# **Predictive Variables?**

**by** 

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**Abstract:** It has recently been argued that the SMB and HML factors proxy for innovations in predictive variables that characterize the investment opportunity set, thereby providing the Fama-French model some theoretical underpinning: an asset pricing model that contains these innovations as risk factors would perform better than the Fama-French model, and the innovations in the predictive variables would make the SMB and HML factors insignificant when introduced in the cross section of asset returns. We show on the contrary that this result is a these results are statistical artifacts. They are shown to follow directly from arbitrarily making the SMB and HML innovations orthogonal to the return on the market. The Fama-French model in fact performs better than a model containing only the innovations in predictive variables. Moreover, when both are present in the regressions, the variables that tend to be driven out are these innovations, not the Fama-French factors. These results are robust to the inclusion of industry portfolios in the investment universe. Therefore, innovations in predictive variables explain at best little of the cross-sectional variation in asset returns. They are also consistent with the view that asset return predictability is present, at best, for investment horizons much longer than a month.

#### **Very Preliminary and Incomplete. Comments are welcome.**

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# **Do the Fama-French Factors Really Proxy for Innovations in Predictive Variables?**

One well established failure of the standard capital asset pricing (CAPM) model stems from its inability to explain the cross section of excess returns of portfolios sorted by firm characteristics such as size and book-to-market ratio. In a series of influential papers, Fama and French (1992, 1993, 1996 and 2006) have shown that the CAPM, even in the long run, is unable to explain the anomaly that high book-to-market firms have high expected excess returns in spite of having low market betas. Among all tentative avenues to solve this value premium puzzle, the Fama-French three-factor (FF3 hereafter) model is beyond doubt the most successful and popular. It adds to the market portfolio factor of the standard CAPM two portfolio factors, one aimed at capturing the size effect (SMB) and the other the value effect (HML).**<sup>1</sup>** These factors are based on purely empirical considerations, lack theoretical underpinnings, are built in a rather arbitrary manner, and have no straightforward economic interpretation. In particular, their economic links to systematic risk are not clear. Fama and French (1996), then Chen and Zhang (1998) among others, hinted that they are related to corporate distress and thus reflect the risk premium required by economic agents to invest into vulnerable firms. In the same spirit but using conditional models, Jagannathan and Wang (1996), Lettau and Ludvigson (2001a) and Petkova and Zhang (2005) reported that value stocks are riskier than growth stocks during bad times when required risk premiums are high and less risky during good times when the price of risk is low. **2** This strand of research, however, has been strongly challenged. For instance, Lewellen and Nagel (2006) questioned the empirical relevance of the conditional models proposed in these studies, as the variation in betas and the equity market premium would have to be unrealistically large to explain the value premium. As to Fama and French's (1996) own interpretation, Campbell et al. (2007) showed that firms with a high probability of failure, therefore in deep distress, display lower equity returns than firms

The SMB and HML returns are computed by Fama and French from six stock portfolios sorted by size (size measured by market value of equity, breakpoint at the median) and book-to-market equity (measured as the ratio of the accounting value of equity to its market value, breakpoints at the  $30<sup>th</sup>$  and the  $70<sup>th</sup>$  percentiles). The SMB return is the average return difference between three small and three big stock portfolios and the HML return is the average return difference between two high and two low book-to-market stock portfolios.

<sup>&</sup>lt;sup>2</sup> In the same vein, Gulen, Xing and Zhang (2008) show that value firms lack the flexibility to adjust to bad economic conditions that growth firms have, which creates strong countercyclical variations in the value-minusgrowth expected returns.

exhibiting a low risk of failure, although the loadings of the former on the market, SMB and HML factors are significantly higher than the latter. Their finding thus is inconsistent with the conjecture that size and value capture compensation for distress risk.

This left the empirical success of the FF3 model essentially unexplained and elicited a strong strand of research that aimed at providing some robust economic interpretation of the Fama-French factors. Among the proposed explanations, we focus on the ones based upon Merton's (1973) Intertemporal CAPM (ICAPM hereafter). As Fama and French (1996) had themselves suggested, their SMB and HML factors could in effect be interpreted as proxies for state variables that describe the random evolution of the investment opportunity set. Ignoring this source of risk made previous models suffer from a misspecification problem and underestimate the risk premium embedded in asset prices. The relevant state variables may belong to the set of macroeconomic real variables such as GNP, real investment or capital, or consumption of durable goods. Liew and Vassalou (2000) for example reported that HML has some predictive ability regarding the GNP growth rate, and that SMB and HML convey significant information about future GDP growth not present in the market portfolio. Hanhardt and Ansotegui (2008) find that this result extends to (twelve countries of) the Eurozone, with the provision that they used the Carhart (1997) model instead of FF3.**<sup>3</sup>** Yogo (2006) showed that disaggregating consumption between durable and non-durable goods, the former being significant, improves the performance of Breeden's (1979) consumption-based CAPM even beyond the level of the FF3 model. Xing (2008) claimed that HML may approximate for the growth rate of capital investment: an investment growth factor, defined as the difference in returns between low investment stocks and high investment stocks, contains some information similar to HML. Simpson and Ramchander (2008) provided evidence that the FF3 model outperforms the standard CAPM in its ability to capture surprises related to various macroeconomic indicators.

Alternatively, the state variables may belong to the macro-finance set. For instance, Fama and Schwert (1977), Campbell (1987), Campbell and Schiller (1988), Fama and French (1989) have proposed various candidates in general related to the characteristics of the yield curve and/or to some aggregate measure of dividend payments.<sup>4</sup> More recently, Petkova

<sup>&</sup>lt;sup>3</sup> Carhart's (1997) model includes, in addition to the FF3 factors, a "momentum" factor. The latter is the return on a portfolio that is long in past winner stocks and short on past losers.

<sup>&</sup>lt;sup>4</sup> Campbell (1996) used both macroeconomic (including, noticeably, labor income) and macro-finance variables.

(2006) and Hahn and Lee (2006) have analyzed the relationship between the HML and SMB factors and innovations in financial variables deemed to describe investment opportunities. In a closely related research, In and Kim (2007) have investigated to what extent these two factors convey the same information as innovations in financial state variables, interpreted as alternative investment opportunities, over various time horizons.<sup>5</sup> More precisely, following the framework adopted by Campbell (1996) and using the innovations in the T-bill rate, a term spread, a default spread and the aggregate dividend yield computed from a vector autoregressive (VAR) process whose elements are these four state variables plus the FF3 factors, Petkova (2006) reached the following conclusions:

(i) a model using these innovations performs better than the FF3 model in explaining crosssectional differences in asset returns;

(ii) a model using the innovations in the SMB and HML factors and in predictive variables performs better than the FF3 model, and the innovations in SMB and HML are not statistically significant;

(iii) the innovations in predictive variables are priced and the risk premiums are sizeable and significant.

These results however are at odds with mainstream findings regarding the optimal asset allocation issue. On theoretical grounds, the fact that state variables are priced is intimately linked to intertemporal hedging. In Merton's (1973) ICAPM, economic agents' optimal portfolios contain terms that hedge against unfavorable shifts in their investment opportunity set. This implies they require risk premiums at equilibrium to compensate for bearing such risks. Yet, empirical studies have consistently reported that those hedging terms are insignificant or at best of second order vis-à-vis the mean-variance component. Consequently, one does not expect to find significant cross-sectional risk premiums attached to the state variables, which makes result (iii) puzzling.

<sup>&</sup>lt;sup>5</sup> Guo, Savickas, Wang and Yang (2008) take a different but related stance. Instead of examining the crosssectional variation among portfolios or individual assets returns, they investigate the risk-return relationship over time for the stock market as a whole. Tests of the standard CAPM for the recent (post-1963) period had lead repeatedly to a negative or insignificant tradeoff. This finding is another well established failure of the standard CAPM for the modern period. See for instance Campbell (1987), Glosten, Jagannathan and Runkle (1993), Whitelaw (1994) and Brandt and Kang (2004). Guo et al. (2008) show that, after controlling for the covariance of market returns with the value premium, the tradeoff is positive. Also, they find that the conditional value premium is countercyclical. Their results thus suggest that value is riskier than growth during recessions when the market price of risk is large and that the value premium can be interpreted as proxying for time-varying investment opportunities. Guo and Whitelaw (2006), using as a proxy the consumption-to-wealth ("cay") ratio proposed by Lettau and Ludvigson (2001b), reached similar conclusions.

