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Macroeconomic risks and characteristic-based factor models

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ABSTRACT

We show that book-to-market, size, and momentum capture cross-sectional variation in exposures to a broad set of macroeconomic factors identified in the prior literature as potentially important for pricing equities. The factors considered include innovations in economic growth expectations, inflation, the aggregate survival probability, the term structure of interest rates, and the exchange rate. Factor mimicking portfolios constructed on the basis of book-to-market, size, and momentum therefore, serve as proxy composite macroeconomic risk factors. Conditional and unconditional cross-sectional asset pricing tests indicate that most of the macroeconomic factors considered are priced. The performance of an asset pricing model based on the macroeconomic factors is comparable to the performance of the Fama and French (1993) model. However, the momentum factor is found to contain incremental information for asset pricing.

1. Introduction

We offer a comprehensive multivariate analysis of the relations between shocks to macroeconomic fundamentals suggested by prior research to be important for equity pricing and the benchmark factors proposed by Fama and French (1993) and Carhart (1997). Although some of these relations have been considered elsewhere, e.g., evidence suggests that the Fama and French (FF) benchmark factors, HML and SMB, capture shocks to economic growth expectations (Liew and Vassalou, 2000; Vassalou, 2003), default risk (Vassalou and Xing, 2004; Hahn and Lee, 2006; Petkova, 2006) and the term structure (Hahn and Lee, 2006; Petkova, 2006), the focus of these studies is on one single macroeconomic fundamental or on a narrow set of factors. However, as most macroeconomic fundamentals at least partially reflect the state of the economy, they are often highly correlated, opening up the possibility that the relations found in existing studies suffer from an omitted variables bias. As an example, a downward revision in economic growth expectations often coincides with increasing aggregate default risk due to more conservative consumer behavior and decreasing interest rates to revive the economy. In this situation, an analysis of the univariate relation between HML or SMB and one of these macroeconomic fundamentals can offer little insights on whether the benchmark factor captures economic growth, default or interest rate risk.

We contribute to the existing literature in the following ways. We first establish the links between our macroeconomic fundamentals, and then estimate a comprehensive macroeconomic factor (MF) model which can take account of these links. In this way, we are able to distinguish between the true determinants of the benchmark factors and factors which only appear important in more limited settings due to their ability to proxy for the omitted true determinants. As a second contribution, we expand the set of benchmark factors by investigating the Carhart (C) momentum factor, which is often denoted by WML. We are aware of only a limited number of other studies testing the relation between momentum and macroeconomic fundamentals, and these studies normally fail to find any significant associations. We also expand the set of macroeconomic fundamentals by adding unexpected inflation and changes in a trade-weighted US dollar exchange rate index. Although prior studies indicate that these factors are both associated with equity returns (e.g., Chen et al., 1986; Doidge et al., 2006; Bartram, 2008), their roles in explaining SMB, HML and WML have not been studied so far. Finally, we add the market return as a pricing factor in our MF model. In an ICAPM world, this factor rewards investors for bearing risks unrelated to the

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macroeconomic fundamentals. Still, as the market return is highly correlated with the macroeconomic fundamentals, its inclusion would distort the links between the macroeconomic fundamentals and the stock-based characteristics. To isolate the variation in market returns not attributable to the macroeconomic fundamentals, we follow the recommendation of Fama (1996) and orthogonalize the market return with respect to our other macroeconomic fundamentals.

Consistent with our intuition, we find strong evidence that macroeconomic fundamentals are substantially related. As a direct result of these relations, our analysis of the links between the benchmark risk factors and the macroeconomic fundamentals can in some cases significantly contradict the main conclusions of other studies. In a nutshell, our analysis corroborates the findings of other studies that book-to-market (BM), and therefore, HML, captures information about shocks to economic growth expectations and the slope of the term structure, while size, and therefore, SMB, captures information about shocks to aggregate default risk (e.g., Vassalou, 2003; Hahn and Lee, 2006; Petkova, 2006). However, in contrast to other studies, we also show that SMB reflects shocks to the average level of the term structure. Importantly, some significant associations documented in the prior literature either change sign, e.g., the relation between HML and shocks to economic growth expectations, or become insignificant, e.g., the relation between HML and shocks to aggregate default risk. Additional tests show that these inconsistencies are driven by the omission of correlated factors in prior studies. We also report findings entirely new to the literature, e.g, we find that WML captures default and term structure risk, and more weakly exchange rate risk.

The close relation between the macroeconomic fundamentals and the benchmark risk factors implies that macroeconomic exposures should be able to approximate the exposures to the benchmark risk factors in empirical asset pricing tests. As the benchmark risk factor exposures command strongly significant risk premia and perform well in pricing the cross-section of most characteristic-sorted portfolios (e.g., Fama and French, 1993; Carhart, 1997), we should expect to observe similar findings for the MF model. To test these conjectures, we compare the relative and incremental pricing ability of the MF model with those of models based on the market return and the FF benchmark risk factors (the FF model) or the market return and the FF and C benchmark risk factors (the C model). We also estimate the risk premia of the pricing factors of the individual asset pricing models. Overall, our test outcomes indicate that shocks to economic growth expectations, aggregate default risk, the term structure, and the exchange rate are priced. The significant risk premium on exposure to aggregate default risk contrasts with the evidence reported in Hahn and Lee (2006) and Petkova (2006), who find an insignificant default risk premium. We conjecture that this inconsistency might be due to the proxy variable chosen for shocks to aggregate default risk and the sample period. Our proxy variable is derived from Merton's (1974) contingent claims analysis.

Our empirical findings further reveal that the MF and FF models exhibit a similar pricing performance on 25 two-way sorted BM and size portfolios, while the pricing performance of the C model is somewhat higher. Consistent with this, the macroeconomic fundamentals render the risk premia on HML and SMB or HML, SMB and WML jointly insignificant on these test assets. When our test assets are 64 portfolios three-way sorted on BM, size and momentum, only the C model can correctly price the test assets, with the MF model still achieving a better pricing ability than the FF model. All three asset pricing models perform well in pricing 32 managed portfolios, i.e., eight three-way sorted size, BM and momentum portfolios interacted with lagged macroeconomic instruments. For the three-way sorted portfolios, the macroeconomic fundamentals are never able to drive out the joint significance of the risk premia on either HML and SMB or HML, SMB and WML.

We interpret our results as showing that the FF benchmark factors contain important information on macroeconomic fundamentals. The macroeconomic fundamentals could matter to investors, either because they capture common variation in equity returns, as in the APT (e.g., Ross, 1976), or because they represent hedgeable sources of state variable risk, as in the ICAPM (e.g., Merton, 1973). Since the macroeconomic fundamentals explain a substantial proportion of equity return variation, but also forecast current and future consumption (Chen, 1991), these interpretations are not mutually exclusive. On the other hand, the pricing ability of the C model is only partially explained by our chosen macroeconomic fundamentals. Hence, there may be other relevant macroeconomic fundamentals not included in our model that could help to explain the role of WML in pricing equities. As characteristic-sorted factors probably capture macroeconomic pricing information efficiently, our results provide a justification for the usage of characteristic-based pricing models like the FF model or the C model.

Our paper is organized as follows. In Section 2, we review the literature and provide the motivation for our research. We describe our research design and data in Section 3. We also analyze the links between our macroeconomic fundamentals in this section. We report our outcomes from the estimation of risk exposures, risk premia and model specification tests in Section 4. In Section 5, we document that our main conclusions are largely robust with respect to our choice of macroeconomic proxy variables. Section 6 summarizes and concludes.

