excess returns on assets:

$$E(R_i) = \gamma_M \beta_{i,M} + \sum (\gamma_{u^K}) \beta_{i,u^K}, \forall i, \tag{1}$$

where $E(R_i)$ is the excess return of asset i, γ_M is the market risk premium, and γ_{u^K} is the price of risk for innovations in state variable K. The betas are the slope coefficients from the return-generating process

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \sum (\beta_{i,u^K}) u_t^K + \varepsilon_{i,t}, \forall i, \tag{2}$$

where $R_{i,t}$ is the return on asset i in excess of the risk-free rate at the end of period t, $R_{M,t}$ is the excess return on the market portfolio at the end of period t, and u_t^K is the innovation to state variable K at the end of period t. The innovation is the unexpected component of the variable. According to the asset pricing model, only the unexpected component of the state variable should command a risk premium. Note that the innovations to the state variables are contemporaneous to the excess market returns. This equation captures the idea that the market portfolio and the innovations to the state variables are the relevant risk factors.

Finally, it is important to specify a process for the time-series dynamics of the state variables in the model. I adopt the vector autoregressive (VAR) approach of Campbell (1996). I write the excess market return as the first element of a state vector z_t. The other elements of z_t are state variables that proxy for changes in the investment opportunity set. The assumption is that the demeaned vector z_t follows a first-order VAR, as given by

$$z_t = A z_{t-1} + u_t. \tag{3}$$

The residuals in the vector u_t are the innovation terms that are the risk factors in equation (2); therefore, $u_t^K \in u_t$ for all state variables K. These innovations are risk factors since they represent the surprise components of the state variables that proxy for changes in the investment opportunity set.

The model described by equations (1)–(3) links the time-series literature on asset returns to the cross-sectional literature. Campbell argues that this is a desirable feature of this model since researchers are less likely to detect spurious patterns when they must link time-series and cross-sectional findings. The model implies that priced factors should not be determined by running a factor analysis on the covariance matrix of returns or by selecting important macroeconomic variables. Rather, researchers should use innovations in variables that proxy for changes in the investment opportunity set in cross-sectional asset pricing studies.

My paper is different from Campbell's since I focus on relating the empirical success of the FF factors to innovations in state variables. In addition, I use portfolios sorted by size and book-to-market since these have proven to be among the most challenging sets of assets for existing asset pricing models. Unlike Campbell, I do not impose intertemporal restrictions on the risk prices in the model and I do not use labor income growth as a risk factor.

B. The State Variables of Interest

For the empirical implementation of the model described in the previous section, it is necessary to specify the identity of the state variables. In this paper I choose a set of state variables to model two aspects of the investment opportunity set, the yield curve and the conditional distribution of asset returns. In particular, I choose the short-term T-bill, term spread, aggregate dividend yield, and default spread.

The ICAPM dictates that the yield curve is an important part of the investment opportunity set. Furthermore, Long (1974) points out that the yield curve is important in an economy with a bond market. Therefore, I use the short-term T-bill yield (*RF*) and the term spread (*TERM*) to capture variations in the level and slope of the yield curve.[2]

In addition to the yield curve, the conditional distribution of asset returns is a relevant part of the investment opportunity set facing investors in the ICAPM world. There is growing evidence that the conditional distribution of asset returns, as characterized by its mean and variance, changes over time. The time-series literature has identified variables that proxy for variation in the mean and variance of returns. The aggregate dividend yield (*DIV*), the default spread (*DEF*), and interest rates are among the most common, which motivates their use in this paper.[3]

The variables described above are good candidates for state variables within the ICAPM. Merton (1973) states that stochastic interest rates are important for changing investment opportunities. In addition, the default spread, dividend yield, and interest rate variables have been used as proxies for time-varying risk premia under changing investment opportunities. Therefore, all these variables are likely to capture the hedging concerns of investors related to the changes in interest rates and to variations in risk premia.

Two other variables proposed as candidates for state variables within the ICAPM are the returns on the HML and SMB portfolios. FF (1993) show that these factors capture common variation in portfolio returns that is independent of the market and that carries a different risk premium. The goal of this paper is to examine whether the FF factors proxy for the state variables described before that have been shown to track time variation in the market risk premium and the yield curve. The analysis in this paper shows that the first set of state variables performs better in asset pricing tests than the FF three-factor model. In addition, the FF factors are no longer significant in the presence of innovations in the dividend yield, term spread, default spread, and short-term T-bill.

[2] Litterman and Scheinkman (1991) show that the two most important factors driving the term structure of interest rates are its level and its slope.

[3] The following is only a partial list of papers that document time variation in the excess market return and the variables they use: Campbell (1987), term spread; Campbell and Shiller (1988), dividend yield; Fama and Schwert (1977), T-bill rate; FF (1989), default spread. In this paper I model only time variation in the first moment of asset returns. Modeling the conditional second moment of the return distribution is beyond the scope of this paper.

C. Econometric Approach

The complete set of candidate state variables within the ICAPM framework examined in this paper includes the dividend yield, term spread, default spread, short-term T-bill, and the FF portfolios. I specify a vector autoregressive (VAR) process for this vector of state variables. The first element of the vector is the excess return on the market, R_M, while the other elements are *DIV, TERM, DEF, RF*, R_{HML}, and R_{SMB}, respectively.[4] For convenience, all variables in the state vector have been demeaned. The first-order VAR is

$$\begin{Bmatrix} R_{M,t} \\ DIV_t \\ TERM_t \\ DEF_t \\ RF_t \\ R_{HML,t} \\ R_{SMB,t} \end{Bmatrix} = A \begin{Bmatrix} R_{M,t-1} \\ DIV_{t-1} \\ TERM_{t-1} \\ DEF_{t-1} \\ RF_{t-1} \\ R_{HML,t-1} \\ R_{SMB,t-1} \end{Bmatrix} + u_t, \tag{4}$$

where u_t represents a vector of innovations for each element in the state vector. From u_t I extract six surprise series, which correspond to the dividend yield, term spread, default spread, one-month T-bill yield, and the FF factors. They are denoted u^{DIV}, u^{TERM}, u^{DEF}, u^{RF}, u^{HML}, and u^{SMB}, respectively.[5] This VAR represents a joint specification of the dynamics of all candidate state variables within the ICAPM. This specification treats the FF factors as potential candidates for state variables that command separate risk premia from the other variables. In the following sections of the paper I show that the subset of variables that proxy for time-varying risk premia and interest rates performs better than the subset that includes only the FF factors. In addition, the FF factors do not command significant risk premia in the cross section in the presence of innovations to the other state variables.

The specification of the VAR system above does not account for the possibility that the full information set used by investors is not observed by the econometrician. It is possible that investors use other information to predict movements in the yield curve and the conditional distribution of asset returns. However, the evidence that follows shows that there is a significant relation among the set of variables that proxy for time-series predictability, *DIV, TERM, DEF, RF*, and the set of variables that are associated with cross-sectional predictability, R_{HML}, R_{SMB}. Therefore, the state variables chosen by following the intuition of the ICAPM are likely to be relevant variables in the information set used by investors as well. Section II provides more details on the estimation of the VAR system.

[4] I thank an anonymous referee for suggesting this augmented VAR system.

[5] I also compute innovations by specifying an AR (1) process for each state variable (e.g., $TERM_t = c_0 + c_1 TERM_{t-1} + u_t^{TERM}$). The results are qualitatively similar to the ones presented for the VAR case.

The innovations derived from the VAR model are risk factors in addition to the excess return of the market portfolio. An asset's exposures to these risk factors are important determinants of its average return according to the ICAPM. To test the ICAPM specification, I use the Fama–MacBeth (1973) cross-sectional method, which is appropriate in this case since not all factors represent portfolio returns. In the first pass of this method, I specify a multiple time-series regression that provides estimates of the assets' loadings with respect to the market return and the innovations in the state variables. More precisely, I examine the following time-series regression for each asset:

$$\begin{aligned} R_{i,t} &= \alpha_i + \beta_{i,M} R_{M,t} + (\beta_{i,\hat{u}^{DIV}})\hat{u}_t^{DIV} + (\beta_{i,\hat{u}^{TERM}})\hat{u}_t^{TERM} + (\beta_{i,\hat{u}^{DEF}})\hat{u}_t^{DEF} \\ &\quad + (\beta_{i,\hat{u}^{RF}})\hat{u}_t^{RF} + (\beta_{i,\hat{u}^{HML}})\hat{u}_t^{HML} + (\beta_{i,\hat{u}^{SMB}})\hat{u}_t^{SMB} + \varepsilon_{i,t}, \forall i. \end{aligned} \tag{5}$$

The $\hat{u}$ terms represent the estimated surprises in the state variables. Note that the innovations terms are generated regressors and they appear on the right-hand side of the equation. However, as pointed out by Pagan (1984), the ordinary least squares (OLS) estimates of the parameters' standard errors will still be correct if the generated regressor represents the unanticipated part of a certain variable. On the other hand, if the $\hat{u}$ terms are only noisy proxies for the true surprises in the state variables, then the estimates of the factor loadings in the above regression will be biased downward, which in turn would bias the results against finding a relation between the innovations and asset returns. In Section III, I describe a Monte Carlo exercise that provides the small-sample distribution of the risk loadings.

The second step of the Fama–MacBeth procedure involves relating the average excess returns of all assets to their exposures to the risk factors in the model. I specify the cross-sectional relation

$$\begin{aligned} R_{i,t} &= \gamma_0 + \gamma_M \hat{\beta}_{i,M} + (\gamma_{\hat{u}^{DIV}})\hat{\beta}_{i,\hat{u}^{DIV}} + (\gamma_{\hat{u}^{TERM}})\hat{\beta}_{i,\hat{u}^{TERM}} + (\gamma_{\hat{u}^{DEF}})\hat{\beta}_{i,\hat{u}^{DEF}} \\ &\quad + (\gamma_{\hat{u}^{RF}})\hat{\beta}_{i,\hat{u}^{RF}} + (\gamma_{\hat{u}^{HML}})\hat{\beta}_{i,\hat{u}^{HML}} + (\gamma_{\hat{u}^{SMB}})\hat{\beta}_{i,\hat{u}^{SMB}} + e_{i,t}, \forall t. \end{aligned} \tag{6}$$

If assets' loadings with respect to the risk factors are important determinants of average returns, then the γ terms from the above regression should be significant—the γ terms represent the prices of risk for innovations in each state variable.

In general, I use two methods to compute the first-pass beta estimates used in the cross-sectional regression. First, I compute the full-sample betas in multiple regressions, as in Lettau and Ludvigson (2001). Second, I compute the betas with five-year rolling multiple regressions, as in Fama and MacBeth (1973). Both methods produce similar results. Therefore, I report estimates for the first method only.