Conclusion (ii) is in fact easy to explain and refute. To assess whether SMB and HML proxy for innovations in predictive variables, the original FF3 model should be compared to a model that includes the market, the two Fama-French factors and innovations in predictive variables, *not* to a model that includes the market, innovations in predictive variables and *innovations* in the SMB and HML factors. We show that tests of the former, proper model exhibit essentially insignificant innovations in the predictive variables while SMB and HML still are significant. Yet the question remains why using innovations in SMB and HML and not the factors themselves leads to the opposite conclusion. The answer lies in the way innovations are computed. All of them are made orthogonal to the market excess return (the market, in brief) and this procedure alone drives the results. This is because making innovations orthogonal to the market drastically reduces the statistical significance of the SMB and HML factors, whether innovations in predictive variables are also present in the regression or not. This is not the case for the four predictive variables, which remain significant after orthogonalization to the market, *provided* SMB and HML are not included as explanatory variables. We show that conclusions (i) and (ii) above are reversed and conclusion (iii) is not vindicated when innovations are computed in a less "ad hoc" manner.

To make our empirical investigation more thorough, we also extend the analysis in several directions. First, we perform tests on a wider set of pricing models and for a somewhat longer sample period and also report results on tests not performed by Petkova (2006). Second, we assess the robustness of our results by using, in addition to the standard Fama-French 25 portfolios on which, by construction, is imposed a factorial structure, 17 industry portfolios which are free from such a bias. Third, in addition to performing « static » cross sections to estimate the market prices of risk associated with the (estimated) factor loadings obtained from time series, we perform so-called « dynamic » cross sections for each date included in the sample then average the resulting coefficients out. This constitutes a robustness test for the significance of the factor loadings. Fourth, we use alternative VAR processes of lower dimension to provide another check of the robustness of our results.

The rest of the paper is structured as follows. Section I describes the data and presents an analysis of the behavior of the innovations in the HML and SMB factors from a VAR process that includes these two factors and the market only, and the consequences of this behavior on the cross-section of portfolio returns. Section II examines whether the innovations in four financial variables from a VAR process of higher dimension that includes these state variables crowd out the HML and SMB factors or their innovations and assesses to what extent making innovations orthogonal to the market is crucial to the results or not. Section III provides some alternative specifications in which the dimensionality of the VAR process is lowered and conditional versions of the competing models allow for the factor loadings in the first-pass time-series to vary randomly over time. Section IV concludes.

## **I. Data and Preliminary Analysis**

## *A. Data*

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This study uses monthly data for the period from July 1963 to December 2007 (534 observations).<sup>6, 7</sup> Data relative to excess returns on the market portfolio, and to returns on the SMB and HML portfolios have been downloaded from Professor Kenneth French's website. The market risk premium is computed as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (obtained from the CRSP files) minus the one-month Treasury bill rate. Also from French's website are the 25 Fama-French (hereafter FF) portfolios sorted by size and book-to-market equity which will constitute our first universe of portfolios.**<sup>8</sup>** However, some authors, such as Lewellen, Nagel and Shanken (2007), have argued that excess return tests are biased favorably due to the factorial structure inherent to the construction of these portfolios. Consequently, to reduce this bias, we will also perform tests on second universe that comprises, in addition to the 25 FF portfolios, the 17 industry portfolios also compiled by Fama and French.

Panel A of Table I reports various statistics for the excess return on the market portfolio over the T-bill rate ("*Market*") and the returns on the SMB and HML portfolios. The average yearly compounded equity market premium is 5.8%. Panels B and C exhibit the average

<sup>&</sup>lt;sup>6</sup> Our starting point thus is the same as that of Petkova's (2006) study, while our sample covers exactly six more years (72 observations). For this reason, and also because alterations have been made to some CRSP series, we cannot reproduce her results exactly. We also use the 3-month T-bill rate, not the 1-month rate, as a predictive variable. However, there is little difference between the results she reports and ours. The study by In and Kim (2007) also starts from July 1963 but extends to December 2005 only.<br><sup>7</sup> We selected the same starting month as did in perticular, the outbox

We selected the same starting month as did, in particular, the authors quoted in the previous footnote partly to facilitate the comparison and partly because the value premium has been shown not to co-move with innovations in investment opportunities in the pre-1963 period as much as in the post-1963 period. See for instance Campbell and Vuolteenaho (2004), Petkova and Zhang (2005), Fama and French (2006) and Ang and Chen (2007).

<sup>8</sup> The 25 portfolios are obtained from an independent sort of all NYSE, AMEX and Nasdaq stocks into *quintiles* based on size and book-to-market ratio. See Fama and French (1993) for more details.

excess returns on the 25 FF and the 17 industry portfolios, respectively. In line with what is reported in the literature on the value premium [e.g. Fama-French (2006)], one finds that (i) there is a positive relationship between risk premium and book-to-market, which implies that value stocks command higher excess returns than growth stocks, and (ii) except for low bookto-market portfolios, there is an inverse relationship between excess return and size.

## **Insert Table I about here**

As to the predictors, keeping in mind model parsimony, we select the same four variables used by Petkova (2006) which are common in the literature and lend themselves to a clear financial interpretation. This choice allows for a meaningful comparison. First, the level and the slope of the yield curve being obvious determinants of investment opportunities, we retain the level of the three-month Treasury bill rate ("*Tbill*") and the level of a term spread measured as the difference between the ten-year constant maturity Treasury bond yield and the 1-year constant maturity Treasury bond yield ("*Term*"). Second, there is mounting evidence that asset returns are partially predicted by the aggregate dividend yield and a measure of financial or economic duress. Accordingly, we select a dividend yield, measured as the total dividends paid off during the last 12 months divided by the actual value of the market portfolio ("*Div*"), and a default spread measured as the difference between the yield of a 10 year Baa-rated bond and that of a 10 year Aaa-rated bond ("*Def*"). These predictors are from the FRED® database of the Federal Reserve Bank of St. Louis.

## *B. VAR Estimation and the FF3 Model*

As results of empirical tests of intertemporal capital asset pricing models may crucially depend on the set of predictive variables used (apart from the SMB and HML factors), our first tests do not involve predictors at all and involves the three FF factors only. Our first objective is to show that whether making innovations in the SMB and HML factors orthogonal to the market or not is crucial to the results.

Therefore, before using Fama and MacBeth's (1973) two-pass standard procedure to test the validity of a CAPM, we need to obtain innovations in the SMB and HML factors. To this end, we estimate a first-order vector autoregressive (VAR) process whose elements are the market excess return ("*Market*") and the SMB and HML returns, namely:

$$
\begin{bmatrix} r_{M,t} \\ r_{SMB,t} \\ r_{HML,t} \end{bmatrix} = B \begin{bmatrix} r_{M,t-1} \\ r_{SMB,t-1} \\ r_{HML,t-1} \end{bmatrix} + e_t
$$
 (1)

where  $e_t$  is a three-dimensional vector of innovations. The innovations regarding SMB and HML contained in  $e_t$  are used in later regressions in four different ways: (i) as such, (ii) after the errors from the VAR have been normalized so as to exhibit the same variance as that of the innovations from the market alone, (iii) after the errors have been made orthogonal to the market, and (iv) after the errors have been both normalized and made orthogonal to the market. The rationale for using these normalization and orthogonalization procedures is discussed below.

Then, following Fama and MacBeth (1973), we run two types of regressions. In a first pass, the time-series of excess returns on a risky portfolio  $(r_{i,t})$  is regressed on the excess returns on the market portfolio and two other factors (SMB and HML, or their innovations), all three being generically denoted here by  $Y_{i,t}$ . We thus have:

$$
r_{j,t} = \alpha_j + \sum_{i=1}^{F} \beta_{j,Y_i} Y_{i,t} + \varepsilon_{j,t} \qquad j = 1, 2, ..., N \qquad (2)
$$

where *F* is the number of factors ( $F = 3$  in this section) and *N* is the number of portfolios (25 or 42).