2. Prior literature and motivation

The ability of macroeconomic fundamentals to explain both equity returns and prices has been known for some time, e.g., see the studies of Chan et al. (1985) and Chen et al. (1986). However, only after the seminal study of Fama and French (1993), which shows that factors based on stock characteristics, like e.g., size or BM, can also capture variation in equity prices, has academic research started to explore the links between stock characteristics and macroeconomic fundamentals. Our analysis contributes to this growing literature. In Table 1, we summarize the main findings from studies documenting links between the FF and C benchmark factors and macroeconomic fundamentals, including shocks to GDP (or alternatively industrial production) growth expectations, inflation, the term structure of interest rates, the aggregate default (or survival) probability and the dividend yield. Overall, the following conclusions can be distilled from this literature:

First, the evidence reported in Liew and Vassalou (2000) suggests that economic growth over the subsequent year can be forecasted using HML and SMB. Kelly (2004) reports weaker evidence that SMB can also be used to forecast future inflation. Related studies show that economic growth risk is weakly priced at the 90% confidence level (Vassalou, 2003).

Second, the evidence from asset pricing studies suggests that betas on changes in the slope of the term structure are negative, and that their magnitude decreases with BM (i.e., low BM stocks have more negative betas on term structure risk than high BM stocks). This is consistent with the notion that growth stocks are higher duration assets. In cross-sectional tests, term structure risk commands a significant risk premium (Hahn and Lee, 2006; Petkova, 2006). Similarly, betas on changes in the aggregate default probability are negative, and their magnitude decreases with size. Still, default risk never attracts a significant risk premium (Chan et al., 1985; He and Ng, 1994; Hahn and Lee, 2006; Petkova, 2006). Prior studies have so far not identified macroeconomic fundamentals able to explain variation in WML (Griffin et al., 2003).

Table 1
Previous work on the association between HML/SMB/WML and macroeconomic fundamentals.[a]

Paper (year of publication and journal)	Data	Risk premia estimated	Dependent variable	Independent variables							
				RM	HML	SMB	GDP/IP growth	Term level	Term slope	Default	Other
Hahn and Lee (2006, JFQA)	Monthly data	Yes	HML	–					+	N/S	
	1963–2001		SMB	+					N/S	–	
Petkova (2006, JF)	Monthly data	Yes	HML	–				N/S	+	N/S	DivYield N/S
	1963–2001		SMB	+				N/S	N/S	–	DivYield N/S
Kelly (2004, WP)	Annual data	No	Real GDP growth	+	+	+					
	1956–2001		Inflation	–	N/S	–					
Vassalou and Xing (2004, JF)	Monthly data	Yes	HML							+	
	1971–1999		SMB							–	
Griffin et al. (2003, JF)	Monthly data	No	WML				N/S		N/S		Inflation N/S
	various periods						N/S		N/S		Inflation N/S
Vassalou (2003, JFE)	Quarterly data	Yes	HML				+				
	1953–1998		SMB				+				
Liew and Vassalou (2000, JFE)	Quarterly data	No	Nominal GDP growth	+	+	+					
	1978–1996										

[a] In this table, we offer an overview of previous studies relating the Fama and French/Carhart benchmark portfolios and/or factors to macroeconomic fundamentals. The column titled "Paper (year of publication and journal)" shows the name(s) of the study's author(s), the year of publication and the title of the journal. The column "Data" reveals the frequency of the studied data and the sample period, whereas the column "Risk premia estimated" indicates whether the study uses cross-sectional tests to estimate the risk premia on the studied pricing factors. The remaining columns, which are the main part of the table, form a matrix with the "Dependent variable" analyzed in the individual studies on the vertical axis, and the corresponding "Independent variables" on the horizontal axis. A "+" sign in this matrix indicates a significant multivariate positive relation between the associated dependent and independent variable, while a "–" sign indicates a negative relation. "N/S" stands for "not significant" relations. It is important to realize that Vassalou and Xing (2004) use innovations in the aggregate survival probability rather than innovations in default risk. To make their results comparable with the other studies, we switch the sign of their loading on default risk in this table, i.e., a positive association between innovations in the aggregate survival probability and SMB in their paper is reported as a negative association between innovations in default risk and SMB in this table. JF stands for the *Journal of Finance*, JFE for the *Journal of Financial Economics* and JFQA for the *Journal of Financial and Quantitative Analysis*. Finally, WP represents a working paper.

A potential difficulty in interpreting the body of literature summarized in Table 1 arises because macroeconomic fundamentals are likely to be substantially correlated. A notable feature of the table is that the cited studies focus on only partially overlapping sets of macroeconomic fundamentals. For example, no prior study considers economic growth and inflation risks together with term structure and default risks. As a result, we cannot rule out the possibility that in existing studies one macroeconomic factor proxies for another "more fundamental" factor. There is also the possibility that beta estimates in existing studies are biased due to correlated relevant pricing factors being omitted from an asset pricing model. We explicitly address these concerns by estimating a macroeconomic factor model that includes a broad set of macroeconomic fundamentals considered in the prior literature. We also expand the set of macroeconomic fundamentals to include unexpected inflation (not shocks to inflation expectations, as, e.g., used in the study of Kelly (2004)) and shocks to a US composite exchange rate. Prior evidence indicates that both factors are related to equity returns (see, e.g., Doidge et al., 2006). We also add the orthogonalized market return, because in an ICAPM world this factor rewards investors for bearing risk unrelated to the state variables (Fama, 1996, p. 460).

3. Research design

3.1. Methodology

We now review the empirical methods used to assess (1) the time-series associations between the macroeconomic fundamentals and the firm characteristics, and (2) the cross-sectional pricing ability of the MF, the FF and the C models. We can obtain the beta coefficients of the FF model and the C model from the following time-series regression:

$$R^p_{t-1,t} = \beta^p_0 + \beta^p_1 \mathrm{RM}_{t-1,t} + \beta^p_2 \mathrm{SMB}_{t-1,t} + \beta^p_3\ \mathrm{HML}_{t-1,t} (+\beta^p_4 \mathrm{WML}_{t-1,t}) + \varepsilon^p_{t-1,t}, \tag{1}$$

where $R^p_{t-1,t}$ is test portfolio p's excess return (net return minus risk-free return), $\mathrm{RM}_{t-1,t}$ is the excess return on a value-weighted stock market index, $\mathrm{SMB}_{t-1,t}$ is the return of a portfolio long small and short big market capitalization stocks (keeping BM and momentum constant), $\mathrm{HML}_{t-1,t}$ is the return on a portfolio long high and short low BM ratio stocks (keeping size and momentum constant), and $\mathrm{WML}_{t-1,t}$ is the return on a portfolio long winner and short loser stocks (keeping size and BM constant). If we impose the restriction $\beta^p_4 = 0$, the model shown in Eq. (1) is the FF model. Otherwise, the model shown in Eq. (1) is the C model.

We estimate the beta coefficients of the MF model from the following time-series regression:

$$R^p_{t-1,t} = \beta^p_0 + \beta^p_1 \mathrm{MYP}_{t,t+12} + \beta^p_2 \mathrm{UI}_{t-1,t} + \beta^p_3 \mathrm{DSV}_{t-1,t} + \beta^p_4 \mathrm{ATS}_{t-1,t} + \beta^p_5 \mathrm{STS}_{t-1,t} + \beta^p_6 \mathrm{FX}_{t-1,t} + \varepsilon^p_{t-1,t}, \tag{2}$$

where $\mathrm{MYP}_{t,t+12}$ is the change in one-year ahead industrial production growth expectations, $\mathrm{UI}_{t-1,t}$ is unexpected inflation, $\mathrm{DSV}_{t-1,t}$ is the change in the aggregate survival probability, $\mathrm{ATS}_{t-1,t}$ and $\mathrm{STS}_{t-1,t}$ are changes in, respectively, the average level and the slope of the term structure, and $\mathrm{FX}_{t-1,t}$ is the change in a multilateral US dollar exchange rate. As discussed, this model nests all the main macroeconomic factor models shown in Table 1, but it also includes two neglected macroeconomic fundamentals, i.e., unexpected inflation and shocks to the exchange rate. We also consider an augmented version of the MF model (the AMF model) which includes the market return. Results reported in Section 4 show that around 74.2% of the variance in market returns is explained by the macroeconomic fundamentals. As the market return cannot be treated as exogenous, we orthogonalize market returns with respect to the other macroeconomic fundamentals.