Since the betas are estimated from the time-series regression in (5), they represent generated regressors in (6). This is the classical errors-in-variables problem, arising from the two-pass nature of this approach. Following Shanken (1992), I use a correction procedure that accounts for the errors-in-variables problem. Shanken's correction is designed to adjust for the overstated precision of the Fama–MacBeth standard errors. It assumes that the error terms from the time-series regression are independently and identically distributed over time, conditional on the time series of observations for the risk factors. The adjustment also assumes that the risk factors are generated by a stationary process. Jagannathan and Wang (1998) argue that if the error terms are heteroskedastic, then the Fama–MacBeth procedure does not necessarily result in smaller standard errors of the cross-sectional coefficients. In light of these two issues, I report both unadjusted and adjusted cross-sectional statistics.[6]

I also examine specifications of the system defined by equations (5) and (6) that contain only the market return and the FF factors, and only the market return and innovations to *DIV, TERM, DEF*, and *RF*. These specifications are discussed in detail in Section III.

II. Data and Time-Series Analysis

A. Data

In this study, I use monthly data for the period from July 1963 to December 2001.[7] The beginning of the period is set to July 1963 to coincide with the beginning of the period examined by FF (1992, 1993). The returns on the market portfolio, HML, and SMB are from Professor Ken French's website, as well as the returns on 25 portfolios sorted by size and book-to-market. The 25 portfolios are the test assets; they have become the benchmark in testing competing asset pricing models. These assets represent one of the most challenging set of portfolios in the asset pricing literature.

[6] I also examine a different estimation approach of the asset pricing model, based on generalized method of moments (GMM). GMM makes it possible to estimate the innovations terms in (4) and the prices of risk in (6) simultaneously. The model takes the form

$$E_t[M_{t+1}(1 + R_{i,t+1})] = 1,$$

where $R_{i,t+1}$ is the return of portfolio i at time $t+1$, $M_{t+1} = b_0 + b'F_{t+1}$, and $F_{t+1} = [R_M, u^{DIV}, u^{TERM}, u^{DEF}, u^{RF}, u^{HML}, u^{SMB}]$. The risk factors in F that represent innovations to state variables are the residuals in the vector u in the following first-order VAR:

$$z_{t+1} = Az_t + u_{t+1}.$$

The vector z consists of the demeaned values of the excess market return, the dividend yield, the term spread, the default spread, the short-term T-bill, and the FF factors HML and SMB.

I estimate the innovations from the VAR system and the coefficients in the stochastic discount factor in one step. To do so, I stack the moment conditions of the VAR on top of the moment conditions of the asset pricing model,

$$g(A, b_0, b) = \begin{bmatrix} E[u_{t+1} \otimes z_t] \\ E[M_{t+1}(1 + R_{t+1}) - 1] \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}.$$

The results based on the GMM estimation are very similar to those derived through the two-step Fama–MacBeth procedure. Further details about the GMM estimation are available upon request.

[7] I also perform the entire analysis for the sample period examined by FF (1992, 1993): July 1963 to December 1991. The results are very similar to those reported in the paper and are omitted for the sake of brevity. However, they are readily available upon request.

In addition to the FF factors, I use four other variables as state variables in the context of the ICAPM. These are the dividend yield of the CRSP value-weighted portfolio (computed as the sum of dividends over the last 12 months, divided by the level of the index), the difference between the yields of a 10-year and a 1-year government bond (term spread), the difference between the yields of a long-term corporate Baa bond and a long-term government bond (default spread), and the 1-month T-bill yield. Data on bond yields are from the FRED® database of the Federal Reserve Bank of St. Louis. The T-bill yield and the term spread are used to measure the level and slope of the yield curve, respectively. The new empirical evidence in this paper is that the HML and SMB portfolios are significantly correlated with the unexpected components of the variables that have been shown to describe time variation in risk premia and interest rates. In addition, an asset pricing model in which the factors are the market return and innovations to *DIV, TERM, DEF*, and *RF* performs better than the FF model and captures common time-varying patterns in returns.

B. VAR Estimation

The state variable candidates are the FF factors and the four predictive variables described above. All are included in a first-order VAR system. Campbell (1996) emphasizes that it is hard to interpret estimation results for a VAR factor model unless the factors are orthogonalized and scaled in some way. In his paper the innovations to the state variables are orthogonal to both the excess market return and labor income. Following Campbell, I triangularize the VAR system in equation (4) in a similar way: The innovation in the excess market return is unaffected, the orthogonalized innovation in *DIV* is the component of the original *DIV* innovation orthogonal to the excess market return, and so on.[8] The orthogonalized innovation to *DIV* is a change in the dividend/price ratio with no change in the market return; therefore, it can be interpreted as a shock to the dividend. Similarly, shocks to the term spread, default spread, short-term rate, and the FF factors are orthogonal to the contemporaneous stock market return. As in Campbell (1996), I also scale all innovations to have the same variance as the innovation in the excess market return.

Orthogonalizing the innovations to the state variables with respect to the excess market return has an additional advantage. The coefficient in front of the market factor in the multiple time-series regression will be equal to the simple market beta computed in a univariate time-series regression. This is a convenient way to assess whether the innovations to the state variables add explanatory power to the simple CAPM model, that is, it is a way of testing whether the ICAPM collapses to the simple CAPM.

[8] The correlation between the excess market return and the innovation in *DIV* that is not orthogonalized is −0.89. Campbell (1996) reports a similar result and uses that as part of the motivation behind forming innovations orthogonal to the excess market return.

Table I

Time-Series Regressions Showing the Contemporaneous Relations between Innovations in State Variables and the Fama–French Factors

This table presents time-series regressions of innovations in the dividend yield ($\hat{u}_t^{DIV}$), term spread ($\hat{u}_t^{TERM}$), default spread ($\hat{u}_t^{DEF}$), and 1-month T-bill yield ($\hat{u}_t^{RF}$) on the excess market return, R_M, and the Fama–French factors R_{HML} and R_{SMB}. The innovations to the state variables are computed in a VAR system. The t-statistics are below the coefficients and are corrected for heteroskedasticity and autocorrelation using the Newey–West estimator with five lags. The Adjusted R^2 is reported in percentage form. The sample period is from July 1963 to December 2001.

Regression: $\hat{u}_t = c_0 + c_1 R_{M,t} + c_2 R_{HML,t} + c_3 R_{SMB,t} + \varepsilon_t$					
Dep. Variable	c_0	c_1	c_2	c_3	Adj. R^2
$\hat{u}_t^{DIV}$	0.00	−0.08	−0.30	−0.01	3.00
	0.85	−0.70	−2.43	−0.09	
$\hat{u}_t^{TERM}$	−0.00	0.06	0.24	0.03	2.00
	−0.56	0.75	2.30	0.59	
$\hat{u}_t^{DEF}$	−0.00	0.07	0.17	−0.12	2.00
	−0.38	1.11	2.10	−1.92	
$\hat{u}_t^{RF}$	0.00	−0.04	−0.13	0.01	0.00
	0.36	−0.51	−1.36	0.14	

It is interesting to note that the returns on the FF factors are very highly correlated with their respective innovation series. For example, the correlation between $R_{HML,t}$ and $\hat{u}_t^{HML}$ is 0.90, while the correlation between $R_{SMB,t}$ and $\hat{u}_t^{SMB}$ is 0.92. Therefore, the returns on the HML and SMB portfolios are good proxies for the innovations associated with these variables.

C. Relation between R_{HML} and R_{SMB} and the VAR Innovations

As a first step toward testing whether the FF factors proxy for innovations in state variables that track investment opportunities, I examine the joint distribution of R_{HML} and R_{SMB} and innovations to *DIV, TERM, DEF*, and *RF*. I run the time-series regression

$$\hat{u}_t = c_0 + c_1 R_{M,t} + c_2 R_{HML,t} + c_3 R_{SMB,t} + \varepsilon_t \tag{7}$$

for each series of innovations in the state variables. The results for these regressions are presented in Table I, with the corresponding t-statistics, below the coefficients, corrected for heteroskedasticity and autocorrelation. Innovations in the dividend yield, $\hat{u}_t^{DIV}$, covary negatively and significantly with the return on HML. In addition, $\hat{u}_t^{TERM}$ covaries positively and significantly with the HML return. These results are robust to the presence of the market factor in the regression. The return on the HML portfolio covaries positively and significantly with $\hat{u}_t^{DEF}$, while the return on the SMB factor covaries negatively with $\hat{u}_t^{DEF}$ (the corresponding t-statistic is marginally significant). The last regression in Table I indicates that the FF factors are not significant determinants of innovations in the T-bill yield. The results in the table remain unchanged if the independent variables in the equation above are the innovations to R_{HML} and R_{SMB} derived from the VAR system.[9]

A recent paper by Hahn and Lee (2003) also provides evidence that HML is related to a *TERM* factor, while SMB is related to a *DEF* factor. The authors use simple changes in the term spread and the default spread to measure their *TERM* and *DEF* variables. There is a major difference between my paper and Hahn and Lee (2003), however: They do not show whether the model they propose is a good conditional model. Given the criticism of the FF model by Ferson and Harvey (1999), it is important to verify the asset pricing abilities of a model that is proposed as an alternative to the FF model. In addition, I include the FF factors in the same VAR system as the other state variables. This enables the joint specification of the time-series dynamics of all factors in the model.

As pointed out by FF (1989), the values of the term spread signal that expected market returns are low during expansions and high during recessions. In addition, FF document that the term spread very closely tracks the short-term fluctuations in the business cycle. Therefore, positive shocks to the term premium are associated with bad times in terms of business conditions, while negative shocks are associated with good times. In light of the results documented by Petkova and Zhang (2004), value stocks are riskier than growth stocks in bad times and less risky during good times, the relation between HML and shocks to the term spread seems natural.

Another interpretation of the relation between shocks to the term spread and the HML portfolio is in the context of cash flow maturities of assets. This point is discussed by Cornell (1999) and Campbell and Vuolteenaho (2004). The argument is that growth stocks are high-duration assets, which makes them similar to long-term bonds and more sensitive to innovations in the long end of the term structure. Similarly, value stocks have lower duration than growth stocks, which makes them similar to short-term bonds and more sensitive to shocks to the short end of the yield curve.

Chan and Chen (1991) have argued that small firms examined in the literature tend to be marginal firms, that is, they generally have lost market value due to poor performance, they are likely to have high financial leverage and cash flow problems, and they are less likely to survive poor economic conditions. In light of this argument, it is reasonable to assume that small firms will be more sensitive to news about the state of the business cycle. Therefore, it is puzzling that I find no significant relation between SMB and surprises to the term spread. Innovations in the term spread seem to be mostly related to HML. This observation suggests that the HML portfolio might represent risk related to cash flow maturity, captured by unexpected movements in the slope of the term structure.