In the second pass, we test in cross-section, for a given date t, the hypothesis that the expected excess returns on portfolios obey:

$$
E(r_j) = \lambda_j + \sum_{i=1}^{F} \gamma_{Y_i} \hat{\beta}_{j, Y_i}
$$
 (3)

where the  $\lambda_j$  should be zero and the independent variables  $\hat{\beta}_{j,Y_i}$  are estimates obtained from regressions (2). The  $\gamma_{Y_i}$  denote the prices of risk. Cross sections such as given by Eq. (3) may be run in two different ways, either only once, as of date  $t = T$  ("static" cross section), or for

each date  $t = 1, 2, ..., T$  ("dynamic" cross sections).<sup>9</sup> Note that both cases use the betas estimated over the whole period. We will perform both.**<sup>10</sup>**

## *C. Static cross sections*

We focus first on the (second-step) cross section of portfolio returns represented by Eq. (3). Table II reports cross-sectional regressions using the excess returns on the 25 FF portfolios sorted by size and book-to-market. The full-sample factor loadings, which are the independent variables in the cross-sectional regressions and are partially shown in Table III, have been computed in time-series simple regressions (for each of the 25 portfolios) in which the dependent variable is the excess return on a given portfolio [Eqs. (2)]. The cross-section regression (Fama-Macbeth) coefficients are obtained by OLS. All the coefficients but the constants have been multiplied by 100 for readability. The t-statistics are corrected for autocorrelation and heteroskedasticity using the Newey-West estimator with four lags, a standard procedure to assess the statistical significance of the independent variables. Since the latter are estimates from a (first-pass) time series regression, we have also reported the tstatistics adjusted for errors-in-variables according to the procedure established by Shanken (1992), a generally more difficult test to pass. Note however that when the homoskedasticity assumption made by Shanken (1992) is relaxed, Jagannathan and Wang (1996) and more recently Shanken and Zhou (2007) have shown that the over-estimation bias may be relatively small if it exists at all. This is why we report both t-statistics. To assess the overall fit of each competing model, we have computed the adjusted  $R^2$  used by Jagannathan and Wang (1996), which measures the proportion of cross-sectional variation in expected returns explained by the model.

Table II reports the cross-sectional results for five competing models. Model #1 refers to the benchmark FF3 model. The other four models use variously the innovations from the VAR system according to the discussion that follows Eq. (1). Model #2 replaces the SMB and HML factors by their plain innovations. In model #3, the errors from the VAR have been normalized so as to have the same variance as that of the market innovations alone. In model

<sup>&</sup>lt;sup>9</sup> See Cochrane (2005) and Shanken and Zhou (2007) for details.

<sup>&</sup>lt;sup>10</sup> Using the generalized method of moments (GMM), we could estimate simultaneously the innovations  $e_t$  in Eq. (1) and the risk premia  $\gamma_{Y_i}$  in Eq. (3). As this estimation procedure yields essentially the same results as the twopass Fama-MacBeth method, we do not discuss it further.

#4, the innovations have been made orthogonal to the market. In model #5, the errors have been both normalized and made orthogonal to the market. Obviously, such massaging of innovations will leave the adjusted  $R^2$  of the regression unaffected and will impact the coefficient and significance of each independent variable only.

Results for the overall goodness-of-fit of the FF3 model are in line with the extant literature in which the reported adjusted  $R^2$  lies roughly in the range 0.70–0.80 depending on the studies.<sup>11</sup> Here the  $R^2$ (*JW*) is 0.77, and the return on the HML is positive and highly significant. Published results regarding the SMB portfolio are more controversial. Contrary to what Petkova (2006) and Yogo (2006), among others, find, but in accordance with Fama and French's (1992) initial results, the return on the SMB factor is (positive and) very significant. Overall, this model performs well and remains the hard-to-beat reference model. Note however that it exhibits the (border-line significant) puzzling wrong sign on the market portfolio coefficient. Also, the constant is significantly positive although it should be zero since the independent variables are portfolios.

# **Insert Table II about here**

Results for models #2 and #3 are surprisingly very similar to those of model #1. The quality of the regressions is the same, and the factors and constant retain the same degree of significance. In particular, the normalization of the variances (model #3) impacts only slightly the value of the HML and SMB coefficients but is otherwise inconsequential. Table II also confirms Shanken and Zhou's (2007) result that, when portfolios, as opposed to macro-variables, are used as explanatory variables, there is little difference between the Newey-West and the Skanken t-statistics. The main conclusion that emerges is that whether one considers the HML and SMB factors or their innovations from a first-order VAR involving also the market is immaterial. Since, according to financial theory, only the unexpected components of state variables should be priced, this finding casts strong doubts on the interpretation of the HML and SMB portfolios as state variables.

By contrast, when the innovations from the VAR process are made orthogonal to the market (model #4), the significance of the innovations in the HML factor drops drastically. It is almost

<sup>&</sup>lt;sup>11</sup> See for instance Fama and French (1992), Jagannathan and Wang (1996), Lettau and Ludvigson (2001a) or Petkova (2006). These studies differ by the period considered and/or the frequency of data.

divided by four as compared to the FF3 model and becomes hardly significant. Whether the variances are normalized or not is again inconsequential as results for models #4 and #5 are identical. This is the first key result of the paper: one seemingly does not need to introduce innovations in the four financial state variables ("*Div*", "*Term*", "*Def*", and "*Tbill*") to almost get rid of the innovation in the HML factor when it is made orthogonal to the market. We will check below that it is indeed this orthogonalization procedure that drives Petkova's (2006) main claim. The significance of the innovation in SMB however is left unaffected. The difference in behavior between the innovations in the HML and SMB factors is all the more striking that most of the attention in the literature has been devoted to the former, the latter being often insignificant.**<sup>12</sup>**

#### *D. Loadings from Time-Series Regressions*

Table III reports the loadings on the market portfolio ("β*-mkt*"), and the SMB ("β*-smb*") and HML ("β*-hml*") factors or their innovations, computed in the first-pass time-series regressions for the 25 FF portfolios. The loadings exhibited in panels A, B and C, led to the cross-sectional models #1, #3 and #5, respectively, reported in Table II. Results for models #2 and #4 are not shown to save space as they do not differ materially from models #3 and #5, respectively. On the right part of each panel are shown the t-statistics associated with the factors. The last rows report the standard adjusted  $R^2$ . As expected from previous studies, for instance Fama and French (1993) and Petkova (2006) for shorter sample periods, the  $R^2$  and t-statistics are very large for the FF3 model, the three factors being portfolio returns.**<sup>13</sup>** Interestingly, when innovations in the SMB and HML factors are used, essentially the same results obtain, whether the errors from the VAR are made orthogonal to the market or not (models #5 and #3). This means that the 25 FF portfolios load significantly on the factors or their innovations. We note however a tendency for the coefficients associated with HML to increase when they are negative and to decrease otherwise, i.e. to converge towards zero, as we move from model #1 to model #5 where innovations are made orthogonal to the market.

## **Insert Table III about here**

<sup>&</sup>lt;sup>12</sup> See for instance Petkova's (2006) Tables II and V or Yogo's (2006) Table III.

<sup>&</sup>lt;sup>13</sup> By contrast, when the factors are not portfolio returns but, say, macroeconomic variables such as those used for instance in production-based CAPMs, the  $R^2$  obtained from time series are much lower. See for example Cochrane (1996), Zhang (2005) and Liu, Whited and Zhang (2007).

## *E. Tests of Robustness: Industry Portfolios and Dynamic Cross-Sections*

We assess the robustness of the previous results in two different ways. First, we enlarge our universe to comprise, in addition to the 25 FF portfolios, 17 Industry portfolios. Some authors, in particular Lewellen, Nagel and Shanken (2007), have indeed strongly argued that excess return tests using the 25 FF portfolios are biased favorably due to the factorial structure inherent to the construction of these portfolios. The fact that it is easy to explain the returns on portfolios possessing a strong factorial structure casts doubts as to the relevance and significance of the tests. Since the Industry portfolios are free from such a bias, as they are not sorted by firms' characteristics other than industry, introducing them makes tests of an asset pricing model more meaningful.

Cross-sectional regressions in Table IV confirm those reported in Table II.**<sup>14</sup>** As expected from the literature and the way the 25 FF portfolios are constructed, the overall quality of each regression is smaller with 42 portfolios than with 25, the adjusted  $R^2$  and  $R^2$ (*JW*) falling from 0.74 and 0.77, respectively, to 0.52 and 0.55. In models #4 and #5, the normalization of variances being once more immaterial, the significance of all independent variables but HML remains the same as in models #1 to #3. And again, innovations in HML made orthogonal to the market become much less significant, the t-statistics being divided by 2.4.