We use the stochastic discount factor/generalized method of moments (GMM) methodology proposed by Cochrane (2001) to assess whether the macroeconomic fundamentals command significant risk premia and to evaluate the pricing ability of the models. When analyzing excess returns, the stochastic discount factor representation is:

$$0 = p_t^p = E_t(m_{t+1} R_{t,t+1}^p), \tag{3}$$

where p_t^p is the market price of portfolio p (zero for excess returns), $E_t(\cdot)$ is the expectation operator conditional on time t information, m_{t+1} is the linear stochastic discount factor, i.e., $m_{t+1} = 1 - b'f_{t+1}$, where f_{t+1} are the models' pricing factors, and $R_{t,t+1}^p$ is portfolio p's excess return. When examining excess returns, the average level of the stochastic discount factor is not identified. To circumvent this problem, we choose to set the constant to unity. We can rearrange Eq. (3) to obtain risk premia and their significance levels (see Appendix A).

3.2. Test assets

We use firm characteristic-sorted portfolios as test assets throughout this study, with the firm characteristics being BM, size and momentum. Moreover, we employ both unconditional and conditional portfolios, where the conditional portfolios are interacted with lagged macroeconomic instruments. We create one-way sorted characteristic portfolios analogous to Fama and French (1993). In particular, we observe the BM decile breakpoints in December of year $t-1$ and the size decile breakpoints and the prior eleven month compounded return (momentum) breakpoints in June of year t. The construction of the momentum characteristic follows Carhart (1997). Consistent with other studies, we only use NYSE firms to obtain the breakpoints. After identification of the breakpoints, we form value-weighted portfolios comprising all stocks from the NYSE, AMEX and NASDAQ within each relevant range of the sorting variable in July of year t. Portfolio composition remains fixed until June of year $t+1$, at which point we reform portfolios.

We construct two-way and three-way independently-sorted portfolios from subsets of the same breakpoints. To limit the number of test assets, we assign firms to (1) eight ($2 \times 2 \times 2$) portfolios based on the median breakpoints, (2) 27 ($3 \times 3 \times 3$) portfolios based on the bottom 30%, middle 40% and top 30% breakpoints, and (3) 64 ($4 \times 4 \times 4$) portfolios based on the bottom 20%, lower-middle 30%, top-middle 30% and top 20% breakpoints. We create the three-way independently-sorted benchmark factors, i.e., HML, SMB, and WML, from the ($3 \times 3 \times 3$) benchmark portfolios in a way identical to Liew and Vassalou (2000).

3.3. Macroeconomic fundamentals

We now introduce the variables we use in our tests to proxy for the macroeconomic fundamentals in the MF model. Our first macroeconomic fundamental is changes in economic growth expectations and should capture revisions in cash flow expectations. To facilitate monthly data analysis, we select industrial production growth as our measure of economic growth rather than GDP growth, which is only observable on a quarterly basis. Unfortunately, changes in *realized* industrial production growth is a poor proxy for the change in economic growth expectations and its usage would result in an errors-in-variables problem. Hence, we adopt an approach also used by Vassalou (2003) and others, and create a mimicking portfolio capturing changes in industrial production growth expectations. Portfolio weights are obtained by regressing the log change in realized industrial production over the subsequent year onto a set of traded base assets and a set of control variables designed to capture all anticipated information in industrial production growth and the base asset returns.

If the mimicking portfolio approach is to be powerful, the base assets must span the space of asset returns. Besides this, theory offers little guidance on the choice of base assets, perhaps explaining the wide range of assets used in related prior research. Since we are interested in establishing the empirical relations between the FF and C benchmark factors (and their underlying benchmark portfolios) and our macroeconomic fundamentals, we are careful not to include the benchmark factors in the set of base assets. Instead, we include the market portfolio, a long-term and an intermediate-term government bond portfolio, a high-yield corporate bond portfolio and gold. All base asset returns are in excess of the risk-free rate, so that mimicking portfolio weights do not need to sum to unity. During two periods in our sample period, namely the 1987 stock market crash and the Internet bubble period, market returns are unlikely to efficiently capture news on economic growth. To control for the possibility that these periods unduly affect the market portfolio weight in the mimicking portfolio, we also add two slope dummies which allow the market portfolio weight to vary during these periods.[1] As controls, we use lagged instruments found in prior studies to predict variation in stock returns.[2] In two alternative specifications, we also add the one-month or one-year lagged base asset excess returns. A complete list of the base assets and control variables is presented in the footnote of Table 2.

We follow Vassalou and Xing (2004) in using an equally-weighted average of stock-level survival probabilities as the aggregate market estimate, where we derive a firm's survival probability over the subsequent year according to the contingent claims model of Merton (1974). Monthly shocks to the aggregate survival probability are defined as changes in the original time-series. Unexpected inflation is approximated through realized inflation minus the fitted value from an MA(1) process (Fama and Gibbons, 1984).[3] We employ two interest rate term structure risk factors: (i) the change in the average level of the term structure (i.e., the change in the mean of the 3-month Treasury bill yield and the 10-year Treasury bond yield); and (ii) the change in the term structure slope (i.e., the change in the difference between the 10-year Treasury bond yield and the 3-month Treasury bill yield). Finally, we capture exchange rate risk through the change in a US composite exchange rate index.

3.4. Data and sample

We obtain the data used to form the benchmark portfolios and characteristic-based factors from the intersection of CRSP and COMPUSTAT. We exclude firms with negative book values and issues other than common stock. Equivalent to Fama and French (1993), we define the book value as the COMPUSTAT book value of stockholders' equity, plus balance-sheet deferred taxes and investment tax credits, minus the book-value of preferred stock, where the value of preferred stock is either the redemption, liquidation, or par value (in this order). The original FF benchmark portfolios and factors and the risk-free rate are from Kenneth French's website. The dividend yield on the S&P 500 index is from Robert Shiller's website. We obtain the aggregate survival probability

[1] The exclusion of the slope dummies does not materially affect the relations between the stock characteristics and the macroeconomic fundamentals. However, their inclusion renders the mimicking portfolio more similar to an out-of-sample rolling window estimate of it, while retaining the important advantage that we can correct standard errors for the additional uncertainty created by the generated regressor.

[2] See, e.g., Fama and French (1988), Chen (2009), and many others.

[3] Unexpected inflation is therefore, also a generated regressor. However, Pagan (1984) proves that, if the generated regressor is the residual from a first-stage estimation, standard errors in a second-stage estimation featuring the generated regressor as an independent variable remain unbiased.

Table 2
Estimation of the mimicking portfolio for industrial production growth.[a]