[9] The R^2s in the regressions reported in Table I are rather low. This does not imply, however, that the innovations in the state variables cannot price assets as well as the FF factors. It could be the case that only the information in the FF factors correlated with the state variables is relevant for the pricing of risky assets. A similar point is made by Vassalou (2003).

Innovations in default spread, u_t^{DEF}, stand for changes in forecasts about expected market returns and changes in forecasts about default spread. FF (1989) show that the default premium tracks time variation in expected returns that tends to persist beyond the short-term fluctuations in the business cycle. A possible explanation for the negative relation between SMB and shocks to the default spread could be that bigger stocks are able to track long-run trends in the business cycle better than the smaller stocks. The result that HML is also related to shocks in the default spread is consistent with the interpretation of HML as a measure of distress risk. [10]

In summary, the empirical literature documents that both value and small stocks tend to be under distress, with high leverage and cash flow uncertainty. The results in this study suggest that the book-to-market factor might be related to asset duration risk, measured by the slope of the term structure, while the size factor is most likely related to asset distress risk, measured by the default premium.

It is reasonable to test whether the significant relation between the state variables surprises and the FF factors gives rise to the significant explanatory power of HML and SMB in the cross section of returns. In the next section, I first examine whether HML and SMB remain significant risk factors in the presence of innovations to the other state variables. The results from the cross sectional regressions suggest that HML and SMB lose their explanatory power for the cross section of returns once accounting for the other variables. This supports an ICAPM explanation behind the empirical success of the FF three-factor model.

III. Cross-Sectional Regressions

A. Incremental Explanatory Power of the Fama–French Factors

In this section, I examine the pricing performance of the full set of state variables considered before over the period from July 1963 to December 2001.[11] The full set of state variables consists of the dividend yield, term spread, default spread, short-term T-bill yield, and the FF factors. The innovations to these state variables derived from a VAR system are risk factors in the ICAPM model. The objective is to test whether an asset's loadings with respect to these risk factors are important determinants of its average return.

The first specification that I examine is

$$\begin{aligned} R_{i,t} = {} & \gamma_0 + \gamma_{MKT}\hat{\beta}_{i,MKT} + (\gamma_{\hat{u}^{DIV}})\hat{\beta}_{i,\hat{u}^{DIV}} + (\gamma_{\hat{u}^{TERM}})\hat{\beta}_{i,\hat{u}^{TERM}} + (\gamma_{\hat{u}^{DEF}})\hat{\beta}_{i,\hat{u}^{DEF}} \\ & + (\gamma_{\hat{u}^{RF}})\hat{\beta}_{i,\hat{u}^{RF}} + (\gamma_{\hat{u}^{HML}})\hat{\beta}_{i,\hat{u}^{HML}} + (\gamma_{\hat{u}^{SMB}})\hat{\beta}_{i,\hat{u}^{SMB}} + e_{i,t}, \end{aligned} \tag{8}$$

[10] The distress risk interpretation of the book-to-market effect is advocated by FF (1992, 1993, 1995, 1996) and Chen and Zhang (1998), among others.

[11] I also perform tests over the period from 1953:05 to 2001:12. The results are qualitatively similar to those for the sample period presented in the paper. The date 1953:05 indicates the beginning of the period for which u_t^{TERM} and u_t^{DEF} data become available from FRED®.

Table II

Cross-Sectional Regressions Showing the Incremental Explanatory Power of the Fama–French Factor Loadings

This table presents Fama–MacBeth cross-sectional regressions using the excess returns on 25 portfolios sorted by book-to-market and size. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed as percentage per month. The table presents results for the model including the excess market return, R_M, and innovations in the dividend yield, term spread, default spread, 1-month T-bill yield, and the Fama–French factors HML and SMB. The Adjusted R^2 follows Jagannathan and Wang (1996) and is reported in percentage form. The first set of t-statistics, indicated by FM t-stat, stands for the Fama–MacBeth estimate. The second set, indicated by SH t-stat, adjusts for errors-in-variables and follows Shanken (1992). The table examines the sample period from July 1963 to December 2001.

The Model with Innovations in All State Variables									
	γ_0	γ_M	$\gamma_{\hat{u}^{DIV}}$	$\gamma_{\hat{u}^{TERM}}$	$\gamma_{\hat{u}^{DEF}}$	$\gamma_{\hat{u}^{RF}}$	$\gamma_{\hat{u}^{HML}}$	$\gamma_{\hat{u}^{SMB}}$	Adj. R^2
Estimate	1.11	−0.57	−0.83	3.87	0.37	−2.90	0.42	0.41	77.26
FM t-stat	3.29	−1.45	−0.94	3.53	0.42	−3.33	1.62	1.75	
SH t-stat	2.36	−1.10	−0.69	2.56	0.31	−2.44	1.40	1.56	

where the $\hat{\beta}$ terms stand for exposures to the corresponding factor, while the γ terms stand for the reward for bearing the risk of that factor. The $\hat{\beta}$ terms are the independent variables in the regression, while the average excess returns of the assets are the dependent variables. If loadings with respect to innovations in a state variable are important determinants of average returns, then there should be a significant price of risk associated with that state variable.

Table II presents results for this cross-sectional regression. Loadings on $\hat{u}^{TERM}$ represent an important cross-sectional determinant of average returns; this result is robust to the errors-in-variables adjustment. Under the errors-in-variables correction, the t-statistic for the hypothesis $H_0 : \gamma_{\hat{u}^{TERM}} = 0$ is 2.56. Loadings on $\hat{u}^{RF}$ are also significant. This result is robust to Shanken's adjustment as well, with a corresponding t-statistic of −2.44. The prices of risk related to dividend yield and default spread surprises are not significant.

This table shows that the exposures of assets to innovations in R_{HML} and R_{SMB} are not significant variables in the cross section in the presence of betas with respect to surprises in the other state variables. The corresponding t-statistics are 1.40 and 1.56, respectively, under the errors-in-variables correction. Therefore, based on the results presented in Table II, the hypothesis that innovations in the dividend yield, term spread, default spread, and short-term T-bill span the information contained in the FF factors cannot be rejected.

B. A Model Based on R_M and Innovations in DIV, TERM, DEF, and RF

In this part of the paper I examine two separate groups from the set of state variable innovations. The first group contains only the FF factors, while the second one contains only innovations in the variables associated with time-series predictability, that is, the dividend yield, term spread, default spread, and short-term T-bill. Therefore, I examine two different asset pricing specifications, each one involving the two-step Fama–MacBeth procedure,

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \beta_{i,HML} R_{HML,t} + \beta_{i,SMB} R_{SMB,t} + \varepsilon_{i,t}, \forall i, \tag{9}$$

and

$$R_{i,t} = \gamma_0 + \gamma_M \hat{\beta}_{i,M} + \gamma_{HML} \hat{\beta}_{i,HML} + \gamma_{SMB} \hat{\beta}_{i,SMB} + e_{i,t}, \forall t, \tag{10}$$

which corresponds to the FF model,[12] and

$$\begin{aligned} R_{i,t} = \alpha_i &+ \beta_{i,M} R_{M,t} + (\beta_{i,\hat{u}^{DIV}}) \hat{u}_t^{DIV} + (\beta_{i,\hat{u}^{TERM}}) \hat{u}_t^{TERM} \\ &+ (\beta_{i,\hat{u}^{DEF}}) \hat{u}_t^{DEF} + (\beta_{i,\hat{u}^{RF}}) \hat{u}_t^{RF} + \varepsilon_{i,t}, \forall i, \end{aligned} \tag{11}$$

and

$$\begin{aligned} R_{i,t} = \gamma_0 &+ \gamma_M \hat{\beta}_{i,M} + (\gamma_{\hat{u}^{DIV}}) \hat{\beta}_{i,\hat{u}^{DIV}} + (\gamma_{\hat{u}^{TERM}}) \hat{\beta}_{i,\hat{u}^{TERM}} \\ &+ (\gamma_{\hat{u}^{DEF}}) \hat{\beta}_{i,\hat{u}^{DEF}} + (\gamma_{\hat{u}^{RF}}) \hat{\beta}_{i,\hat{u}^{RF}} + e, \forall t, \end{aligned} \tag{12}$$

which corresponds to a model in which the relevant risk factors are innovations to predictive variables.[13] The objective is to compare the pricing performance of these two models for the cross section of returns sorted by book-to-market and size. The second specification is motivated by the previous observation that HML and SMB do not add explanatory power to the set of state variables that are associated with time-series predictability.

B.1. The Pattern of the Factor Loadings

Here I report the estimates of the factor loadings computed in the first-pass time-series regressions (9) and (11). I also present joint tests of the significance of the corresponding loadings, computed from a SUR system. I do this in order to show that the innovations factors are relevant in the sense that the 25 portfolios load significantly on them. Table III presents results for the FF three-factor model for the period from July 1963 to December 2001. The factor loadings in the table are consistent with those reported by FF (1993) for a shorter sample period.

[12] Note that the risk factors in this specification are the actual returns on the HML and SMB portfolio. If these returns are substituted with the corresponding innovations to HML and SMB derived from the VAR system, the results are qualitatively very similar. This indicates that the FF factor returns and their VAR innovations are good proxies for each other. In addition, using the actual returns on the HML and SMB portfolios makes for an easier comparison with previous studies of the FF model that use these returns.

[13] The innovations to the state variables used in this specification are still computed in a VAR system that includes the FF factors.

Table III

Loadings on the Fama–French Factors from Time-Series Regressions

This table reports loadings on the excess market return, R_M, and the Fama–French factors R_{HML} and R_{SMB} computed in time-series regressions for 25 portfolios sorted by size and book-to-market. The corresponding t-statistics are also reported and are corrected for autocorrelation and heteroskedasticity using the Newey–West estimator with five lags. The sample period is from July 1963 to December 2001. The intercepts are in percentage form. The last column reports F-statistics and their corresponding p-values from an SUR system, testing the joint significance of the corresponding loadings. The p-values are in percentage form. R^2s from each time-series regression are reported in percentage form.