## **Insert Table IV about here**

Our second check consists in performing so-called "dynamic" cross-sectional regressions, as opposed to the "static" ones reported in Table II, to obtain estimates of the market prices of risk associated with the factor loadings estimated from time series. We thus conduct robustness tests for the significance of the loadings. Adopting a procedure borrowed from Fama and Macbeth (1973), we first perform an OLS cross section for each of the 534 months available from July 1963 to December 2007 rather than for the entire sample period, and then average the constant and the regression coefficients over the 534 estimates. Note that we still use the (time series) loadings estimated over the whole period. Table V reports the results of these cross-sectional regressions using (i) the 25 FF portfolios (Panel A) and (ii) the 42 FF and Industry portfolios (Panel B). The resulting cross-section coefficients appear on  $1<sup>st</sup>$  rows. The (Fama-Macbeth) t-

<u>.</u>

 $14$  To save space, we do not report the loadings from the time-series regressions; they are available upon request.

statistics of the various averages are displayed on  $2<sup>nd</sup>$  rows. All the coefficients but the constants have been multiplied by 100 for readability. We do not report the  $R^2$  as they are unchanged from those obtained from the "static" cross-sectional regressions.

# **Insert Table V about here**

The key finding is that for models #4 and #5, where innovations are made orthogonal to the market, HML is insignificant, whether we use 25 or 42 portfolios, although it is very significant for models #1 to #3. This reinforces the suspicion that making innovations in the HML and SMB factors orthogonal to the market completely modifies the very nature and interpretation of the FF3 model.

## **II. The Determinants of Portfolio Returns**

## *A. Predictive variables*

We address now the main question of the paper and try to assess whether the SMB and HML factors proxy for the four predictive variables ("*Div*", "*Term*", "*Def*", and "*Tbill*"). The innovations in the latter are deemed to reflect unanticipated changes in the investors' opportunity set and thus to command compensating risk premiums. Table VI exhibits various summary statistics for the levels (not the innovations from a VAR process) of the four macro variables as well as their correlations. The salient feature emerging from the Table is the high value of the first-order auto-regression coefficients, in particular for the aggregate dividend yield. This will bear on the interpretation of the results discussed below.

## **Insert Table VI about here**

We now estimate the innovations from a first-order VAR process that includes, in addition to the three FF factors, the aforementioned financial variables:

$$
\begin{bmatrix}\nr_{M,t} \\
r_{SMB,t} \\
r_{HML,t} \\
Div_t \\
Term_t \\
Def_t \\
Tbill_t\n\end{bmatrix} = B \begin{bmatrix}\nr_{M,t-1} \\
r_{SMB,t-1} \\
r_{HML,t-1} \\
P_{HML,t-1} \\
Term_{t-1} \\
Term_{t-1} \\
Def_{t-1} \\
Tbill_{t-1}\n\end{bmatrix} + u_t
$$
\n(4)

where  $u_t$  is a seven-dimensional vector of innovations. The innovations regarding all variables but the market contained in  $u_t$  are used in later regressions either after they have been normalized so as to exhibit the same variance as that of the innovations from the market alone, or after they have been also made orthogonal to the market.<sup>15</sup> That leaves us with 12 ( $2\times6$ ) series of innovations.

Panel A of Table VII exhibits the correlation between one variable and its own normalized innovation or its own innovation orthogonal to the market. Several conclusions emerge from this panel. First, correlation coefficients are close to one for the FF factors. This signals that there is little difference between using the SMB and HML factors or their innovations. More to the point, it also suggests that over a one-month horizon, there is almost no predictability attached to these factors as the surprise component represents almost all the monthly variation. This vindicates the results of Tables II and IV in which little, if any, difference was found between models #1, #2 and #3. By contrast, the correlations reported for the four state variables are much smaller, in particular for the dividend yield (0.06). Here, the difference between the level of the variable and its innovation from the VAR is substantial. This is consistent with the finding in Table VI of an auto-regressive coefficient close to one (0.99 for the dividend yield), making the state variables highly predictable. Also, regarding the four state variables, the correlation between one variable and its innovation orthogonal to the market is the same as the correlation between the variable and its innovation. This is less the case for the FF factors, in particular HML, for which the orthogonalization procedure has the most effect. This result is consistent with both our preliminary findings and the fact that HML is the variable most correlated with the market.**<sup>16</sup>**

<sup>&</sup>lt;sup>15</sup> Since not normalizing the innovations has been shown in section II to produce the same results, we do not discuss this case.

<sup>&</sup>lt;sup>16</sup> The correlation between HML and the market is while that between SMB and the market is only.

This is also confirmed by the correlation matrix of the innovations in the six variables shown in Panel B, and the correlation matrix for the orthogonal innovations in the variables shown in Panel C. First, the correlation between innovations in the state variables and innovations in the FF factors is very weak, ranging from -0.07 to 0.08. This suggests that if innovations in the state variables contain information useful for explaining the cross-sectional differences in portfolio returns, this information is not included in the FF factors. Second, comparing the two panels reveals that the correlation coefficients materially differ (and increase in absolute value) only when HML is involved. This again points at the peculiarity of this factor.

#### **Insert Table VII about here**

## *B. Cross Sections and Loadings from Time Series*

We reproduce the same two-pass procedure on the 25 FF portfolios as in section I except that when innovations in variables are involved, we use the first-order VAR process (4) instead of process (1) to include the influence of the four financial variables. This makes a direct comparison with Petkova's (2006) findings possible. Table VIII reports the results from the second-step cross-sectional regressions. Model #1 is again the FF3 model reproduced for the sake of comparison. Model #2 replaces the SMB and HML factors by their innovations. Model #3 is a variant of model #2 where the errors from the VAR have been made orthogonal to the market. The results plainly confirm those of Table II: Model #2 fares almost exactly as FF3, but when orthogonal innovations in SMB and HML are used, the significance of HML drops considerably to a borderline level (the t-statistics corrected by Shanken and Newey-West decrease from 7.31 to 2.02 and from 7.19 to 1.99, respectively).

Models #4 to #6 use the market and the four state variables but not the FF factors. In model #4, all are expressed in levels. Models #5 and #6 are variants where the four state variables have been replaced by their innovations, and their orthogonal innovations, respectively. Three salient features emerge. First the market portfolio disappears as a significant variable, which is hard to reconcile with both financial theory and numerous previous studies. Note that models #4 and #5 are absent from Petkova (2006). Second, model #6 does as well as, but not better than, the benchmark FF3 model, with "*Term*" and "*Tbill*" very significant, but not "*Div*" and "*Def*". Third, there is no sizeable difference between models #5 and #6, which is

consistent with the fact that the market is not significant, so that making the innovations orthogonal to its excess return or not is immaterial. Together, these findings suggest that while the level and slope of the yield curve do possess explanatory power for the crosssectional variation in portfolio returns, the model does not improve on FF3 and its economic interpretation is problematic as the market portfolio is never significant.

## **Insert Table VIII about here**

Models #7 to #9 use the market, the two FF factors and the four state variables. In model #7, all are expressed in levels. In models #8 and #9 the four state variables have been replaced by their innovations, and their orthogonal innovations, respectively. As in Petkova (2006), model #8 uses the errors from a *six*-dimensional VAR where the market has been removed from Eq. (4). Model #9 is a variant where these errors have been made orthogonal to the market. Three main conclusions can be drawn. First, models #7 and #8 yield similar results in terms of the (large) significance of HML or its innovation. This result thus is robust to the model specification. Second, in models #8 and #9, the "*Term*" and "*Tbill*" predictors are no longer significant according to Shanken's t-statistics, and "*Div*" and "*Term*" are hardly significant according to the Newey-West t-statistics. Third, the significance of HML drops in model #9 to a borderline level, but, in view of our previous results, we claim that this is due to the orthogonalization process more than to the presence of the four predictors. In particular, model #8 is specially damaging to interpreting the FF factors as proxies for innovations in predictive variables since HML is very significant while the four predictors are not (according to Shanken's t-statistics). Campbell (1996) had already checked whether innovations in some state variables (similar to our "*Div*", "*Term*" and "*Tbill*") were helpful to explain the cross section of portfolio excess returns. His results were mitigated as the market prices of risk associated with the state variables were hardly significant. Therefore his findings did not loom very promising as to the explanatory power of these innovations.

The loadings for the first-pass time-series regressions which led to the cross-sectional models #7 and #9 of Table VIII are reported in Table IX, Panels A and B, respectively.**<sup>17</sup>** It is readily apparent that the Newey-West t-statistics associated with the loadings of the HML factor are across the board a lot higher than those associated with the loadings of the four state variables.