	Parms	t-statistic	Parms	t-statistic	Parms	t-statistic
Panel A: Parameter estimates						
Base assets						
Market portfolio excess return (RM)$_{t-1,t}$	**0.12**	[1.83]	**0.13**	[1.88]	**0.12**	[1.91]
Long-term government bond excess return$_{t-1,t}$	−**0.14**	[−1.19]	−**0.20**	[−1.70]	−**0.13**	[−1.04]
Medium-term government bond excess return$_{t-1,t}$	**0.18**	[0.42]	**0.39**	[0.98]	**0.13**	[0.29]
High-yield bond portfolio excess return$_{t-1,t}$	−**0.01**	[−0.09]	−**0.05**	[−0.72]	−**0.01**	[−0.16]
Gold return$_{t-1,t}$	−**0.04**	[−1.68]	−**0.05**	[−1.79]	−**0.04**	[−1.64]
Slope dummy market portfolio excess return (1987)	−**0.12**	[−1.96]	−**0.16**	[−2.13]	−**0.12**	[−2.04]
Slope dummy market portfolio excess return (1996–2002)	**0.04**	[0.39]	**0.04**	[0.50]	**0.04**	[0.47]
Control variables						
Intercept	**0.02**	[1.10]	**0.02**	[1.55]	**0.01**	[0.60]
Risk-free rate of return$_{t-1,t}$	−**8.30**	[−2.03]	−**9.66**	[−2.48]	−**6.50**	[−1.10]
10-year minus 3-month government bond yield$_{t-1}$	**0.25**	[0.47]	**0.02**	[0.04]	**0.49**	[0.65]
1-year minus 3-month government bond yield$_{t-1}$	**0.73**	[1.04]	**1.30**	[1.71]	**0.64**	[1.08]
Baa minus Aaa corporate bond yield$_{t-1}$	−**0.11**	[−0.07]	−**0.04**	[−0.02]	**0.02**	[0.01]
Dividend yield$_{t-1}$	**1.68**	[2.80]	**1.76**	[3.09]	**1.43**	[1.98]
Industrial production growth$_{t-13,t-1}$	−**0.09**	[−0.83]	−**0.10**	[−0.95]	−**0.10**	[−0.75]
Inflation$_{t-13,t-1}$	−**0.38**	[−1.78]	−**0.41**	[−1.96]	−**0.25**	[−0.91]
Market portfolio excess return (RM)$_{t-13,t-1}$	**0.10**	[5.76]	**0.10**	[5.72]	**0.09**	[2.96]
1-month lagged base asset returns		No		Yes		No
1-year lagged (compounded) base asset returns		No		No		Yes
Adjusted R^2		39.12%		41.36%		39.35%
Adjusted R^2 (base assets only)		3.36%		3.36%		3.36%
Lower bound adjusted R^2		3.51%		4.11%		3.59%
Correlation with survey changes in IP expectations		0.504		0.472		0.493
	F-Stat.	p-value	F-Stat.	p-value	F-Stat.	p-value
Panel B: Exclusion tests						
All base assets	2.00	*(0.05)*	2.32	*(0.03)*	1.77	*(0.09)*
All base assets except market portfolio and dummies	0.95	*(0.44)*	1.26	*(0.29)*	1.16	*(0.33)*
All base assets except bond returns	2.69	*(0.03)*	3.41	*(0.01)*	2.03	*(0.09)*

[a] In this table, we show the outcomes from OLS estimations of the log change in industrial production over the next year onto on a set of base asset excess returns and lagged control variable realizations (Panel A). Our base assets consist of the market portfolio, two government bond portfolios, a default bond portfolio, and gold. To allow for time-variation in the market portfolio weight, we also include two market portfolio slope dummies for the period from April 1987 to April 1988 (the one year surrounding the October 1987 stock market crash) and the period from January 1996 to December 2002 (the Internet bubble period). All base asset returns are in excess of the risk-free rate of return, and thus weights do not need to sum up to unity. We control for the expected level of returns by including a set of lagged control variables, containing the risk-free rate, the yield spread between long-term and short-term government bonds, the yield spread between one-year and short-term government bonds, the yield spread between Baa-rated and Aaa-rated corporate bonds and the dividend yield on the S&P 500. We also include industrial production growth, inflation and excess market returns over the last year. The specifications in columns (2) and (3) add to the former variables the one-month or one-year lagged base asset excess returns. Since realized industrial production growth has an overlap with its lagged value of eleven months, we correct for heteroscedasticity and autocorrelation using the Newey and West (1987) correction with $l = 11$. To measure how well the base assets captures changes in industrial production over the next year, we compute the adjusted R^2s for all three specifications with and without control variables. The lower-bound adjusted R^2s are computed from the regression of changes in industrial production growth expectations on unexpected stock returns. In particular, we first regress realized industrial production growth onto our control variables. Subsequently, we regress the mimicking portfolio return onto our control variables. Finally, regressing the residuals from the former regression onto the residuals from the latter regression, we obtain the lower-bound adjusted R^2. To analyze how accurately the mimicking portfolio reflects 'real' changes in industrial production growth expectations, we compound its returns to a bi-annual frequency and then compute the correlation between the bi-annual series and changes in industrial production growth expectations obtained from survey data (correlation with survey changes in IP expectations). The survey data are from the Livingston Surveys of Professional Forecasters. The F-statistics in Panel B test the hypothesis that a subset of the parameter estimates is zero. The sample period extends from January 1975 to April 2008.

from January 1975 to December 1999 from Maria Vassalou's website.[4] We extend these data to December 2008 following the approach of Vassalou and Xing (2004).[5] Yield data on 3-month US government Treasury bills, 10-year Treasury bonds, Aaa/Baa-rated corporate bond portfolios and the exchange rate (in foreign currency per unit of home currency) between the US dollar and a broad trade-weighted composite currency index are from the Federal Reserve Bank's website. Return data on the US bond portfolios and gold are from Ibbotson Associates. We obtain the seasonally-adjusted level of the US industrial production index and the consumer price index from DataStream. All our variables are at a monthly frequency and are for the sample period from January 1975 to April 2008.[6]

3.5. Summary statistics and Granger causality tests

In Table 2, we report the outcomes from OLS regressions used to find the base asset weights of the mimicking portfolio for changes in economic growth expectations. As monthly industrial production growth is measured over rolling one-year windows, we adjust the t-statistics for the induced moving average error in residuals using the Newey and West (1987) correction with the lag parameter l set to eleven. Overall, the asset weights are fairly similar across the three model specifications shown in the table. The t-statistics and exclusion tests both indicate that, of the base assets, the market portfolio, the intermediate-term government bond portfo-

[4] We thank Kenneth French, Robert Shiller, and Maria Vassalou for making these data available.

[5] The correlation coefficient between the monthly DSV series obtained from Maria Vassalou's website and ours is 0.95 during the period from February 1971 to December 1999. We extend Maria Vassalou's data from December 1999 to December 2008 through the prediction from an OLS regression of her series onto our series. The intercept and slope coefficient of this regression equal 0.002 and 0.918, respectively. Our main conclusions do not change, if we entirely use our own series in our empirical tests.

[6] Although most of our data extend to December 2008, we require the 12-month lead level of the industrial production index to construct our proxy for changes in economic growth expectations.

Table 3
Summary statistics and correlations.[a]