Regression: $R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \beta_{i,HML} R_{HML,t} + \beta_{i,SMB} R_{SMB,t} + \varepsilon_{i,t}$

	Low	2	3	4	High	Low	2	3	4	High	
			α					t_α			F
Small	−0.38	0.01	0.04	0.18	0.12	−3.40	0.18	0.56	2.84	1.91	2.96
2	−0.17	−0.10	0.08	0.08	−0.00	−2.25	−1.45	1.15	1.28	−0.01	0.01
3	−0.07	−0.00	−0.09	0.01	0.00	−1.03	−0.03	−1.26	0.17	0.06	
4	0.16	0.21	−0.08	0.04	−0.05	1.67	−2.27	−0.99	0.61	−0.54	
Large	0.21	−0.04	−0.02	−0.09	−0.21	3.25	−0.53	−0.27	−1.29	−2.36	
			β_M					t_{β_M}			F
Small	1.04	0.96	0.93	0.92	0.98	44.38	39.40	50.88	46.60	43.39	>100
2	1.11	1.03	1.00	0.99	1.08	48.84	45.42	46.47	60.69	52.11	<0.01
3	1.09	1.07	1.03	1.01	1.10	52.59	38.53	32.93	52.70	38.97	
4	1.05	1.11	1.08	1.03	1.17	46.03	36.33	36.86	41.15	36.74	
Large	0.96	1.04	0.99	1.01	1.04	45.08	49.22	36.71	46.18	31.59	
			β_{HML}					$t_{\beta_{HML}}$			F
Small	−0.31	0.09	0.31	0.47	0.69	−5.86	1.79	9.62	14.97	17.10	>100
2	−0.38	0.18	0.43	0.59	0.76	−8.52	2.96	7.36	13.97	23.28	<0.01
3	−0.43	0.22	0.52	0.67	0.82	−14.90	3.10	7.39	10.58	15.94	
4	−0.45	0.26	0.51	0.61	0.83	−10.55	3.42	7.43	11.92	16.07	
Large	−0.38	0.14	0.27	0.64	0.85	−10.47	2.58	5.65	11.82	20.56	
			β_{SMB}					$t_{\beta_{SMB}}$			F
Small	1.41	1.33	1.12	1.04	1.09	36.39	24.68	36.50	24.34	25.40	>100
2	1.00	0.89	0.75	0.70	0.82	27.61	18.51	15.90	25.31	25.68	<0.01
3	0.72	0.51	0.44	0.38	0.53	24.97	7.68	6.81	8.28	8.87	
4	0.37	0.20	0.16	0.20	0.26	9.26	3.42	2.64	6.70	4.22	
Large	−0.26	−0.24	−0.24	−0.22	−0.08	−9.25	−6.92	−6.12	−6.81	−2.11	

		R^2		
92.61	94.32	94.89	94.51	94.58
95.16	93.99	93.56	93.85	94.62
94.88	90.22	89.49	89.69	90.31
93.52	88.31	87.65	88.41	85.77
93.35	89.79	84.32	87.39	80.60

Table IV presents results for the model with R_M, $\hat{u}_t^{DIV}$, $\hat{u}_t^{TERM}$, $\hat{u}_t^{DEF}$, and $\hat{u}_t^{RF}$ over the same period. An F-test implies that the 25 loadings on innovations to the term spread are jointly significant, with the corresponding p-value being 0.47%. Furthermore, portfolios' loadings on $\hat{u}_t^{TERM}$ are related to book-to-market: Within each size quintile, the loadings increase monotonically from lower to higher book-to-market quintiles. In fact, the portfolios within the lowest book-to-market quintile have negative sensitivities with respect to $\hat{u}_t^{TERM}$, while the portfolios within the highest book-to-market quintile have positive loadings on $\hat{u}_t^{TERM}$. This pattern closely resembles the one observed in Table III for the loadings on R_{HML}.

Similarly, loadings on shocks to default spread are jointly significant in Table IV, with the corresponding p-value being 0.24%. Moreover, the slopes on $\hat{u}_t^{DEF}$ are systematically related to size. Within each book-to-market quintile, the loadings increase almost monotonically from negative values for the smaller size quintiles to positive values for the larger size quintiles. This pattern closely resembles the mirror image of the one observed in Table III for the loadings on R_{SMB}. The slopes on dividend yield and T-bill innovations do not exhibit any systematic patterns related to size or book-to-market. However, both of these are jointly significant.

Note that the R^2s in the time-series regressions with the innovations factors are smaller than those in the regressions with the FF factors. This indicates that potential errors-in-variables problems that arise in measuring the factor loadings will be more serious in the case of the innovations terms. Therefore, the results will be potentially biased against finding significant factor loadings on the shocks to the predictive variables.[14]

B.2. The Prices of Risk

Panels A and B of Table V contain the results for equations (10) and (12) that correspond to the second pass of the Fama–MacBeth method. Since the dependent variables in the two regressions are excess returns, the intercept, γ_0, of each cross-sectional regression should be zero. This hypothesis is strongly rejected in the case of the FF model: The t-statistic reported in Panel A is 3.19 under the errors-in-variables adjustment. Panel B reveals that the intercept in the model with the four innovations factors is not significant at any conventional level under Shanken's adjustment.

Loadings on $\hat{u}^{TERM}$ and $\hat{u}^{RF}$ continue to be important cross-sectional determinants of average returns. Under the errors-in-variables correction, the t-statistics for the hypotheses $H_0 : \gamma_{\hat{u}^{TERM}} = 0$ and $H_0 : \gamma_{\hat{u}^{RF}} = 0$ are 2.79 and -2.40, respectively. The prices of risk related to dividend yield and default spread surprises are not individually significant.

Panel A also reveals that loadings on HML represent a significant factor in the cross section of the 25 portfolios, even after correcting for the sampling error

[14] Kan and Zhang (1999) emphasize that checking the joint significance of the assets' factor loadings is an important step in detecting useless factors in the cross section.

Table IV

Loadings on R_M, $\hat{u}_t^{DIV}$, $\hat{u}_t^{TERM}$, $\hat{u}_t^{DEF}$, and $\hat{u}_t^{RF}$ from Time-Series Regressions

This table reports loadings on the excess market return, R_M, and innovations in the dividend yield ($\hat{u}_t^{DIV}$), term spread ($\hat{u}_t^{TERM}$), default spread ($\hat{u}_t^{DEF}$), and short-term T-bill ($\hat{u}_t^{RF}$) computed in time-series regressions for 25 portfolios sorted by size and book-to-market. The corresponding t-statistics are also reported and are corrected for autocorrelation and heteroskedasticity using the Newey–West estimator with five lags. The sample period is from July 1963 to December 2001. The last column reports F-statistics and their corresponding p-values from an SUR system, testing the joint significance of the corresponding loadings. The p-values are in percentage form. R^2s from each time-series regression are reported in percentage form.

Regression: $R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \beta_{i,\hat{u}^{DIV}} \hat{u}_t^{DIV} + \beta_{i,\hat{u}^{TERM}} \hat{u}_t^{TERM} + \beta_{i,\hat{u}^{DEF}} \hat{u}_t^{DEF} + \beta_{i,\hat{u}^{RF}} \hat{u}_t^{RF} + \varepsilon_{i,t}$

	Low	2	3	4	High	Low	2	3	4	High	
	β_{MKT}					$t_{\beta_{MKT}}$					F
Small	1.44	1.23	1.09	1.01	1.02	24.20	22.74	20.76	19.57	18.87	>100
2	1.44	1.18	1.04	0.98	1.05	31.33	25.11	22.63	21.90	18.76	<0.01
3	1.38	1.12	0.98	0.90	0.98	39.96	32.34	22.52	21.58	17.66	
4	1.27	1.08	0.97	0.90	0.99	45.46	29.07	24.02	23.95	19.60	
Large	1.01	0.95	0.85	0.78	0.78	42.69	36.55	26.89	20.47	15.34	
	$\beta_{\hat{u}^{DIV}}$					$t_{\beta_{\hat{u}^{DIV}}}$					F
Small	4.75	0.43	−5.02	−5.61	−7.88	0.76	0.08	−0.89	−1.10	−1.44	2.33
2	3.38	−4.01	−7.66	−6.76	−6.51	0.76	−0.79	−1.55	−1.35	−1.09	0.02
3	7.45	−1.30	−5.91	−8.27	−9.18	2.34	−0.35	−1.16	−1.53	−1.36	
4	8.65	−5.83	−6.17	−8.18	−11.81	2.90	−1.29	−1.21	−1.72	−2.04	
Large	−0.78	−3.49	−1.73	−9.69	−9.50	−0.29	−1.18	−0.47	−1.83	−1.49	
	$\beta_{\hat{u}^{TERM}}$					$t_{\beta_{\hat{u}^{TERM}}}$					F
Small	1.51	1.04	1.69	2.82	8.68	0.26	0.26	0.47	0.79	2.24	1.89
2	−8.21	−2.73	−0.19	1.36	5.16	−1.87	−0.75	0.06	0.46	1.44	0.47
3	−6.34	−3.52	−1.72	2.08	4.39	−1.77	−1.17	−0.55	0.55	1.18	
4	−0.73	−1.51	0.21	0.02	2.13	−0.26	−0.59	0.06	0.01	0.54	
Large	−5.98	−3.26	0.78	−0.90	2.90	−2.22	−1.37	0.31	−0.26	0.74	
	$\beta_{\hat{u}^{DEF}}$					$t_{\beta_{\hat{u}^{DEF}}}$					F
Small	−15.45	−14.54	−6.86	−4.79	−8.58	−2.27	−2.17	−1.39	−1.09	−1.68	1.99
2	−10.03	−5.90	−4.78	0.82	−2.20	−2.04	−1.62	−1.37	0.22	−0.49	0.24
3	−11.17	0.22	1.73	4.03	0.81	−2.75	0.08	0.49	1.15	0.18	
4	−5.80	4.81	4.80	8.03	1.08	−2.10	1.92	1.44	2.50	0.25	
Large	−2.45	3.99	9.12	7.25	2.56	−0.96	1.91	3.85	1.91	0.63	
	$\beta_{\hat{u}^{RF}}$					$t_{\beta_{\hat{u}^{RF}}}$					F
Small	4.07	−2.58	0.07	1.03	2.77	0.77	−0.50	0.01	0.22	0.56	1.76
2	−4.37	−5.20	−6.25	−4.57	0.97	−1.00	−1.19	−1.60	−1.16	0.20	1.08
3	−7.63	−4.40	−6.53	−4.08	0.71	−2.29	−1.38	−2.07	−1.09	0.15	
4	−3.43	0.47	−2.04	−5.74	−3.71	−1.12	0.16	−0.69	−1.61	−0.90	
Large	−3.55	−0.59	4.81	−0.89	0.30	−1.14	−0.22	1.41	−0.25	0.06	

R^2				
61.51	60.92	63.41	62.41	59.93
73.93	73.95	74.47	71.88	67.96
79.81	81.80	77.54	73.58	68.96
84.99	86.05	80.32	77.51	69.42
87.65	86.11	77.89	67.67	55.88

Table V

Cross-Sectional Regressions with the Fama–French Factor Loadings and Loadings on Innovations to State Variables

This table presents Fama–MacBeth cross-sectional regressions using the excess returns on 25 portfolios sorted by book-to-market and size. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed as percentage per month. Panel A presents results for the Fama–French three-factor model. Panel B presents results for the model including the excess market return, R_M, and innovations in the dividend yield, term spread, default spread, and one-month T-bill yield. The Adjusted R^2 follows Jagannathan and Wang (1996) and is reported in percentage form. The first set of t-statistics, indicated by FM t-stat, stands for the Fama–MacBeth estimate. The second set, indicated by SH t-stat, adjusts for errors-in-variables and follows Shanken (1992). The last column reports F-statistics and their corresponding p-values (in percentage form) for the test that the pricing errors in the model are jointly zero. Each panel examines the sample period from July 1963 to December 2001.