 $17$  To save space, we omit the comparatively less interesting loadings obtained for the other models. They are available upon request.

As a matter of fact, the loadings of the HML are extremely significant while those of the predictors are almost always very insignificant. This is irrespective of whether levels (Panel A) or innovations (Panel B) for the explanatory variables are used, which reinforces the case against interpreting the FF factors as proxies for the latter variables. In fact, the preliminary evidence provided by Petkova's (2006) Table I and Hahn and Lee's (2006) Table II already cast doubts on this interpretation, as the adjusted  $R^2$  they obtained for the time-series regressions of innovations in each state variable on the three FF factors were close to zero. It seems therefore highly implausible that these state variables should contain the information embedded in HML and SMB. At best, they are other pricing factors that do not capture what HML et SMB do.

#### **Insert Table IX about here**

To check the robustness of these results, we redo the two-pass procedure above with 42 portfolios instead of 25, in the same spirit as in section II. As expected and for a reason already mentioned, the goodness-of-fit of all cross-sectional regressions #1 to #9 exhibited in Table X decreases rather markedly, as the favourable bias inherent to the use of the 25 FF portfolios s attenuated. The first interesting point, however, is that the original FF3 model now fares significantly better than the model that includes the market and the four state variables. This can be seen from comparing the adjusted  $R^2$  and the  $R^2$ (*JW*) for models #1 to #3 on the one hand and for models #4 to #6 on the other. Only if the two FF factors are introduced as explanatory variables along with the four predictors do the models (#7 to #9) exhibit a better goodness-of-fit than FF3. This is in accordance with e.g. Avramov and Chordia (2006) who show that, for individual equity stocks, a conditional version of the FF3 model performs much better than its standard CAPM counterpart. The second, even more relevant result is that, when all innovations are made orthogonal to the market (model #9), the HML factor still is significant and thus is not driven out by the presence of the four predictive variables. Therefore, Petkova's (2006) main results do not survive at all when the universe of portfolios is expanded.

Similarly to Table IX relative to the 25 FF portfolios, Table XI report the loadings for the firstpass time-series regressions involving the 17 Industry portfolios which led to the crosssectional models #7 and #9 of Table X. The conclusion is exactly the same as for Table IX. The loadings of the HML are generally very significant while those of the predictive variables are almost always insignificant, regardless of whether levels (Panel A) or innovations (Panel B) for the explanatory variables are used. Therefore, the case against interpreting the FF factors as proxies for the predictive variables seems robust against the set of portfolios under scrutiny.

## **Insert Tables X and XI about here**

## **III. Alternative Specifications**

#### *A. Portfolio Returns and Innovations from a Modified VAR*

Since using either the levels of the HML and SMB factors or their (non orthogonalized) innovations from the VAR process (4) leads to similar results and since we fail to interpret these factors as proxies for the predictive variables, we redo the whole analysis using an alternative VAR process of smaller dimension that involves the four predictive variables but not the FF3 factors:

$$
\begin{bmatrix} Div_{t} \\ Term_{t} \\ Def_{t} \\ Tbill_{t} \end{bmatrix} = B \begin{bmatrix} Div_{t-1} \\ Term_{t-1} \\ Def_{t-1} \\ Tbill_{t-1} \end{bmatrix} + v_{t}
$$
\n(5)

where  $v_t$  is a four-dimensional vector of innovations. In this way we can assess in a more convincing manner the respective influence on portfolio returns of the FF3 factors and the own innovations in the predictive variables deemed to reflect unanticipated changes in the investment opportunity set. This is, incidentally, more in line with what Campbell (1996) did, although he used macroeconomic variables along with financial ones. Our procedure thus is consistent with *not* interpreting the HML and SMB factors as proxies for changes in (not yet identified) state variables, but as mere artifacts built from more or less arbitrary portfolio sorting with no *a priori* economic content.

Another, perhaps decisive, advantage of this specification is that the innovations  $v_t$  are truly synchronous with the FF3 factors. The latter are in effect *monthly* ex post returns (*HML<sup>t</sup>* for instance is computed as the relative capital gain on HML between the end of month *t* and the end of month  $(t-1)$ ), and innovations  $v<sub>t</sub>$  involve the difference between *instantaneous* rates (or spreads) at date *t* and instantaneous rates (or spreads) at date (*t*-1). By contrast, for the VAR specification represented by Eq. (4), data relative to date (*t*-2) are required to compute the FF3 factors lagged once.<sup>18</sup>

Table XIII reports correlations for the SMB and HML factors (expressed in levels) and contemporaneous innovations in the four state variables obtained from the VAR process (5). The correlation matrix is reported in Panel A. The correlations involving HML or SMB are rather different from those appearing in Table VII (Panel B). In particular, the correlation of each variable with "*Div*" is much increased in absolute value, as well as the absolute correlation between "*Def*" and SMB. Panel B of Table XIII reports the correlation matrix when the innovations in the state variables have been made orthogonal to the market. As compared to those exhibited in Table VII (Panel C), all the correlations involving SMB have increased in absolute value. This is also the case, but to a lesser extent, for all the correlations involving HML. This suggests that results obtained with innovations estimated from the modified VAR process (5) might be significantly different from those reported in section II (sub-section *B*) above.

# **Insert Table XIII about here**

### *B. Cross Sections of Portfolio Returns*

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We thus reproduce the same two-pass procedure on the 25 and 42 portfolios as in section II using the innovations obtained from the first-order VAR process (4), dubbed hereafter the *modified* VAR, instead of process (1). To ease the comparison, when it is relevant, we adopt in Table XIV the same numbering of models as in Table VIII, with a \* attached to each number for differentiation. Model #5\* uses the market and the innovations in the four state variables. Model #6\* is a variant of model #5\* where innovations were made orthogonal to the market. Model #8\* uses the market, the SML and HML factors, all expressed in levels, and the innovations in the four state variables. Model #9\* is a variant of model #8\* with innovations orthogonal to the market.**<sup>19</sup>**

<sup>&</sup>lt;sup>18</sup> Campbell (1996) did not face this asynchronous problem since he used the market return expressed in levels. AB, je n'ai pas bien compris ton point ici. Rephrase-le, je corrigerai l 'anglais.

<sup>&</sup>lt;sup>19</sup> Note that models  $#5*$  and  $#6*$  are directly comparable to models  $#5$  and  $#6$ , respectively. Such is not exactly the case for model #8\* since, in model #8, innovations in HML and SMB are used instead of their levels. This should not, however, be problematic since using these variables or their innovations from a VAR was shown to yield similar results (compare for instance models #1 and #2 in Table IV). Model #9\*, in spite of its tag, cannot

Consider first the universe of 25 portfolios (Panel A). Model #5\* improves on model #5 as the state variable "*Def*" becomes significant, along with "*Term*" and "*Tbill*", and the overall goodness-of-fit is better. Model #6\* also fares better than the analogous model #6 as to the significance of the explanatory variables and its overall goodness-of-fit. In particular, "*Def*" becomes significant and its coefficient exhibits the intuitively correct negative sign. Models #8\* and #9\* improve on models #8 and #9, respectively, in that not only HML and SMB are even more significant but "*Term*" and "*Tbill*" become significant. These models fare better than FF3 in terms of goodness-of-fit (see model #1 in Table VIII). Three main conclusions emerge from Table XIV:

(i) two state variables are priced and do partially explain, as implied by Merton's (1973) ICAPM, the cross-sectional variation in the 25 FF portfolio returns,

(ii) the HML and SMB factors remain strongly priced and not driven away by the presence of the predictors, and

(iii) whether innovations in the predictive variables are made orthogonal to the market or not, introducing the two FF factors enhances the overall goodness-of-fit of the cross-sectional regression, as comparing models  $#5^*$  and  $#8^*$  on the one hand, and  $#6^*$  and  $#9^*$  on the other, clearly shows.

# **Insert Table XIV about here**

As evidenced by Panel B of Table XIV, the second and third conclusions, but not the first, are robust to the enlargement of the universe to 42 portfolios. HML and SMB are still strongly priced and the state variables become insignificant, whether they are made orthogonal to the market or not. The interpretation of the two FF factors as proxies for innovations in predictive variables thus breaks down.

*C. Dynamic Cross-Sections*

be directly compared to model #9 since whether SMB and HML are made orthogonal to the market (model #9) or not (model #9\*) does make a large difference.