Variable symbol				Mean ($\times 10^3$)	Median ($\times 10^3$)	StDev ($\times 10^3$)	Skew	Kurt	Max ($\times 10^3$)	Min ($\times 10^3$)
Panel A: Summary statistics										
MYP				0.80	0.72	5.86	−0.29	4.79	19.28	−25.55
UI				−0.02	−0.03	2.81	−0.25	4.53	8.95	−12.31
DSV				0.22	0.20	8.55	0.55	13.68	64.00	−43.80
ATS				−0.17	−0.25	5.72	−0.74	11.05	25.95	−38.05
STS				0.05	−0.30	4.24	0.77	7.89	21.30	−15.10
FX				−0.78	0.10	16.81	−0.29	3.83	54.60	−69.00
	HML	SMB	WML	RM	MYP	UI	DSV	ATS	STS	FX
Panel B: Correlations										
MYP	−0.39	0.16	−0.16	0.79						
UI	0.04	0.02	−0.02	−0.14	−0.09					
DSV	−0.21	0.45	−0.30	0.61	0.48	−0.07				
ATS	−0.06	0.10	−0.03	−0.16	0.11	0.13	0.00			
STS	0.06	0.05	−0.21	−0.04	0.13	0.05	0.09	−0.21		
FX	0.05	−0.01	−0.06	−0.08	0.02	0.00	−0.09	0.13	−0.08	
BM decile 1 (low)	−0.59	0.17	0.01	0.93	0.76	−0.15	0.50	−0.14	−0.09	−0.06
BM decile 2	−0.42	0.13	−0.07	0.95	0.75	−0.17	0.54	−0.16	−0.04	−0.06
BM decile 3	−0.32	0.09	−0.06	0.95	0.74	−0.16	0.57	−0.15	−0.05	−0.07
BM decile 4	−0.24	0.09	−0.07	0.92	0.70	−0.13	0.56	−0.14	−0.04	−0.06
BM decile 5	−0.18	0.07	−0.07	0.90	0.69	−0.11	0.54	−0.13	−0.07	−0.06
BM decile 6	−0.18	0.11	−0.13	0.92	0.71	−0.14	0.58	−0.17	−0.06	−0.06
BM decile 7	−0.02	0.04	−0.21	0.86	0.66	−0.15	0.56	−0.19	0.00	−0.05
BM decile 8	0.01	0.09	−0.17	0.86	0.64	−0.13	0.57	−0.20	0.00	−0.03
BM decile 9	−0.02	0.10	−0.20	0.85	0.66	−0.13	0.60	−0.17	0.01	−0.05
BM decile 10 (high)	0.01	0.22	−0.25	0.80	0.62	−0.12	0.60	−0.12	0.05	−0.04
Size decile 1 (small)	−0.39	0.74	−0.14	0.75	0.59	−0.06	0.73	−0.01	0.00	−0.04
Size decile 2	−0.43	0.66	−0.11	0.83	0.67	−0.11	0.72	−0.06	0.01	−0.05
Size decile 3	−0.41	0.57	−0.12	0.87	0.69	−0.13	0.69	−0.08	0.00	−0.05
Size decile 4	−0.40	0.51	−0.10	0.89	0.70	−0.15	0.67	−0.10	0.01	−0.04
Size decile 5	−0.40	0.46	−0.10	0.91	0.72	−0.15	0.67	−0.11	0.01	−0.04
Size decile 6	−0.37	0.37	−0.08	0.93	0.73	−0.16	0.65	−0.14	−0.01	−0.07
Size decile 7	−0.36	0.35	−0.07	0.95	0.74	−0.15	0.65	−0.15	−0.01	−0.08
Size decile 8	−0.36	0.30	−0.09	0.96	0.76	−0.14	0.63	−0.17	−0.01	−0.06
Size decile 9	−0.34	0.19	−0.06	0.97	0.75	−0.13	0.59	−0.18	−0.06	−0.07
Size decile 10 (big)	−0.39	0.01	−0.06	0.97	0.78	−0.14	0.52	−0.17	−0.06	−0.08
Momentum decile 1 (low)	−0.43	0.42	−0.40	0.83	0.71	−0.09	0.67	−0.08	0.08	−0.04
Momentum decile 2	−0.33	0.25	−0.38	0.87	0.73	−0.12	0.61	−0.12	0.05	−0.05
Momentum decile 3	−0.23	0.05	−0.38	0.86	0.70	−0.13	0.60	−0.16	0.04	−0.03
Momentum decile 4	−0.22	0.01	−0.26	0.89	0.72	−0.16	0.54	−0.21	−0.01	−0.04
Momentum decile 5	−0.27	0.10	−0.15	0.90	0.69	−0.15	0.54	−0.23	−0.04	−0.07
Momentum decile 6	−0.18	−0.05	−0.12	0.87	0.65	−0.16	0.50	−0.21	−0.07	−0.04
Momentum decile 7	−0.24	−0.01	−0.04	0.88	0.67	−0.16	0.51	−0.18	−0.05	−0.06
Momentum decile 8	−0.23	0.02	0.11	0.89	0.66	−0.15	0.45	−0.15	−0.09	−0.08
Momentum decile 9	−0.31	0.08	0.18	0.90	0.67	−0.13	0.49	−0.13	−0.09	−0.09
Momentum decile 10 (high)	−0.51	0.30	0.23	0.89	0.71	−0.10	0.53	−0.11	−0.06	−0.10

[a] In this table, we provide summary statistics on our analysis variables. Panel A shows the mean, the median, the standard deviation (StDev), skewness (Skew), kurtosis (Kurt), the maximum (Max) and the minimum (Min) of all regressors used in the analysis, i.e., the mimicking portfolio on changes in industrial production growth expectations (MYP), unexpected inflation (UI), changes in the survival probability (default risk) (DSV), changes in the average level of the term structure of risk-free interest rate yields (ATS), changes in the slope of the term structure of risk-free interest rate yields (STS) and changes in the exchange rate between the US dollar and a trade-weighted composite currency (FX). Panel B provides the cross-correlations between our set of macroeconomic pricing factors, the benchmark factors, i.e., RM, HML, SMB and WML, and the one-way sorted book-to-market, size and momentum portfolios. The sample period extends from January 1975 to April 2008.

lio and gold are most significantly related to one-year ahead changes in the industrial production index. The weight of the market portfolio is reduced to virtually zero during the 1987 stock market crash, but it is significantly higher during the Internet bubble period.[7] Some control variables, e.g., the risk-free rate, are also significant.

A central question is how well the mimicking portfolio reflects changes in one-year ahead economic growth expectations. Across the three specifications, the lower-bound adjusted R^2 from a hypothetical OLS regression of changes in industrial production growth expectations on the unexpected base asset returns is at least 3.51%. Although this estimate is slightly lower than those reported in other studies, the low value is mainly driven by the fact that our sample period starts shortly after the oil crises. Besides this, our parameter estimates and significance levels are very similar to those reported elsewhere (Vassalou, 2003). In addition, we also compound the mimicking portfolio to a semi-annual frequency and then compute its correlation coefficient with changes in industrial production growth expectations obtained from the Livingston Surveys of Professional Forecasters over the period from June 1975 to December 2007. For all three specifications, the correlation coefficient is around 0.50, suggesting that our approach can capture a large fraction of changes in the survey participants' expectations. Our correlation estimates are conservative, as the survey data are based on 14-month forecast horizons[8] and survey participants are not generally major equity investors. We employ the second mim-

[7] One explanation is that firms raised new capital during the initial rise of the stock market, which was subsequently used to increase their production capacity.

[8] Although survey participants are asked to predict the level of the industrial production index twelve months after the survey publication date, the questionnaires have to be returned two months ahead of the publication date.

icking portfolio specification in the remainder of the study, as this specification yields the highest lower-bound adjusted R^2.[9]

We present summary statistics on the macroeconomic fundamentals in Panel A of Table 3. The sample mean of the mimicking portfolio on economic growth (MYP) is positive, but insignificant when not controlling for the influence of other risk factors. The most important feature of Table 3 is shown in Panel B. Several macroeconomic fundamentals are highly correlated, e.g., MYP with DSV, ATS, and STS or FX with ATS and STS, confirming that interpretation of some prior studies could be ambiguous. Panel B also shows correlations of the one-way sorted characteristic portfolios with the benchmark risk factors and macroeconomic fundamentals. While the correlation coefficients often suggest associations between the benchmark risk factors and the macroeconomic fundamentals, our multivariate results presented later indicate that bivariate correlations are not always a good guide to the sign and significance of macroeconomic exposures captured by characteristic portfolios.

The summary statistics shown so far reveal nothing about causality between the benchmark risk factors and the macroeconomic fundamentals. Hence, we report the results of Granger causality tests analyzing whether certain benchmark risk factors or macroeconomic fundamentals help to forecast others in Table 4. Although most of the relations between our analysis variables should be contemporaneous, the tests in Table 4 check whether some fraction of the change in one variable leads changes in other variables.[10]

We first consider monthly data over the sample period from January 1975 to April 2008 with the lag length set to one. We have checked that other lag lengths do not substantially affect our main conclusions. Considering first the links between the macroeconomic fundamentals, MYP and ATS seem to be exogenously determined with respect to the other factors. However, an upward revision in economic growth expectations associates significantly with a higher aggregate survival probability and a higher US dollar value in the future. In a similar way, an increase in the average term structure associates significantly with a higher unexpected inflation and US dollar value and a lower aggregate survival probability and term structure slope in the future. In contrast, while DSV and STS can be predicted by the other macroeconomic fundamentals, they have no predictive ability themselves. Both UI and FX form a feedback system with the other factors.

It is also interesting to check whether the macroeconomic fundamentals Granger-cause the benchmark risk factors, or vice versa. With the notable exception of UI, which will turn out to be relatively unimportant for equity pricing, only STS can be forecasted with SMB at the 90% confidence level. In contrast, HML can be forecasted with ATS and FX, SMB with UI and DSV and WML with MYP and ATS. As a result, we conclude that the macroeconomic fundamentals often precede the benchmark risk factors in time, and therefore appear more elementary. The in-sample adjusted R^2s (IS-R^2) are between −0.4% (MYP) and 14.9% (FX). Finally, the low out-of-sample adjusted R^2s (OOS-R^2) based on residuals constructed from estimates obtained over the prior ten years of data suggest that investors at the time were not able to forecast the analysis variables with any success.