Panel A: The Fama–French Three-Factor Model

	γ_0	γ_M	γ_{HML}	γ_{SMB}			Adj. R^2	F
Estimate	1.15	−0.65	0.44	0.16			71.00	2.48
FM t-stat	3.30	−1.60	3.09	1.04				0.03
SH t-stat	3.19	−1.55	3.07	1.00				

Panel B: The Model with R_M and Innovations in *DIV, TERM, DEF*, and *RF*

	γ_0	γ_M	$\gamma_{\hat{u}^{DIV}}$	$\gamma_{\hat{u}^{TERM}}$	$\gamma_{\hat{u}^{DEF}}$	$\gamma_{\hat{u}^{RF}}$	Adj. R^2	F
Estimate	0.64	−0.07	−1.39	4.89	−0.54	−3.22	77.00	1.41
FM t-stat	1.74	−0.16	−1.56	4.44	−0.58	−3.79		11.83
SH t-stat	1.08	−0.11	−0.99	2.79	−0.37	−2.40		

in the loadings. Loadings on SMB do not appear to be significant in the cross section of portfolio returns. None of the models in Table V shows that the market beta, $\hat{\beta}_M$, is an important factor in the cross section of returns. Furthermore, the estimate of the market risk premium tends to be negative. These results are consistent with previous studies.[15]

Fama (1996) points out that the sign of the market risk premium in the ICAPM is indeterminate due to the properties of the market portfolio as a hedge against state variable risk. Fama argues that in a well-specified ICAPM, the market portfolio orthogonalized to all state variable hedging demands must have a positive premium. Therefore, one possible interpretation for the negative estimates of the market risk premium in the model is that the market portfolio acts as a hedge against uncertainty in the state variables under consideration. Polk (2002) analyzes the characteristics of the market portfolio once that portfolio has been orthogonalized to all state variables against which investors want to hedge. It is beyond the scope of this paper to study the properties of

[15] FF (1992), Jagannathan and Wang (1996), and Lettau and Ludvigson (2001) report negative estimates for the market risk premium, using monthly or quarterly data.

the orthogonal market portfolio. Even though the market beta is not priced in the cross section of average returns, some preliminary results suggest that the presence of this variable tends to increase the cross-sectional R^2 of the model.[16] Nevertheless, the fact that the market beta is not priced remains a puzzle and warrants further investigation.

In summary, the model that includes both the excess return of the market portfolio and innovations to the dividend yield, term spread, default spread, and short-term T-bill cannot be rejected using Shanken's t-statistics, while the FF model is rejected over the 1963 to 2001 period. The results further reveal that assets' covariances with a term spread and a T-bill surprise factor are important in the cross section of average portfolio returns.

B.3. Fitted Versus Realized Returns

To judge the goodness of fit of the two models, I use the cross-sectional R^2 measure employed by Jagannathan and Wang (1996) and Lettau and Ludvigson (2001). This measure is calculated as

$$R^2 = \frac{\sigma_C^2(\overline{R}) - \sigma_C^2(\overline{e})}{\sigma_C^2(\overline{R})}, \tag{13}$$

where σ_C^2 represents the in-sample cross-sectional variance, $\overline{R}$ is a vector of average excess returns, and $\overline{e}$ stands for the vector of average residuals. This R^2 shows the fraction of cross-sectional variation in average returns that is explained by the model. It is a measure of unconditional deviations from the model considered.

The adjusted R^2 measure is a summary statistic for the overall fit of each cross-sectional model. Based on the measure of 77%, the specification in Panel B of Table V performs better than the FF model. The FF model explains 71% of the cross-sectional variation in average returns. The 6% gain in explanatory power relative to the FF model seems impressive given the nature of the factors considered. HML and SMB are sorted on the same basis as the 25 portfolios and they represent portfolio returns, while the innovations terms stand for realizations of factors that capture time-varying investment opportunities.

It is also helpful to provide a visual comparison of the performance of the two models. To do so, I plot the fitted expected return of each portfolio against its realized average return in Figure 1. The fitted expected return is computed using the estimated parameter values from a given model specification. The realized average return is the time-series average of the portfolio return. If the fitted expected return and the realized average return for each portfolio are the same, then they should lie on a 45-degree line through the origin.

Figure 1 shows the fitted versus realized returns for the 25 portfolios in two different models for the period from July 1963 to December 2001. Each two-digit number represents a separate portfolio. The first digit refers to the size quintile

[16] These results are available upon request from the author.

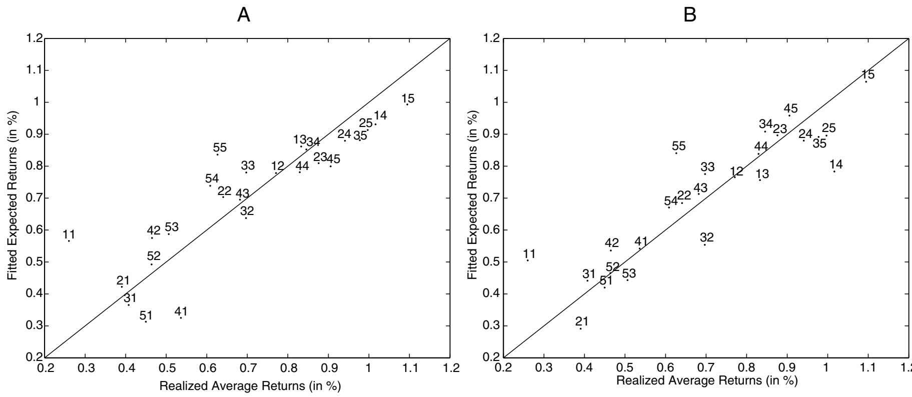

Figure 1. Fitted expected returns vs. average realized returns for 1963:07–2001:12. This figure shows realized average returns (%) on the horizontal axis and fitted expected returns (%) on the vertical axis for 25 size and book-to-market sorted portfolios. Each two-digit number represents a separate portfolio. The first digit refers to the size quintile (1 being the smallest and 5 the largest), while the second digit refers to the book-to-market quintile (1 being the lowest and 5 the highest). For each portfolio, the realized average return is the time-series average of the portfolio return and the fitted expected return is the fitted value for the expected return from the corresponding model. The straight line is the 45-degree line from the origin. Panel A: The Fama–French three-factor model. Panel B: The model with the excess market return and innovations in the dividend yield, term spread, default spread, and short-term T-bill.

of the portfolio (1 being the smallest and 5 the largest), while the second digit refers to the book-to-market quintile (1 being the lowest and 5 the highest). For example, portfolio 15 has the highest book-to-market value among the portfolios in the smallest size quintile. In other words, it is the smallest value portfolio.

Panel A of Figure 1 shows the performance of the FF three-factor model. It can be seen from the graph that the model goes a long way toward explaining the value effect: In general, the fitted expected returns on value portfolios (larger second digit) are higher than the fitted expected returns on growth portfolios (smaller second digit). This is consistent with the data on realized average returns for these portfolios. Similarly, Panel B indicates that the model with the market portfolio and four innovations terms is also successful at explaining the value effect.

By inspection of Panel A, a few portfolios stand out as problematic for the FF model in terms of distance from the 45-degree line, namely, the growth portfolios within the smallest and largest size quintiles (11, 41, and 51) and the value portfolios within the largest size quintiles (45, 54, and 55). In contrast, Panel B shows that the model with $R_M, \hat{u}^{DIV}, \hat{u}^{TERM}, \hat{u}^{DEF}$, and $\hat{u}^{RF}$ is more successful at pricing the portfolios that are challenging for the FF model. The realized returns on growth portfolios within the smallest and largest size groups and the value portfolios within the largest size groups are brought closer to the 45-degree line under the model with the four innovations factors.

An interesting observation that emerges from Figure 1 is that the model with the innovations terms is very successful at pricing the smallest value portfolio (15), which appears to be problematic for the FF model.

In summary, the superior performance of the model with the four innovations terms relative to the FF three-factor model seems to derive mainly from value and growth portfolios within the largest size quintile. In addition, there is some performance gain from pricing the smallest growth portfolio, portfolio 11. However, this portfolio remains problematic even for the model with the predictive variable surprises.[17]

Although the regression R^2 is an intuitive measure, some authors argue that it might be somewhat problematic since it gives equal weights to each asset included in the set of test assets even though some assets may be much more highly correlated than others. To address this concern, I also report a composite pricing error and its corresponding p-value for a 5% significance test. The composite pricing error is computed as

$$Q = T\bar{e}'\hat{\Sigma}^{-1}\bar{e}, \tag{14}$$

where T is the number of time-series observations, $\bar{e}$ stands for the average residual vector in the cross section, and $\hat{\Sigma}$ is the estimated covariance matrix of the time-series residuals. The Q-statistic shown above has an asymptotic chi-squared distribution. Following Shanken (1985), I compute a transformation of the Q-statistic that has an approximate F-distribution in small samples.[18] In addition, the composite pricing error is adjusted for the errors-in-variables problem that arises from using estimated factor loadings in the cross section.

The last column of Table V reports the F-tests and the corresponding p-values for the null hypothesis that the pricing errors in each model are jointly equal to zero. The table shows that the pricing errors of the FF model are not equal to zero: The corresponding F-statistic is 2.48, associated with a p-value of 0.03%. In contrast, the null of zero pricing errors cannot be rejected for the model based on the four innovations factors: The corresponding p-value is 11.83%.

[17] If the levels of the predictive variables, rather than their innovations, are used as factors as in Hodrick and Zhang (2001), the resulting model does not perform better than the FF three-factor specification. When the model includes loadings on MKT, DIV, TERM, DEF, and RF, the cross-sectional adjusted R^2 is 65.25% for the period from July 1963 to December 2001. The reason behind the poor performance of this specification could be that it is necessary to filter out the unexpected components of these variables to diminish the errors-in-variables problem. This becomes even more important given the high autocorrelations of these series (the first-order autocorrelations of the predictive variables are higher than 0.95 for the sample period from July 1963 to December 2001). Furthermore, asset pricing theory predicts that the shocks to the state variables should be priced in the cross section of average returns.