As in sub-section II-E, we perform "dynamic" cross-sectional regressions to obtain estimates of the market prices of risk associated with the factor loadings estimated from time series. We thus perform an OLS cross-sectional regression for each of the 534 months available and then average the coefficients over the 534 estimates. We consider the four preceding models, numbered 5\*, 6\*, 8\* and 9\*. Results are reported in Table XV for 25 (Panel A) and 42 (Panel B) portfolios. They vindicate the findings of the previous Table. The HML factor is priced, so is the market in the universe of 25 portfolios. As to the predictive variables, "*Term*" and "*Tbill*" are significant with 25 portfolios but not in the enlarged universe. The fact that "*Div*" is never priced is at odds with previous findings by Campbell and Shiller (1988) among others.

#### **Insert Table XV about here**

## *D. Conditional ICAPMs*

The previous analysis does not take into account the fact that the loadings used in crosssectional regressions are time-varying and influenced by random changes in the investment opportunity set. To deal with this issue, numerous authors have tested various conditional versions of the CAPM.

The test procedure we use is the one described for the unconditional models above except that in the first-pass time-series regression of excess returns on a portfolio  $(r_{j,t})$ , the  $\beta_{j,Y_i}$  in Eq. (2) are time-varying and depend linearly on the four state variables lagged once. Note that, to avoid undue complexity, and in view of the generally weak short term predictability of individual portfolios, we follow Ferson and Harvey (1999) and choose to let  $\alpha_j$  constant. We thus have

$$
r_{j,t} = \alpha_j + \sum_{i=1}^F \left( \beta_{j,i,0} + \sum_{l=1}^K \beta_{j,i,l} Y_{l,t-1} \right) Y_{i,t} + \varepsilon_{j,t} \qquad \forall j
$$
 (6)

where *F* is the number of factors (Market, HML, SMB) and/or state variables ("Div", "Term", "Def", "Tbill"), so that  $F = 3$ , 4 or 7 here and *K* is the number of lagged predictors ( $K = 4$ ) here). Developing the double sum, we thus have, for each portfolio *j*, to estimate  $(1+K)F = 15$ , 20 or 35 betas according to the models being tested.

In the second pass, we conduct cross-section regressions to test the hypothesis that the conditional expected risk premiums on portfolios obey:

$$
E(r_j) = \lambda_j + \sum_{i=1}^{F} \gamma_{Y_i} \hat{\beta}_{j, Y_i} + \sum_{i=1}^{F} \sum_{l=1}^{K} \gamma_{Y_{i,j}} \hat{\beta}_{j, Y_i, X_l}
$$
(7)

where the independent variables  $\hat{\beta}_{i}$  are estimates obtained from regression (6).

## **Insert Table XVI about here**

Table XVI presents the second-step cross-sectional regressions using 42 portfolios.**<sup>20</sup>** Model #A is a conditional version of the FF3 model in which all three loadings are time-varying and depend on the four predictors lagged once. Model #B is a conditional version of the fourstate-variable model in which the four loadings are time-varying. Model #C combines the two previous models and is therefore a conditional model in which all seven loadings (on the Market, SMB, HML, "*Div*", "*Tbill*", "*Term*" and "*Def*") are time-varying.

In model #A, conditioning the loadings slightly improves the overall goodness-of-fit as measured by  $R^2$ (*JW*) (compare with model #1 in Table X). But none of the cross-betas are significant. This is consistent with the observation made by Ferson and Harvey (1999) that the FF3 model is unable to capture the effect of conditioning information. In model #B, conditioning the loadings highly improves the  $R^2$  and  $R^2$ (*JW*) (see model #4 in Table X) although none of the betas or cross-betas are significant. Model #C by contrast is extremely successful in terms of both goodness-of-fit and significance of loadings (compare with model #7 in Table X) and is by far superior to the original FF3 model. The loading on the market is significantly affected by the slope of the yield curve. For the first time, "*Div*" plays a role through its positive influence on HML. The significance of the SMB and particularly HML factors is again vindicated.

We repeat the exercise on the three conditional models by conducting "dynamic" crosssectional regressions as in sub-section *C*. Results are reported in Table XVII. As compared to the static regressions, in all three models more betas or cross-betas (especially for model #B) are significant. In particular, in models #A and #C, three loadings associated with HML are

<u>.</u>

 $20$  The relatively large number of explanatory variables precludes conducting tests on 25 portfolios only.

significant, implying that betas are time varying and affected by the state variables which describes the investment opportunity set.

# **Insert Table XV about here**

**IV Conclusion** 

To be Added.

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To be Completed.

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## **Table I: Summary Statistics**

Panel A reports various statistics for the excess return on the market portfolio ("Market") and the returns on the Fama-French "small minus big" size-related ("SMB") and "high minus low" book-to-market-related ("HML") portfolios. Panel B and C exhibit the average excess returns on the 25 Fama-French portfolios sorted by size and book-to market, and on the 17 industry portfolios also compiled by Fama and French, respectively. All data are in percent monthly (and non-annualized) and cover the period 1963:07 to 2007:12 (534 observations).

#### **Panel A: excess returns (Market) and returns (SMB, HML)**



#### **Panel B: average excess returns on the 25 Fama-French portfolios**



#### **Panel C: average excess returns on the 17 Industry portfolios**



#### **Table II: Cross-Sectional Regressions with the Fama-French Factors (25 Portfolios)**

This Table presents cross-sectional regressions using the excess returns on the 25 Fama-French portfolios sorted by size and book-to-market. The full-sample factor loadings, which are the independent variables in the crosssectional regressions, have been computed in time-series simple regressions (for each of the 25 portfolios) in which the dependent variable is the excess return on a given portfolio (see Table III below). The cross-section regression (Fama-Macbeth) coefficients (1<sup>st</sup> rows, "Coeff.") are obtained by OLS. All the coefficients but the constants have been multiplied by 100 for readability. The t-statistics have been corrected for both autocorrelation and heteroskedasticity using the Newey-West estimator with four lags and appear on  $2<sup>nd</sup>$  rows ("t(NW)"). t-statistics adjusted for errors-in-variables following Shanken (1992) are shown on  $3<sup>rd</sup>$  rows ("t(S)"). The last two columns report the standard adjusted  $R^2$  and the  $R^2$  (" $R^2$ (JW)") as computed by Jagannathan and Wang (1996). All data are monthly. The sample period is 1963:07 to 2007:12.

Model #1 refers to the standard Fama-French three-factor model. Model #2 replaces the SMB and HML factors by their innovations from a first-order VAR system that contains the market, SMB and HML, all lagged one period. Model #3 is a variant of model #2 where the errors from the VAR have been normalized so as to have the same variance as that of the market innovations alone. Model #4 is also a variant of model #2 where the errors from the VAR have been made orthogonal to the market. Model #5 is a variant of model #4 where the variance of errors from the VAR has been made equal to the variance of the market.



#### **Table III: Loadings on the Market and the SMB and HLM factors or Their Innovations From Time-Series Regressions (25 Fama-French Portfolios)**

This Table reports the loadings on the market portfolio ("β-mkt"), and the SMB ("β-smb") and HML ("β-hml") factors or their innovations from a first-order VAR, computed in time-series regressions for the 25 Fama-French portfolios sorted by size (from Small (S) to Big (B)) and book-to-market (from Low (L) to High (H)). All values are monthly excess returns compiled for the period 1963:07 to 2007:12. The loadings exhibited in panels A, B and C, led to the cross-sectional models #1, #3 and #5, respectively, reported in Table II. On the right part are shown the t-statistics associated with the factors. The last rows report the standard adjusted  $\mathbb{R}^2$ .