We also explore whether the causality between the macroeconomic fundamentals and the benchmark risk factors can change during an economic recession. Therefore, we also estimate the VAR system on daily data covering the recent crisis in 2008. While the benchmark risk factors can be obtained at a daily frequency from Kenneth French's website, we construct a daily mimicking

Table 4
VAR estimations.[a]

		HML		SMB		WML		MYP		UI		DSV		ATS		STS		FX	
	Lag	Parms	*t*-stat.	Parms	*t*-stat.	Parms	*t*-stat.	Parms	*t*-stat.	Parms	*t*-stat.	Parms	*t*-stat.	Parms	*t*-stat.	Parms	*t*-stat.	Parms	*t*-stat.
Constant		**0.00**	[2.00]	**0.00**	[1.19]	**0.00**	[3.64]	**0.00**	[2.77]	**0.00**	[−1.24]	**0.00**	[-0.21]	**0.00**	[−0.84]	**0.00**	[0.55]	**0.00**	[−0.70]
HML	1	**0.15**	[1.44]	**−0.14**	[−0.98]	**−0.10**	[−1.30]	**−0.02**	[−1.48]	**0.01**	[1.50]	**−0.01**	[−0.76]	**0.00**	[−0.05]	**0.00**	[−0.58]	**0.00**	[−0.06]
SMB	1	**0.11**	[2.07]	**−0.02**	[−0.29]	**−0.03**	[−0.77]	**0.00**	[0.42]	**0.01**	[2.16]	**0.01**	[0.67]	**0.01**	[1.06]	**−0.01**	[−2.18]	**0.00**	[0.12]
WML	1	**−0.08**	[−1.14]	**−0.16**	[−1.59]	**0.05**	[1.07]	**−0.01**	[−0.52]	**0.01**	[2.53]	**−0.02**	[−0.94]	**−0.01**	[−0.28]	**−0.01**	[−1.30]	**−0.05**	[−1.64]
MYP	1	**0.28**	[0.85]	**0.54**	[0.99]	**−0.92**	[−3.68]	**−0.08**	[−1.06]	**0.04**	[1.36]	**0.20**	[1.84]	**0.07**	[1.51]	**0.00**	[0.10]	**0.31**	[1.68]
UI	1	**0.58**	[1.19]	**−1.88**	[−2.23]	**0.20**	[0.51]	**−0.02**	[−0.25]	**0.31**	[7.28]	**−0.21**	[−1.80]	**0.11**	[1.18]	**0.16**	[2.58]	**0.02**	[0.08]
DSV	1	**−0.14**	[−0.53]	**0.53**	[1.97]	**0.37**	[1.53]	**−0.05**	[−0.95]	**0.00**	[−0.08]	**0.09**	[1.36]	**0.06**	[0.86]	**−0.04**	[−1.11]	**0.08**	[0.67]
ATS	1	**−0.50**	[−1.84]	**−0.22**	[−0.50]	**0.52**	[2.33]	**−0.06**	[−1.33]	**0.04**	[2.57]	**−0.30**	[−3.76]	**0.16**	[2.22]	**−0.13**	[−2.13]	**0.56**	[3.43]
STS	1	**−0.43**	[−1.22]	**−0.09**	[−0.16]	**0.13**	[0.51]	**0.06**	[0.79]	**0.01**	[0.36]	**0.08**	[0.82]	**−0.06**	[−0.84]	**0.11**	[2.98]	**−0.22**	[−1.32]
FX	1	**0.23**	[3.15]	**−0.02**	[−0.26]	**−0.11**	[−1.35]	**0.01**	[0.53]	**0.00**	[0.20]	**0.00**	[0.02]	**−0.02**	[−0.67]	**0.03**	[2.24]	**0.28**	[8.68]
IS-R^2			4.1%		6.0%		2.7%		−0.4%		11.1%		11.2%		5.0%		7.8%		14.9%
OOS-R^2			−14.3%		−25.2%		−20.3%		−17.0%		−0.4%		−3.7%		−33.8%		−26.0%		4.9%

[a] In this table, we report the empirical outcomes from estimations of VAR systems on the Fama and French and Carhart benchmark factors, i.e., HML, SMB and WML, and the macroeconomic fundamentals. The macroeconomic fundamentals are the mimicking portfolio on changes in industrial production growth expectations (MYP), unexpected inflation (UI), changes in the survival probability (DSV), changes in the average level of the term structure of risk-free interest rate yields (ATS), changes in the slope of the term structure of risk-free interest rate yields (STS) and changes in the exchange rate between the US dollar and a trade-weighted composite currency (FX). We use monthly data from January 1975 to April 2008 with a lag size equal to one. Bold numbers are parameter estimates and numbers in parentheses are *t*-statistics. The column 'lag' indicates by how many periods the independent variable is lagged. IS-R^2 is the in-sample adjusted R^2. OOS-R^2 is the out-of-sample adjusted R^2, which is computed from the residuals obtained through rolling window estimations using the prior 120 observations. The OOS-R^2 are therefore, computed over the period January 1985 to April 2008.

[9] Results are insensitive to the choice of model for the mimicking portfolio.

[10] We thank the referee for motivating this analysis.

portfolio through combining the weights obtained from the monthly estimations in Table 2 with daily data on the base assets. To obtain a daily aggregate survival probability, we assume that asset volatilities are constant over one month, and then use the Merton (1974) model to first back out daily asset values and to then construct the default probabilities. We obtain daily time-series on the 3-month Treasury Bill yield, the 10-year Treasury bond yield and the composite exchange rate from the website of the Federal Reserve Bank. Unfortunately, we are unable to compute daily unexpected inflation, and, therefore, omit this variable from the daily estimations. In unreported tests, which are available upon request, we find that the links between our analysis variables are much stronger in an economic recession. All macroeconomic fundamentals now form a feedback system. Next, the benchmark risk factors now often also forecast the macroeconomic fundamentals, although they can also still be forecasted by them. Finally, the in-sample adjusted R^2s are often much higher than those in Panel A.

4. Results

4.1. Macroeconomic risk exposures

We now analyze the estimation outcomes from the time-series regression in Eq. (2) of the one-way or three-way sorted characteristic portfolio returns onto the macroeconomic fundamentals. We use Hansen's (1982) GMM methodology to estimate all parameters, with standard errors corrected for the additional uncertainty induced through the generated regressor MYP. We offer more details on the GMM methodology in Appendix A. We show the regression coefficients and t-statistics of the one-way sorted portfolios in Fig. 1. In Panel A of Table 5, we report χ^2 statistics testing whether the spread in one macroeconomic exposure across the one-way sorted characteristic portfolios is significantly different from zero. Although the table does not report adjusted R^2s for the one-way sorted portfolios, these range from 49.4% to 70.4%, suggesting that the macroeconomic fundamentals capture a large fraction of the variation in the portfolio returns.

In Fig. 1, we illustrate that, of the macroeconomic fundamentals, MYP, DSV, and STS play significant roles in explaining the one-way sorted characteristic portfolio returns. The absolute values of the t-statistics on the MYP betas are greater than 2.0 for all 30 characteristic portfolios. In contrast, their absolute values on the DSV and STS betas are only greater than 2.0 for 24 and 26 portfolios, respectively. Consistent with intuition, the portfolio returns are positively related to MYP and DSV and negatively to STS. More importantly, the figure shows vividly that some macroeconomic exposures strongly relate to the BM, size and momentum characteristics of the portfolios. For instance, when we compare macroeconomic exposures across the BM deciles, the MYP exposures generally decrease, while the DSV, STS and FX exposures increase with BM. Panel A of Table 5 reveals that the spread in the MYP and STS exposures are strongly significant, while those in the DSV and FX exposures are more weakly significant. The figure also illustrates that the DSV, ATS, STS, and FX exposures almost monotonically decrease with the size characteristic of the size-sorted portfolios, while only the smallest firm decile has a lower MYP exposure than the others. The spread in exposures is strongly significant for MYP, DSV and ATS, and more weakly significant for STS. Finally, the DSV, STS and FX exposures all decrease with the momentum characteristic of the momentum-sorted portfolios, with all spreads being significant.