[18] The transformation accounts for the problem that reliance on the asymptotic χ^2 distribution in this cross-sectional context leads to overrejection of the null hypothesis (i.e., zero pricing errors) when it is true.

B.4. The Role of Conditioning Information

In this section, I examine whether the model that includes innovations in the dividend yield, term spread, default spread, and short-term T-bill is able to capture common time-varying patterns in portfolio returns. The discussion follows Ferson and Harvey (1999), who show that portfolio-specific loadings on lagged predictive variables have significant explanatory power for the cross section of 25 portfolios sorted by size and book-to-market in the FF model. Similarly, I check whether sensitivities with respect to predictive variables have explanatory power in the model with the innovations risk factors. This test serves two goals. The first goal is to show that the model based on innovations in *DIV, TERM, DEF*, and *RF* is a good candidate for a conditional model. The second one is to provide a specification test of the model by including an additional explanatory variable in the cross section of average returns.

I use four instruments to proxy for time-varying patterns in returns: *DIV, TERM, DEF*, and *RF*. First, for each portfolio, I estimate the univariate regression coefficient, δ, on a single lagged instrument, using time-series regressions. Then I study the significance of the loadings with respect to a given instrument in the presence of loadings with respect to a set of risk factors. If the model based on the innovations terms is able to explain the cross section of conditional expected returns, then the δ variable should not have explanatory power over and above the factors in the model. The following specification forms the basis of the test:

$$R_{i,t} = \gamma_0 + \gamma_M \hat{\beta}_{i,M} + (\gamma_{\hat{u}^{DIV}})\hat{\beta}_{i,\hat{u}^{DIV}} + (\gamma_{\hat{u}^{TERM}})\hat{\beta}_{i,\hat{u}^{TERM}} + (\gamma_{\hat{u}^{DEF}})\hat{\beta}_{i,\hat{u}^{DEF}} + (\gamma_{\hat{u}^{RF}})\hat{\beta}_{i,\hat{u}^{RF}} + (\gamma_{\hat{\delta}})\hat{\delta}_i + e_{i,t}. \tag{15}$$

The null hypothesis that I test is that $\gamma_{\hat{\delta}} = 0$.

Ferson and Harvey (1999) report that the FF model leaves out important time-varying patterns in expected returns that are related to cross-sectional differences in sensitivities to lagged interest rates. I uncover a similar result based on a different sample period. Specifically, portfolios' loadings on lagged values of the T-bill rate and the term spread are significant determinants of the cross section of returns over and above betas with respect to the FF factors. However, I show that the model based on the innovations terms is able to capture cross-sectional differences in sensitivities to lagged interest rates.

Table VI contains the results for the case of *RF* and *TERM*. Panel A shows that $\hat{\delta}^{RF}$ has significant explanatory power for the cross section of returns in the FF model. For the sample period from July 1963 to December 2001, the t-statistic for the hypothesis $\gamma_{\hat{\delta}^{RF}} = 0$ is 2.35 under the errors-in-variables adjustment. Panel B shows that the null hypothesis is not rejected in the case of the model with R_M, $\hat{u}^{DIV}$, $\hat{u}^{TERM}$, $\hat{u}^{DEF}$, and $\hat{u}^{RF}$. Loadings on lagged values of the T-bill rate do not have marginal explanatory power in the model with the innovations terms. Therefore, the ICAPM model is able to capture common time-varying patterns related to cross-sectional differences in sensitivities to lagged short-term rates.

Table VI

Cross-Sectional Regressions Showing the Incremental Explanatory Power of Portfolio-Specific Loadings on Lagged Values of *RF* and *TERM*

This table presents Fama–MacBeth cross-sectional regressions using the excess returns on 25 portfolios sorted by book-to-market and size. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed as percentage per month. The variables $\hat{\delta}^{RF}$ and $\hat{\delta}^{TERM}$ represent the loadings of each portfolio return on lagged values of RF and TERM, respectively, computed in separate time-series regressions. Panel A examines whether loadings on $\hat{\delta}^{RF}$ have incremental explanatory power in the Fama–French model. Panel B examines whether loadings on $\hat{\delta}^{RF}$ have incremental explanatory power in the model with the excess market return, R_M, and innovations in the dividend yield, term spread, default spread, and T-bill yield. Panel C examines whether loadings on $\hat{\delta}^{TERM}$ have incremental explanatory power in the Fama–French model. Panel D examines whether loadings on $\hat{\delta}^{TERM}$ have incremental explanatory power in the model with R_M and innovations in the dividend yield, term spread, default spread, and T-bill yield. The Adjusted R^2 follows Jagannathan and Wang (1996) and is reported in percentage form. The first set of t-statistics, indicated by FM t-Stat, stands for the Fama–MacBeth estimate. The second set, indicated by SH t-stat, adjusts for errors-in-variables and follows Shanken (1992). Each panel examines the sample period from July 1963 to December 2001.

Panel A: Loadings on Lagged Values of *RF* in the Fama–French Model

	γ_0	γ_M	γ_{HML}	γ_{SMB}	$\gamma_{\hat{\delta}^{RF}}$	Adj. R^2
Estimate	1.67	−0.98	0.33	0.26	0.17	74.14
FM t-stat	4.95	−2.52	2.19	1.63	2.49	
SH t-stat	4.77	−2.45	2.18	1.62	2.35	

Panel B: Loadings on Lagged Values of *RF* in the Model with R_M and Innovations in *DIV, TERM, DEF*, and *RF*

	γ_0	γ_M	$\gamma_{\hat{u}^{DIV}}$	$\gamma_{\hat{u}^{TERM}}$	$\gamma_{\hat{u}^{DEF}}$	$\gamma_{\hat{u}^{RF}}$	$\gamma_{\hat{\delta}^{RF}}$	Adj. R^2
Estimate	0.68	−0.07	−1.34	4.88	−0.69	−3.05	0.03	76.50
FM t-stat	1.71	−0.15	−1.47	4.41	−0.83	−3.58	0.51	
SH t-stat	1.06	−0.11	−0.93	2.76	−0.53	−2.28	0.31	

Panel C: Loadings on Lagged Values of *TERM* in the Fama–French Model

	γ_0	γ_{MKT}	γ_{HML}	γ_{SMB}	$\gamma_{\hat{\delta}^{TERM}}$	Adj. R^2
Estimate	0.76	−0.58	0.45	0.08	0.68	74.46
FM t-stat	1.83	−1.38	3.16	0.46	2.39	
SH t-stat	1.77	−1.35	3.14	0.45	2.27	

Panel D: Loadings on Lagged Values of *TERM* in the Model with R_M and Innovations in *DIV, TERM, DEF*, and *RF*

	γ_0	γ_M	$\gamma_{\hat{u}^{DIV}}$	$\gamma_{\hat{u}^{TERM}}$	$\gamma_{\hat{u}^{DEF}}$	$\gamma_{\hat{u}^{RF}}$	$\gamma_{\hat{\delta}^{TERM}}$	Adj. R^2
Estimate	0.31	0.09	−1.44	4.81	−0.19	−2.88	0.53	77.69
FM t-stat	0.71	0.19	−1.60	4.39	−0.20	−3.45	1.81	
SH t-stat	0.46	0.13	−1.04	2.85	−0.13	−2.27	1.18	

Panels C and D of Table VI contain the results for the case of *TERM*. Panel C shows that $\hat{\delta}^{TERM}$ is a significant factor in the cross section of returns even after accounting for the FF factor loadings. However, as shown in Panel D, loadings on lagged values of the term spread are not significant cross-sectional predictors in the model in which the risk factors are R_M, $\hat{u}^{DIV}$, $\hat{u}^{TERM}$, $\hat{u}^{DEF}$, and $\hat{u}^{RF}$. The model based on the innovations factors explains away cross-sectional differences in sensitivities to the slope of the term structure.

In summary, the ICAPM model in which the relevant risk factors are both the market return and shocks to the dividend yield, term spread, default spread, and short-term rate captures time-varying patterns in returns related to movements in the level and slope of the yield curve. In addition, the model passes this specification test since loadings with respect to term spread and T-bill innovations remain significant in the presence of the new portfolio-specific variables.

C. Robustness Results

The results so far suggest that innovations in the FF factors do not add explanatory power to the model that contains innovations in variables that are associated with time-series return predictability. Furthermore, an ICAPM model in which the risk factors are the excess market return and innovations in *DIV, TERM, DEF*, and *RF* performs better than the FF three-factor model for the cross section of average returns. This section provides a variety of robustness checks that are designed to test whether these results reflect economic content or random chance.

C.1. Monte Carlo Analysis

As shown in Panel B of Table V, the betas with respect to innovations in four state variables explain 77% of the cross-sectional differences in average returns. However, the time-series regressions in Table IV used to compute these betas indicate that the factor loadings are imprecisely estimated. Therefore, to evaluate the empirical evidence on the ICAPM model in light of the beta estimates, I present a Monte Carlo experiment. This experiment describes the small sample empirical distributions of different parameters of interest.[19] Furthermore, the experiment confirms that the empirical results reported in Table V reflect the presence of significant state variable risk premia rather than random factors.

The Monte Carlo exercise is designed as follows. First, I estimate factor loadings for 25 size and book-to-market portfolios from time-series regressions,

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + (\beta_{i,\hat{u}^{DIV}})\hat{u}_t^{DIV} + (\beta_{i,\hat{u}^{TERM}})\hat{u}_t^{TERM} + (\beta_{i,\hat{u}^{DEF}})\hat{u}_t^{DEF} + (\beta_{i,\hat{u}^{RF}})\hat{u}_t^{RF} + \varepsilon_{i,t}. \quad (16)$$

[19] I thank an anonymous referee for suggesting this Monte Carlo experiment.

Then I run cross-sectional regressions to determine the risk premia associated with the loadings on the innovations,

$$R_{i,t} = \gamma_0 + \gamma_M \hat{\beta}_{i,M} + (\gamma_{\hat{u}^{DIV}})\hat{\beta}_{i,\hat{u}^{DIV}} + (\gamma_{\hat{u}^{TERM}})\hat{\beta}_{i,\hat{u}^{TERM}} + (\gamma_{\hat{u}^{DEF}})\hat{\beta}_{i,\hat{u}^{DEF}} + (\gamma_{\hat{u}^{RF}})\hat{\beta}_{i,\hat{u}^{RF}} + e_{i,t}. \tag{17}$$

I take the OLS estimates of the betas in (16) and the risk premia in (17) as given, that is, the null hypothesis is that the model in (16) and (17) is correct. Then, I simulate 10,000 time series of returns under the estimated model as follows:

$$R^*_{i,t} = \hat{\alpha}_i + \hat{\beta}_{i,M} R_{M,t} + (\hat{\beta}_{i,\hat{u}^{DIV}})\hat{u}_t^{DIV} + (\hat{\beta}_{i,\hat{u}^{TERM}})\hat{u}_t^{TERM} + (\hat{\beta}_{i,\hat{u}^{DEF}})\hat{u}_t^{DEF} + (\hat{\beta}_{i,\hat{u}^{RF}})\hat{u}_t^{RF} + \varepsilon^*_{i,t}, \tag{18}$$

where ε^*_t stands for the bootstrap OLS residual. The simulated returns are then used to estimate a new set of factor loadings for each asset, as well as factor risk premia and cross-sectional adjusted R^2s. In this way, the small-sample distributions of the betas, the cross-sectional risk premia, and the R^2s are generated.