## **Panel A: Model #1**



B 0.93 0.90 0.84 0.88 0.79

## **Panel B: Model #3**



B 0.93 0.90 0.84 0.88 0.79

# **Panel C: Model #5**

4 0.94 0.88 0.87 0.88 0.85 B 0.93 0.90 0.84 0.88 0.79



#### **Table IV: Cross-Sectional Regressions with the Fama-French Factors (42 Portfolios)**

This Table is similar to Table II and presents cross-sectional regressions using the excess returns on 42 portfolios, i.e. the 25 Fama-French portfolios sorted by size and book-to-market and the 17 industry portfolios also complied by Fama-French. The full-sample factor loadings, which are the independent variables in the cross-sectional regressions, have been computed in time-series simple regressions (for each of the 42 portfolios) in which the dependent variable is the excess return on a given portfolio. The cross-section regression (Fama-Macbeth) coefficients  $(1<sup>st</sup> rows, "Coeff.")$  are obtained by OLS. All the coefficients but the constants have been multiplied by 100 for readability. The t-statistics have been corrected for both autocorrelation and heteroskedasticity using the Newey-West estimator with four lags and appear on 2<sup>nd</sup> rows ("t(NW)"). t-statistics adjusted for errors-in-variables following Shanken (1992) are shown on  $3<sup>rd</sup>$  rows ("t(S)"). The last two columns report the standard adjusted  $R^2$  and the  $R^2$  (" $R^2$ (JW)") as computed by Jagannathan and Wang (1996). All data are monthly. The sample period is 1963:07 to 2007:12.

Model #1 refers to the standard Fama-French three-factor model. Model #2 replaces the SMB and HML factors by their innovations from a first-order VAR that contains the market, SMB and HML. Model #3 is a variant of model #2 where the errors from the VAR have been normalized so as to have the same variance as that of the market innovations alone. Model #4 is also a variant of model #2 where the errors from the VAR have been made orthogonal to the market. Model #5 is a variant of model #4 where the variance of errors from the VAR has been made equal to the variance of the market.



**Table V: Dynamic Cross-Sectional Regressions with the Fama-French Factors (25 and 42 Portfolios)** 

This Table presents the results of dynamic cross-sectional regressions using the excess returns on the 25 Fama-French (FF) portfolios sorted by size and book-to-market (Panel A) and on 42 (25 FF plus 17 Industry) portfolios (Panel B). The full-sample factor loadings, which are the independent variables in the cross-sectional regressions, have been computed in time-series regressions (for each of the 42 portfolios) in which the dependent variable is the excess return on a given portfolio. We have used as explanatory variables the market portfolio, and the SMB and HML factors or their innovations from a VAR (see Table II for the definitions of models #1 to #5). The sample period is 1963:07 to 2007:12 (534 monthly observations). Consequently, for each of the two sets (A and B) of portfolios, 534 cross sections have been performed, for  $t = 1, \ldots, 534$ , using OLS. Then the constant and the regression coefficients have each been averaged over these 534 estimates. The resulting crosssection coefficients appear on 1<sup>st</sup> rows ("Coeff."). All the coefficients but the constants have been multiplied by 100. The (Fama-Macbeth) t-statistics of the various averages are displayed on  $2<sup>nd</sup>$  rows ("t(FM)").





# **Table V: Dynamic Cross-Sectional Regressions with the Fama-French Factors (25 and 42 Portfolios) (Continued)**

# **Panel B: 42 portfolios**



#### **Table VI: Summary Statistics for Four State Variables**

Panel A reports various statistics for the levels of four state variables: the three-month Treasury bill rate ("Tbill"), the term spread measured as the difference between the ten-year (constant maturity) Treasury bond yield and the three-month Treasury bill rate ("Term"), the default spread measured as the difference between the yield of a Baa-rated bond and that of an Aaa-rated bond both having a constant 10 year maturity ("Def"), and the dividend yield measured as the total dividends paid off during the last 12 months divided by the actual price of the market portfolio ("Div"). "AR(1)" stands for the first-order auto-regression coefficient. Panel B reports the correlation matrix for the above four variables. All data are monthly, expressed in percent and annualized, and cover the period 1963:07 to 2007:12 (534 observations).

## **Panel A**



**Panel B** 



#### **Table VII: Correlations Between Innovations in State Variables and in SMB and HML Factors**

This Table reports correlation coefficients for the SMB and HML factors and the four state variables defined in Table VI. Innovations in each of the six variables have been obtained from a first-order VAR that included the six variables plus the market portfolio, all lagged one period, and normalized so as to exhibit the same variance as that of the innovations from the market alone. Panel A exhibits the correlation between one variable and its own normalized innovation (column 2) or its own normalized innovation made orthogonal to the contemporaneous market excess return (column 3). Panel B reports the correlation matrix for the innovations in the above six variables. Panel C reports the correlation matrix for the beforehand orthogonalized innovations in the above six variables. All data are monthly, expressed in percent and annualized, and cover the period 1963:07 to 2007:12 (534 observations).

Innov. Orth. Innov.

#### **Panel A: variables and their own innovations**



Tbill 0.01 -0.16 -0.02 -0.84 -0.29 1

#### **Table VIII: Cross-Sectional Regressions with the Fama-French Factors and Innovations in the State Variables (25 Portfolios)**

This Table presents cross-sectional regressions using the excess returns on the 25 Fama-French portfolios sorted by size and book-to-market. The full-sample factor loadings, which are the independent variables in the crosssectional regressions, have been computed in time-series simple regressions (for each of the 25 portfolios) in which the dependent variable is the excess return on a given portfolio (see Table IX below). The cross-section regression (Fama-Macbeth) coefficients (1<sup>st</sup> rows, "Coeff.") are obtained by OLS. All the coefficients but the constants have been multiplied by 100 for readability. The t-statistics have been corrected for both autocorrelation and heteroskedasticity using the Newey-West estimator with four lags and appear on 2<sup>nd</sup> rows ("t(NW)"). t-statistics adjusted for errors-in-variables following Shanken (1992) are shown on  $3^{rd}$  rows ("t(S)"). The last two columns report the standard adjusted  $R^2$  and the  $R^2$  (" $R^2$ (JW)") as computed by Jagannathan and Wang (1996). All data are monthly. The sample period is 1963:07 to 2007:12.

Model #1 refers to the standard Fama-French three-factor model and is the same as in Table II. Model #2 replaces the SMB and HML factors by their innovations from a first-order VAR that contains the market, SMB, HML and the four state variables defined in Table VI, all lagged one period. Model #3 is a variant of model #2 where the errors from the VAR are orthogonal to the market. Model #4 uses the market and the four state variables expressed in levels. Models #5 and #6 are variants of model #4 where the four state variables have been replaced by their innovations, and their orthogonalized (to the market) innovations, respectively. Model #7 uses the market, the two Fama-French factors and the four state variables, all expressed in levels. Model #8 uses the innovations from the VAR in all variables but the market. Model #9 is a variant of model #8 where innovations are orthogonal to the market.



#### **Table IX: Loadings on the Market, the Fama-French Factors and Innovations in Four State Variables from Time-Series Regressions (25 Portfolios)**

This Table reports the loadings on the market portfolio ("β-mkt"), and on the innovations in the SMB ("β-smb") and HML ("β-hml") factors and in the four state variables defined in Table VI ("β-div", "β-term", "β-def", "βtbill") computed in time-series regressions for the 25 Fama-French portfolios sorted by size and book-to-market. All values are monthly excess returns compiled for the period 1963:07 to 2007:12. These loadings led to the cross-sectional models #7 (Panel A) and #9 ((Panel B) reported in Table VIII. In addition to the coefficients, the Table provides their t-statistics and the standard adjusted  $\mathbb{R}^2$ .

## **Panel A: Model #7**





# **Panel B: Model #9**





#### **Table X: Cross-Sectional Regressions with the Fama-French Factors and Innovations in the State Variables (42 Portfolios)**

This Table is exactly the same as Table VIII except that it uses the 17 Industry portfolios listed in Table I in addition to the 25 Fama-French portfolios sorted by size and book-to-market.

Model #1 refers to the standard Fama-French three-factor model and is the same as in Table IV. Model #2 replaces the SMB and HML factors by their innovations from a first-order VAR that contains the market, SMB, HML and the four state variables defined in Table VI, all lagged one period. Model #3 is a variant of model #2 where the errors from the VAR are orthogonal to the market. Model #4 uses the market and the four state variables expressed in levels. Models #5 and #6 are variants of model #4 where the four state variables have been replaced by their innovations, and their orthogonalized (to the market) innovations, respectively. Model #7 uses the market, the two Fama-French factors and the four state variables, all expressed in levels. Model #8 uses the innovations from the VAR in all variables but the market. Model #9 is a variant of model #8 where innovations are orthogonal to the market.