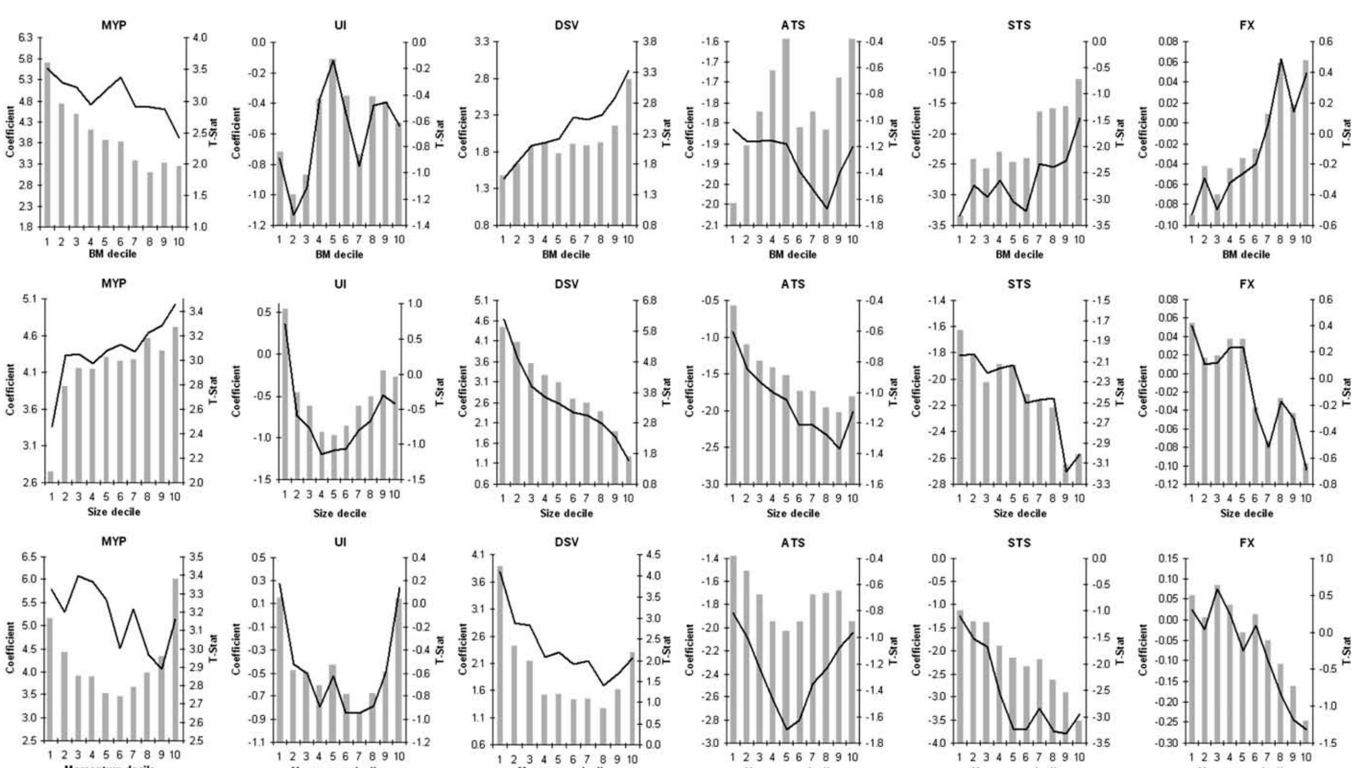

Fig. 1. In this figure, we show the macroeconomic risk exposure estimates of the one-way sorted firm characteristic deciles on the macroeconomic fundamentals and their t-statistics. The macroeconomic fundamentals are changes in industrial production growth expectations (MYP), unexpected inflation (UI), changes in the aggregate survival probability (DSV), changes in the average level and the slope of the term structure of risk-free interest rate yields (ATS and STS, respectively), and changes in the exchange rate between the US dollar and a trade-weighted composite currency (FX). The bars are the estimated risk exposures, while the lines are the t-statistics. The first row shows the outcomes related to the one-way sorted book-to-market deciles, the second those related to the one-way sorted size deciles, and the third those related to the one-way sorted momentum deciles.

As the size, BM and momentum firm characteristics are themselves correlated, our evidence on the one-way sorted portfolios is not unambiguous. More specifically, the correlation coefficients between the BM and size decile indicators (which range from 1 to 10), the BM and momentum decile indicators and the size and momentum decile indictors are −0.17, −0.11, and 0.17, respectively. Hence, the spread in one specific macroeconomic exposure across the size portfolios could be driven by the fact that small (large) firms often have high (low) BM ratios. For this reason, Fama and French (1993) orthogonalize the benchmark risk factor HML (SMB) with respect to size (BM). We thus expect that the evidence based on three-way sorted portfolios should draw out more clearly the role of each firm characteristic in capturing macroeconomic exposures.

We report the estimation outcomes from the three-way sorted benchmark portfolios and RM, HML, SMB, and WML in Panel B of Table 5. The t-statistics on the macroeconomic exposures of the benchmark risk factors can be interpreted as tests of differences in macroeconomic exposures across the top three and the bottom three BM, size or momentum deciles, respectively, after controlling for correlation between firm characteristics. Most results in the table align with those obtained from the one-way sorted portfolios. For example, consistent with the exposures of the benchmark portfolios, HML loads negatively on MYP and positively on STS, SMB loads positively on DSV and ATS, and WML loads negatively on DSV, STS and FX. Two important inconsistencies between the results on the one-way sorted portfolios and those on the three-way sorted portfolios are that, after controlling for other firm characteristics, HML relates no longer to DSV, and SMB relates no longer to MYP. We can explain these inconsistencies by noting that both size and momentum capture DSV risk, and that controlling for these relations probably drives out the link between BM and DSV.

Table 5
Macroeconomic risk exposures.[a]