In Table VII, I present the finite distribution of betas, risk premia, and adjusted cross-sectional R^2s. Panel A of Table VII reports the distribution of the betas with respect to term spread and T-bill innovations, along with the betas estimated under the null model. I focus on the term spread and T-bill surprises since they represent the two significant variables in the cross section. For all 25 portfolios, the loadings with respect to $\hat{u}_t^{TERM}$ and $\hat{u}_t^{RF}$ are unbiased: The 50% critical value of each distribution is very close to the value under the null hypothesis. The betas with respect to innovations in the term spread and T-bill are very dispersed. For example, the smallest value portfolio (15) has a $\hat{u}_t^{TERM}$ beta with a 2.5% critical value of −0.0103 and a 97.5% critical value of 0.1848. In summary, the estimates of the factor loadings are unbiased and their standard errors are large.

Panel B of Table VII presents the finite distribution of the risk premia parameters and the adjusted R^2. Note that the distributions of the risk premia on $\hat{u}_t^{TERM}$ and $\hat{u}_t^{RF}$ exhibit a downward bias. This is to be expected due to the sampling error in the estimated betas. The mean value for the risk premium on term spread innovations is 3.24, which is below the population value of 4.89. Similarly, the mean value for the risk premium on T-bill innovations is −2.09, which is lower in magnitude than the population value of −3.22. The null hypothesis that the $\hat{u}_t^{TERM}$ and the $\hat{u}_t^{RF}$ risk premia are equal to zero is strongly rejected, given the 95% range of their finite sample distributions. The cross-sectional R^2 is also far away from zero; its finite distribution captures a downward bias as well.

Therefore, despite the fact that the betas have large standard errors, the cross-sectional dimension of the model captures the fact that there are significant risk premia associated with term spread and T-bill innovations. The Monte Carlo experiment indicates that the innovations with respect to the state

Table VII

Monte Carlo Experiment

This table presents a Monte Carlo experiment, designed as follows. First, factor loadings for 25 size and book-to-market portfolios are estimated from time-series regressions. Then the risk premia associated with the loadings are determined in cross-sectional regressions. The OLS estimates from this two-step procedure are taken as given, that is, the null hypothesis is that the estimated model is correct. Then, 10,000 time series of returns are generated under the estimated model. The simulated returns are used to estimate a new set of factor loadings for each asset, as well as factor risk premia and cross-sectional adjusted R^2s. In this way, the small-sample distributions of the betas, the cross-sectional risk premia, and the R^2s are generated. Panel A reports the distribution of the betas with respect to term spread and T-bill innovations, along with the betas estimated under the null model. Panel B presents the finite distribution of the risk premia parameters and the adjusted R^2.

Panel A: Time Series

	$\beta_{\hat{u}^{TERM}}$						$\beta_{\hat{u}^{RF}}$					
	Null	2.5	10	50	90	97.5	Null	2.5	10	50	90	97.5
11	1.51	−11.73	−7.17	1.42	9.97	14.67	4.07	−10.29	−5.13	4.11	13.61	18.21
12	1.04	−10.38	−6.31	1.03	8.35	12.41	−2.58	−14.79	−10.44	−2.64	5.64	9.85
13	1.69	−7.86	−4.62	1.69	7.91	11.24	0.07	−10.27	−6.55	0.11	6.94	10.44
14	2.82	−6.34	−3.12	2.86	8.65	11.85	1.03	−8.57	−5.18	1.02	7.47	10.77
15	8.68	−1.03	2.36	8.66	15.02	18.48	2.77	−7.60	−3.94	2.76	9.63	13.22
21	−8.21	−18.20	−14.60	−8.20	−1.83	1.50	−4.37	−15.02	−11.35	−4.32	2.74	6.23
22	−2.73	−10.84	−7.95	−2.72	2.53	5.50	−5.20	−13.72	−10.70	−5.21	0.50	3.35
23	−0.19	−7.46	−4.90	−0.16	4.46	6.87	−6.25	−13.66	−11.09	−6.20	−1.28	1.16
24	1.36	−5.70	−3.24	1.43	6.00	8.63	−4.57	−12.00	−9.48	−4.55	0.26	2.78
25	5.16	−3.22	−0.32	5.17	10.66	13.72	0.97	−7.87	−4.88	0.91	6.75	9.67
31	−6.34	−14.39	−11.53	−6.38	−1.14	1.67	−7.63	−16.34	−13.17	−7.59	−1.96	0.99
32	−3.52	−9.64	−7.48	−3.54	0.54	2.57	−4.40	−10.95	−8.56	−4.39	−0.16	2.09
33	−1.72	−7.95	−5.76	−1.71	2.37	4.51	−6.53	−12.95	−10.62	−6.48	−2.38	−0.04
34	2.08	−4.18	−1.97	2.11	6.22	8.50	−4.08	−10.63	−8.40	−4.07	0.20	2.43
35	4.39	−3.27	−0.60	4.42	9.47	12.24	0.71	−7.32	−4.54	0.71	6.08	8.71
41	−0.73	−6.97	−4.75	−0.77	3.15	5.45	−3.43	−10.10	−7.72	−3.36	0.89	3.28
42	−1.51	−6.57	−4.83	−0.47	1.79	3.51	0.47	−4.81	−2.99	0.50	4.01	5.88
43	0.21	−5.29	−3.43	0.25	3.93	5.96	−2.04	−7.93	−5.84	−2.00	1.80	3.94
44	0.02	−5.71	−3.72	0.04	3.79	5.69	−5.74	−11.85	−9.66	−5.78	−1.85	0.23
45	2.13	−5.67	−2.89	2.21	7.16	9.76	−3.71	−11.81	−9.08	−3.70	1.51	4.27
51	−5.98	−10.35	−8.87	−5.98	−3.08	−1.48	−3.55	−8.24	−6.59	−3.54	−0.39	1.27
52	−3.26	−7.77	−6.11	−3.26	−0.40	1.23	−0.59	−5.42	−3.70	−0.59	2.43	4.14
53	0.78	−4.65	−2.60	0.75	4.17	6.00	4.81	−0.79	1.16	4.79	8.46	10.39
54	−0.90	−7.11	−4.96	−0.84	3.21	5.55	−0.89	−7.57	−5.24	−0.97	3.41	5.74
55	2.90	−5.20	−2.37	2.89	8.26	10.95	0.30	−8.50	−5.38	0.30	5.89	8.88

Panel B: Cross Section

	Null	2.5	10	50	90	97.5
γ_0	0.64	−0.33	0.08	0.81	1.45	1.81
γ_M	−0.07	−1.23	−0.87	−0.24	0.50	0.93
$\gamma_{\hat{u}^{DIV}}$	−1.39	−4.21	−3.13	−1.42	0.10	0.98
$\gamma_{\hat{u}^{TERM}}$	4.89	0.37	1.51	3.24	5.04	6.06
$\gamma_{\hat{u}^{DEF}}$	−0.54	−3.01	−2.05	−0.44	1.03	1.87
$\gamma_{\hat{u}^{RF}}$	−3.22	−4.48	−3.60	−2.09	−0.55	−0.01
Adj. R^2	77.00	23.18	39.63	70.14	79.27	84.68

variables considered here are not useless factors, but rather important sources of risk for portfolio returns.

C.2. The Role of Portfolio Characteristics

The previous sections of the paper show that a multifactor model that includes the market return and innovations in predictive variables performs very well in explaining the cross section of unconditional average returns. Jagannathan and Wang (1998) argue that a valid test for the correct specification of a given cross-sectional regression model is the inclusion of additional cross-sectional predictors of returns. Therefore, in this section I examine the robustness of the model with the innovations terms to the presence of portfolio characteristics. The two characteristics that I focus on are book-to-market and size of the 25 portfolios. The corresponding specification is

$$R_{i,t} = \gamma_0 + \gamma_M \hat{\beta}_{i,M} + (\gamma_{\hat{u}^{DIV}})\hat{\beta}_{i,\hat{u}^{DIV}} + > (\gamma_{\hat{u}^{TERM}})\hat{\beta}_{i,\hat{u}^{TERM}} + (\gamma_{\hat{u}^{DEF}})\hat{\beta}_{i,\hat{u}^{DEF}} + (\gamma_{\hat{u}^{RF}})\hat{\beta}_{i,\hat{u}^{RF}} + (\gamma_Z)Z_{i,t-1} + e_{i,t}, \tag{19}$$

where Z_i stands for the natural log of book-to-market or size. The null hypothesis tested is that $\gamma_Z = 0$. In Table VIII, returns from July of year t to June of year $t+1$ are matched with the log of the book-to-market ratio for December of year $t-1$ and the log of size for June of year t, as in FF (1992). Panels A and B show that there are no residual book-to-market or size effects when the characteristics are included separately in the model with R_M, $\hat{u}^{DIV}$, $\hat{u}^{TERM}$, $\hat{u}^{DEF}$, and $\hat{u}^{RF}$.

Note that the magnitude and significance of $\gamma_{\hat{u}^{TERM}}$ and $\gamma_{\hat{u}^{RF}}$ decrease in the presence of book-to-market or size. Even so, loadings on these innovations remain strongly significant, even under Shanken's adjustment. The cross-sectional adjusted R^2s indicate that the two characteristics do not add much to the explanatory power of the model.