#### **Table XI: Loadings on the Market, the Fama-French Factors and Innovations in the State Variables from Time-Series Regressions (17 Industry Portfolios)**

This Table is similar to Table IX and reports the loadings on the market portfolio ("β-mkt"), and on the innovations in the SMB ("β-smb") and HML ("β-hml") factors and in the four state variables defined in Table VI ("β-div", "β-term", "β-def", "β-tbill") computed in time-series regressions for 17 industry portfolios. All values are monthly excess returns compiled for the period 1963:07 to 2007:12. These loadings led to the crosssectional models #7 (Panel A) and #9 ((Panel B) reported in Table X. In addition to the coefficients, the Table provides their t-statistics and the standard adjusted  $\mathbb{R}^2$ .

# **Panel A: Model #7**



# **Panel B: Model #9**



#### **Table XII: Dynamic Cross-Sectional Regressions with the Fama-French Factors and Innovations in the State Variables (25 and 42 Portfolios)**

This Table presents the results of dynamic cross-sectional regressions using the excess returns on the 25 Fama-French (FF) portfolios sorted by size and book-to-market (Panel A) and on 42 (25 FF plus 17 industry) portfolios (Panel B). The full-sample factor loadings, which are the independent variables in the cross-sectional regressions, have been computed in time-series regressions (for each of the 42 portfolios) in which the dependent variable is the excess return on a given portfolio. We have used as explanatory variables the market portfolio, the SMB and HML factors and/or the four state variables defined in Table VI or their innovations from a first-order VAR (see Table VIII for the definitions of models #1 to #9). The sample period is 1963:07 to 2007:12 (534 monthly observations). Consequently, for each of the two sets (A and B) of portfolios, 534 cross sections have been performed, for t =1,..., 534, using OLS. Then the constant and the regression coefficients have each been averaged over these 534 estimates. The resulting cross-section coefficients appear on 1<sup>st</sup> rows ("Coeff."). All the coefficients but the constants have been multiplied by 100. The (Fama-Macbeth) t-statistics of the various averages are displayed on  $2<sup>nd</sup>$  rows ("t(FM)").

## **Panel A: 25 Fama-French portfolios**





#### **Table XIII: Correlations Between the SMB and HML Factors and the Modified Innovations in State Variables**

This Table reports correlations for the SMB and HML factors (expressed in levels) and contemporaneous innovations in the four state variables defined in Table VI. Innovations in each of the four variables have been obtained from a first-order VAR that included these four variables *only*. The correlation matrix is exhibited in Panel A. Panel B reports the correlation matrix when the innovations in the state variables are orthogonal to the market. All data are monthly, expressed in percent and annualized, and cover the period 1963:07 to 2007:12 (534 observations).

#### **Panel A: levels and innovations**



#### **Panel B: levels and orthogonalized innovations**



#### **Table XIV: Cross-Sectional Regressions with Fama-French Factors and Modified Innovations in the State Variables (25 and 42 Portfolios)**

This Table presents cross-sectional regressions using the excess returns on the 25 Fama-French (FF) portfolios sorted by size and book-to-market (Panel A) and on 42 (25 FF plus 17 industry) portfolios (Panel B). The fullsample factor loadings, which are the independent variables in the cross-sectional regressions, have been computed in time-series simple regressions (for each of the 42 portfolios) in which the dependent variable is the excess return on a given portfolio. The cross-section regression (Fama-Macbeth) coefficients ( $1<sup>st</sup>$  rows, "Coeff.") are obtained by OLS. All the coefficients but the constants have been multiplied by 100 for readability. The tstatistics have been corrected for both autocorrelation and heteroskedasticity using the Newey-West estimator with four lags and appear on  $2^{nd}$  rows ("t(NW)"). t-statistics adjusted for errors-in-variables following Shanken (1992) are shown on  $3<sup>rd</sup>$  rows ("t(S)"). The last two columns report the standard adjusted  $R<sup>2</sup>$  and the  $R<sup>2</sup>$ (" $R^2$ (JW)") as computed by Jagannathan and Wang (1996). All data are monthly. The sample period is 1963:07 to 2007:12.

The SMB and HML factors are expressed in levels, and innovations in the four state variables, whether orthogonalized or not, are obtained from a first-order VAR process that included these four variables only. Model  $#5^*$  uses the market and the innovations in the four state variables. Model  $#6^*$  is a variant of model  $#5^*$ where the innovations are orthogonal to the market. Model #8\* uses the market and the two Fama-French factors, expressed in levels, and the innovations in the four state variables. Model #9\* is a variant of model #8\* where these innovations are orthogonal to the market.



#### **Panel A: 25 Fama-French portfolios**



#### **Table XV: Dynamic Cross-Sectional Regressions with the Fama-French Factors and Modified Innovations in the State Variables (25 and 42 Portfolios)**

This Table is similar to Table XII and presents the results of dynamic cross-sectional regressions using the excess returns on the 25 Fama-French (FF) portfolios sorted by size and book-to-market (Panel A) and on 42 (25 FF plus 17 industry) portfolios (Panel B). The full-sample factor loadings, which are the independent variables in the cross-sectional regressions, have been computed in time-series regressions (for each of the 42 portfolios) in which the dependent variable is the excess return on a given portfolio. We have used as explanatory variables the market portfolio, the SMB and HML factors (expressed in levels) and/or the innovations in the state variables (defined in Table VI) from a first-order VAR process that included these state variables only (see Table XIV for the definitions of the ensuing four starred models). The sample period is 1963:07 to 2007:12 (534 monthly observations). Consequently, for each of the two sets (A and B) of portfolios, 534 cross sections have been performed, for t =1,…, 534, using OLS. Then the constant and the regression coefficients have each been averaged over these 534 estimates. The resulting cross-section coefficients appear on  $1<sup>st</sup>$  rows ("Coeff."). All the coefficients but the constants have been multiplied by 100. The (Fama-Macbeth) t-statistics of the various averages are displayed on  $2<sup>nd</sup>$  rows ("t(FM)").

#### **Panel A: 25 Fama-French portfolios**



#### **Panel B: 42 portfolios**



#### **Table XVI: Cross-Sectional Regressions for Conditional Models (42 Portfolios)**

This Table presents cross-sectional regressions using the excess returns on the 25 Fama-French portfolios sorted by size and book-to-market plus the 17 industry portfolios. The full-sample factor loadings, which are the independent variables in the cross-sectional regressions, have been computed in time-series simple regressions (for each of the 42 portfolios) in which the dependent variable is the excess return on a given portfolio. In these time-series regressions, betas which are time-varying depend linearly on the four state variables defined in Table VI ("Div", "Tbill", "Term" and "Def") that are here used as predictors. The cross-section regression (Fama-Macbeth) coefficients are obtained by OLS and then multiplied by 100 (column "Coeff."). The t-statistics are corrected for autocorrelation and heteroskedasticity using the Newey-West estimator with four lags and appear on column "t(NW)". The t-statistics adjusted for errors-in-variables following Shanken (1992) are shown on column "t(S)". The last two rows report the standard adjusted  $R^2$  and the  $R^2$  as computed by Jagannathan and Wang (1996). All data are monthly. The sample period is 1963:07 to 2007:12.

Model #A is a conditional version of the Fama-French 3-factor model in which all three loadings (on the Market, the SMB and the HML factors) are time-varying and depend on the four predictors. Model #B is a conditional version of the 4-state-variable model in which all four loadings (on "Div", "Tbill", "Term" and "Def") are timevarying and depend on the four predictors. Model #C combines the two previous models and is therefore a conditional model in which all seven loadings (on the Market, SMB, HML, "Div", "Tbill", "Term" and "Def") are time-varying and depend on the four predictors.





#### **Table XVII: Dynamic Cross-Sectional Regressions for Conditional Models (42 Portfolios)**

This Table presents the results of dynamic cross-sectional regressions using the excess returns on the 25 Fama-French portfolios sorted by size and book-to-market plus the 17 industry portfolios. The full-sample factor loadings, which are the independent variables in the cross-sectional regressions, have been computed in timeseries regressions (for each of the 42 portfolios) in which the dependent variable is the excess return on a given portfolio. We have used as explanatory variables the three factors of the Fama-French model and/or the four state variables defined in Table VI, as well as their associated predictors "T-bill", "Term", "Def" and "Div" as in Table XVI. The sample period is 1963:07 to 2007:12 (534 monthly observations). Consequently, 534 cross sections have been performed, for  $t = 1, ..., 534$ , using OLS. Then the constant and the regression coefficients have each been averaged over these 534 estimates, à la Fama-Macbeth. The resulting cross-section coefficients have been reported as "Coeff.". All these coefficients but the constants have been multiplied by 100 for readability. The Table also reports the average t-statistics as "t(FM)".