In Panel C of Table VIII, both characteristics are included as a specification test of the model. As before, the two characteristics do not add cross-sectional explanatory power. They are not significant determinants of the cross section of returns in the presence of loadings on R_M, $\hat{u}^{DIV}$, $\hat{u}^{TERM}$, $\hat{u}^{DEF}$, and $\hat{u}^{RF}$. Overall, these results provide further support for the earlier finding that the model based on surprises in predictive variables provides an explanation for the empirical success of the FF factors.[20]

[20] I also use portfolios sorted on risk loadings to test the performance of the ICAPM model. Risk-sorted portfolios are constructed in the following way. Each month, each stock's risk loadings are computed from a multiple regression of returns over the previous 60 months on the factors in the ICAPM model over the same 60 months. The factors are the excess market return and innovations to the dividend yield, the term spread, the default spread, and the T-bill rate. Each month I perform a sort on every risk loading in the model, that is, I form five value-weighted portfolios sorted on the market beta, five value-weighted portfolios sorted on beta with innovations to the dividend yield, etc. This procedure leads to the formation of 25 portfolios whose returns are recorded every month beginning with July 1963. I add the set of 25 portfolios sorted by risk loadings to the set of

Table VIII

Cross-Sectional Regressions Showing the Incremental Explanatory Power of Portfolio Characteristics

This table presents Fama–MacBeth cross-sectional regressions using the excess returns on 25 portfolios sorted by book-to-market and size. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed as percentage per month. Panel A examines whether book-to-market (BM) has incremental explanatory power in the model including the excess market return, R_M, and innovations in the dividend yield, term spread, default spread, and 1-month T-bill yield. Returns from July of year t to June of year $t + 1$ are matched with BM measured in December of year $t - 1$. Panel B examines whether size has incremental explanatory power in the model including R_M and innovations in the dividend yield, term spread, default spread, and 1-month T-bill yield. Returns from July of year t to June of year $t + 1$ are matched with size measured in June of year t. Panel C examines whether BM and size have incremental explanatory power in the model including R_M and innovations in the dividend yield, term spread, default spread, and 1-month T-bill yield. The Adjusted R^2 follows Jagannathan and Wang (1996) and is reported in percentage form. The first set of t-statistics, indicated by FM t-stat, stands for the Fama–MacBeth estimate. The second set, indicated by SH t-stat, adjusts for errors-in-variables and follows Shanken (1992). Each panel examines the sample period from July 1963 to December 2001.

Panel A: BM in the Model with R_M and Innovations in *DIV, TERM, DEF*, and *RF*

	γ_0	γ_M	$\gamma_{\hat{u}^{DIV}}$	$\gamma_{\hat{u}^{TERM}}$	$\gamma_{\hat{u}^{DEF}}$	$\gamma_{\hat{u}^{RF}}$	γ_{BM}	Adj. R^2
Estimate	0.79	−0.18	−0.73	4.68	−0.78	−3.04	0.07	76.45
FM t-stat	2.01	−0.40	−0.80	4.31	−0.85	−3.68	1.49	
SH t-stat	1.30	−0.28	−0.52	2.75	−0.56	−2.38	0.89	

Panel B: Size in the Model with R_M and Innovations in *DIV, TERM, DEF*, and *RF*

	γ_0	γ_M	$\gamma_{\hat{u}^{DIV}}$	$\gamma_{\hat{u}^{TERM}}$	$\gamma_{\hat{u}^{DEF}}$	$\gamma_{\hat{u}^{RF}}$	γ_{Size}	Adj. R^2
Estimate	1.48	−0.49	−0.42	3.32	0.21	−2.66	−0.07	77.18
FM t-stat	3.26	−1.30	−0.50	3.16	0.24	−3.02	−1.70	
SH t-stat	2.51	−1.09	−0.39	2.44	0.19	−2.33	−1.34	

Panel C: BM and Size in the Model with R_M and Innovations in *DIV, TERM, DEF*, and *RF*

	γ_0	γ_M	$\gamma_{\hat{u}^{DIV}}$	$\gamma_{\hat{u}^{TERM}}$	$\gamma_{\hat{u}^{DEF}}$	$\gamma_{\hat{u}^{RF}}$	γ_{BM}	γ_{Size}	Adj. R^2
Estimate	1.69	−0.64	0.39	2.95	−0.04	−2.41	0.08	−0.07	77.69
FM t-stat	3.62	−1.71	0.47	2.92	−0.05	−2.81	1.76	−1.79	
SH t-stat	2.82	−1.45	0.38	2.30	−0.04	−2.21	1.25	−1.37	

C.3. Relation between the Innovations and GDP Growth

The previous sections of the paper show the relation between the FF factors and innovations in state variables that describe financial investment

the 25 Fama–French portfolios. If the success of the ICAPM model with the characteristic-sorted portfolios is spurious, then the additional risk-sorted portfolios should expose the weakness of the model. The results from cross-sectional regressions reveal that the model is robust to the inclusion of the 25 risk portfolios. These results are available upon request.

opportunities. Other authors study the relation between the FF factors and important macroeconomic variables. For example, Vassalou (2003) shows that news related to future GDP growth is an important factor, in addition to the market portfolio, for the cross section of returns. She shows further that the FF factors HML and SMB may be proxies for news about future GDP growth. The time-series literature shows that some of the state variables considered in this paper, for example, the term spread and the short-term interest rate, are good predictors of future GDP growth. Therefore, a natural question arises as to whether the innovations in the state variables simply capture news about future GDP growth.[21] Next, I briefly examine this possibility. I show that the innovations terms are related to GDP news, but this is not why they are successful in the cross section of returns. Rather, they contain information that is important for asset pricing and independent of the information they contain about GDP news. The conclusion is that the innovations in the state variables that I choose contain information about the time variation in the financial investment opportunity set. This information is not necessarily related to news about future GDP growth.

Following Vassalou (2003), I construct two portfolios that track news about future GDP growth. One of the portfolios contains eight base assets, namely, six equity portfolios and two fixed income portfolios, and is denoted as TP_{GDP}. The other tracking portfolio contains only two fixed income assets and is denoted as $TP_{GDP^{FX}}$.[22] To examine whether GDP news adds explanatory power to the model based on the innovations factors, I include the tracking portfolio for GDP news as an additional risk factor in the ICAPM specification.

The results are presented in Table IX. Panel A refers to the case in which the tracking portfolio for GDP news contains both equity and fixed income base assets. Panel B refers to the case in which only fixed income assets are used to track news about future GDP growth. Both panels tell the same story: The information in the innovations terms is still a significant determinant of average returns. Therefore, even if we account for the possibility that the state variables contain information about changes in GDP growth, this is not the driving force behind their significant risk premia in the cross section. Rather, they contain information about time variation in the investment opportunity set, which is independent of GDP-related news. The state variables are related to variation in the financial investment opportunity set, and this variation is not necessarily related to changes in future GDP growth.

[21] I thank an anonymous referee for suggesting that there might exist a relation between news about future GDP growth and innovations in state variables.

[22] The equity portfolios are constructed by Fama and French from the intersection of two size and three book-to-market portfolios. The fixed income portfolios are the returns on both a portfolio that represents a spread between long-term corporate and government bonds, and a portfolio that represents the difference between a long-term and a short-term government bond. In both cases, lagged control variables are used in addition to the returns on the base assets. The control variables are the same as the ones used in Vassalou (2003).

Table IX

Relation between GDP Growth and the Innovations in State Variables

This table presents Fama–MacBeth cross-sectional regressions using the excess returns on 25 portfolios sorted by book-to-market and size. The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The coefficients are expressed as percentage per month. The variables TP_{GDP} and $TP_{GDP^{FX}}$ represent two portfolios that track news about future GDP growth. The former contains eight base assets, six equity portfolios and two fixed income portfolios. The latter contains only two fixed income assets. Panel A examines whether loadings on TP_{GDP} have incremental explanatory power in the model with the excess market return, R_M, and innovations in the dividend yield, term spread, default spread, and 1-month T-bill. Panel B examines whether loadings on $TP_{GDP^{FX}}$ have incremental explanatory power in the model with R_M and innovations in the dividend yield, term spread, default spread, and 1-month T-bill. The Adjusted R^2 follows Jagannathan and Wang (1996) and is reported in percentage form. The first set of t-statistics, indicated by FM t-stat, stands for the Fama–MacBeth estimate. The second set, indicated by SH t-stat, adjusts for errors-in-variables and follows Shanken (1992). Each panel examines the sample period from July 1963 to December 1998.

Panel A: Loadings on TP_{GDP} in the Model with R_M and Innovations in DIV, $TERM$, DEF, and RF

	γ_0	γ_M	$\gamma_{\hat{u}DIVO}$	$\gamma_{\hat{u}TERMO}$	$\gamma_{\hat{u}DEFO}$	$\gamma_{\hat{u}RFO}$	$\gamma_{TP_{GDP}}$	Adj. R^2
Estimate	0.87	−0.30	−0.61	2.44	−1.00	−1.95	0.02	77.82
FM t-stat	2.37	−0.70	−0.75	2.67	−1.24	−2.62	0.65	
SH t-stat	1.85	−0.58	−0.60	2.14	−0.98	−2.12	0.53	

Panel B: Loadings on $TP_{GDP^{FX}}$ in the Model with R_M and Innovations in DIV, $TERM$, DEF, and RF

	γ_0	γ_M	$\gamma_{\hat{u}DIVO}$	$\gamma_{\hat{u}TERMO}$	$\gamma_{\hat{u}DEFO}$	$\gamma_{\hat{u}RFO}$	$\gamma_{TP_{GDP}FX}$	Adj. R^2
Estimate	0.90	−0.30	−1.34	3.30	−1.21	−1.70	0.05	76.58
FM t-stat	2.53	−0.70	−1.46	3.26	−1.43	−2.04	1.34	
SH t-stat	1.80	−0.55	−1.06	2.36	−1.03	−1.76	0.89	

IV. Conclusion

This paper contributes to the ongoing debate about the economic nature of the Fama–French (1993) size and book-to-market factors. I investigate whether the FF factors HML and SMB are related to shocks in state variables that describe time variation in investment opportunities. The results show that HML and SMB are significantly correlated with innovations in state variables that predict the excess market return and its variance. Specifically, I find that HML proxies for a term spread surprise factor in returns, while SMB proxies for a default spread surprise factor. Therefore, this paper establishes a significant link between a set of variables associated with time-series return predictability and a set of variables associated with cross-sectional return predictability.

In addition, I examine an ICAPM model that contains as factors the market return and shocks to the dividend yield, term spread, default spread, and 1-month T-bill yield. This model explains the cross section of average returns on 25 portfolios sorted by size and book-to-market better than the FF three-factor model. The parts of HML and SMB that are important for pricing risky assets are those explained by surprises in state variables. Thus, this paper provides evidence for an ICAPM explanation of the empirical success of the FF model. The ICAPM model based on innovations in variables that predict the market return and the yield curve is robust to different specification tests.

Despite the ICAPM interpretation of the FF model, the results in this paper indicate that it is not the best model to capture assets' covariances with time-varying investment opportunities. I propose the model based on innovations in the dividend yield, term spread, default spread, and short-term T-bill rate as a better ICAPM model for the cross section of average return. The superiority of the model comes from its ability to explain common time-varying patterns in returns. Namely, it captures cross-sectional differences in sensitivities with respect to conditioning information, represented by loadings on lagged values of predictive variables. The FF model, however, is not successful at capturing the effect of conditioning information, as shown in Ferson and Harvey (1999).

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