Dependent variable		Independent variables							Adj. R^2
		Constant	MYP	UI	DSV	ATS	STS	FX	
Panel A: χ^2-difference test statistics:									
BM10 – BM1	Estimate		**−2.44**	**0.19**	**1.31**	**0.57**	**2.23**	**0.15**	
	p-value		*(0.00)*	*(0.80)*	*(0.00)*	*(0.12)*	*(0.00)*	*(0.21)*	
Mean(BM10-6) – Mean(BM1-5)	Estimate		**−1.21**	**0.14**	**0.40**	**0.07**	**0.96**	**0.08**	
	p-value		*(0.00)*	*(0.63)*	*(0.08)*	*(0.72)*	*(0.00)*	*(0.07)*	
Size10 – Size1	Estimate		**1.96**	**−0.82**	**−3.16**	**−1.24**	**−0.94**	**−0.15**	
	p-value		*(0.00)*	*(0.20)*	*(0.00)*	*(0.00)*	*(0.10)*	*(0.19)*	
Mean(Size10-6) – Mean(Size1-5)	Estimate		**0.59**	**−0.01**	**−1.52**	**−0.66**	**−0.49**	**−0.09**	
	p-value		*(0.02)*	*(0.98)*	*(0.00)*	*(0.00)*	*(0.07)*	*(0.11)*	
Mom10 – Mom1	Estimate		**0.84**	**−0.01**	**−1.58**	**−0.57**	**−2.40**	**−0.31**	
	p-value		*(0.37)*	*(0.99)*	*(0.00)*	*(0.21)*	*(0.00)*	*(0.04)*	
Mean(Mom10-6) – Mean(Mom1-5)	Estimate		**0.11**	**−0.14**	**−0.69**	**−0.08**	**−1.13**	**−0.14**	
	p-value		*(0.77)*	*(0.71)*	*(0.00)*	*(0.78)*	*(0.00)*	*(0.04)*	
Panel B: Regression results:									
BM1Size1Momentum1	Estimate	**0.01**	**4.31**	**−0.53**	**4.11**	**−1.00**	**−1.51**	**0.09**	65.2%
	t-stat.	[2.25]	[3.02]	[−0.67]	[4.59]	[−0.69]	[−1.68]	[0.58]	
BM1Size1Momentum2	Estimate	**0.01**	**4.57**	**−0.77**	**3.46**	**−1.46**	**−2.64**	**0.02**	58.9%
	t-stat.	[3.27]	[2.97]	[−0.84]	[3.54]	[−0.95]	[−2.56]	[0.11]	
BM1Size2Momentum1	Estimate	**0.00**	**4.55**	**−0.56**	**1.62**	**−1.87**	**−1.86**	**−0.01**	65.2%
	t-stat.	[2.20]	[3.43]	[−0.71]	[1.99]	[−1.21]	[−2.15]	[−0.07]	
BM1Size2Momentum2	Estimate	**0.01**	**4.91**	**−0.44**	**1.40**	**−1.81**	**−3.08**	**−0.11**	65.5%
	t-stat.	[3.13]	[3.34]	[−0.60]	[1.54]	[−1.08]	[−3.30]	[−0.72]	
BM2Size1Momentum1	Estimate	**0.01**	**2.82**	**−0.40**	**3.78**	**−1.05**	**−0.82**	**0.16**	63.3%
	t-stat.	[5.11]	[2.61]	[−0.55]	[5.35]	[−1.07]	[−1.15]	[1.20]	
BM2Size1Momentum2	Estimate	**0.01**	**2.98**	**−0.76**	**2.97**	**−1.61**	**−1.71**	**0.03**	55.3%
	t−stat	[6.53]	[2.66]	[−1.07]	[4.00]	[−1.57]	[−2.21]	[0.26]	
BM2Size2Momentum1	Estimate	**0.01**	**3.70**	**−0.65**	**1.92**	**−1.97**	**−1.54**	**0.17**	54.3%
	t-stat.	[3.84]	[3.11]	[−0.83]	[2.54]	[−1.54]	[−2.04]	[1.18]	
BM2Size2Momentum2	Estimate	**0.01**	**3.32**	**−0.37**	**1.58**	**−1.81**	**−2.32**	**−0.04**	47.3%
	t-stat.	[4.28]	[2.62]	[−0.46]	[1.93]	[−1.51]	[−3.28]	[−0.31]	
RM	Estimate	**0.00**	**4.51**	**−0.30**	**1.86**	**−1.74**	**−2.44**	**−0.09**	74.2%
	t-stat.	[0.89]	[3.33]	[−0.46]	[2.28]	[−1.15]	[−2.93]	[−0.66]	
HML	Estimate	**0.01**	**−1.72**	**0.03**	**−0.19**	**−0.13**	**0.88**	**0.09**	16.1%
	t-stat.	[4.06]	[−2.97]	[0.05]	[−0.42]	[−0.23]	[2.03]	[1.33]	
SMB	Estimate	**0.00**	**−0.61**	**0.45**	**2.39**	**0.80**	**0.40**	**0.05**	21.4%
	t-stat.	[1.94]	[−1.26]	[0.64]	[6.09]	[2.03]	[0.87]	[0.50]	
WML	Estimate	**0.00**	**0.10**	**−0.25**	**−1.01**	**−0.31**	**−1.39**	**−0.16**	12.8%
	t-stat.	[2.14]	[0.20]	[−0.54]	[−3.53]	[−0.98]	[−3.18]	[−2.12]	

[a] In this table, we show the outcomes from OLS estimations of characteristic portfolio returns onto macroeconomic fundamental realizations. The macroeconomic fundamental realizations are changes in industrial production growth expectations (MYP), unexpected inflation (UI), changes in the aggregate survival probability (DSV), changes in the average level and the slope of the term structure (ATS and STS, respectively) and changes in a multilateral US dollar exchange rate (FX). Panel A reveals the results from χ^2-tests on the difference between the (average) macroeconomic exposure of one-way sorted high characteristic deciles and that of one-way sorted low characteristic deciles. The one-way sorted characteristic deciles are formed on book-to-market, size and momentum. The χ^2-tests check whether the spread is significantly different from zero. The bold number is the difference in the (average) exposure and the number in parentheses is the p-value. Panel B shows the estimates, significance levels and adjusted R^2s from the time-series regressions using the three-way sorted book-to-market, size, and momentum benchmark portfolios, the market portfolio, and the three-way sorted benchmark factors, i.e., HML, SMB, and WML, as dependent variables. The bold numbers are parameter estimates, and the numbers in square parentheses are t-statistics. The first element in the portfolio name indicates the book-to-market, the second the size and the final element the momentum category of the portfolio (with the fundamentals increasing from 1 to 2). In the one-step GMM approach, we stack the moment conditions of the mimicking portfolio onto the moment conditions of the asset pricing model. Since this system is exactly identified, we obtain the same parameter estimates as if we had used a two-stage regression approach. The one-step GMM procedure, however, corrects standard errors for the additional uncertainty induced through the generated regressor. All estimation procedures correct for heteroscedasticity and autocorrelation by using the Newey and West (1987) correction with $l = 12$. The sample period extends from January 1975 to April 2008.

Table 6
Unconditional cross-sectional tests of alternative asset pricing models.[a]

	Pricing factors											J-test	Adj. R^2
	MYP	UI	DSV	ATS	STS	FX	RM*	RM	SMB	HML	WML		
Macroeconomic factor (MF) model													
b-estimate (stochastic discount factor)	**−58.45**	**69.12**	**54.78**	**−154.70**	**−120.80**	**−17.26**						29.04	30.9%
t-stat.	[−2.72]	[1.92]	[5.26]	[−5.78]	[−5.02]	[−2.79]						(1.00)	
Risk premia (×10^2)	**−0.19**	**0.01**	**0.24**	**-0.45**	**−0.13**	**−0.68**							
t-stat.	[−2.30]	[0.47]	[2.69]	[−5.41]	[−3.19]	[−3.62]							
Augmented macroeconomic factor (AMF) model													
b-estimate (stochastic discount factor)	**−75.78**	**130.01**	**53.70**	**−142.93**	**−77.70**	**−12.86**	**13.21**					29.14	35.9%
t-stat.	[−2.96]	[3.74]	[4.31]	[−4.41]	[−2.81]	[−1.92]	[2.09]					(1.00)	
Risk premia (×10^2)	**−0.24**	**0.07**	**0.19**	**−0.41**	**−0.07**	**−0.55**	**0.62**						
t-stat.	[−2.60]	[2.44]	[1.98]	[−4.13]	[−1.44]	[−2.75]	[2.09]						
Fama and French (FF) model													
b-estimate (stochastic discount factor)								**4.45**	**4.03**	**8.81**		29.47	10.6%
t-stat.								[5.87]	[5.08]	[08.97]		(1.00)	
Risk premia (×10^2)								**0.53**	**0.33**	**0.46**			
t-stat.								[3.65]	[3.95]	[5.86]			
Carhart (C) model													
b-estimate (stochastic discount factor)								**5.62**	**4.03**	**12.44**	**5.94**	29.11	61.5%
t-stat.								[8.12]	[7.88]	[13.22]	[7.25]	(1.00)	
Risk premia (×10^2)								**0.63**	**0.39**	**0.49**	**0.35**		
t-stat.								[4.53]	[4.45]	[7.41]	[4.62]		

[a] In this table, we show the stochastic discount factor and risk premia estimations for the macroeconomic factor (MF) model, an augmented macroeconomic factor (AMF) model, the Fama and French (FF) model and the Carhart (C) model. We use 64 three-way sorted book-to-market, size, and momentum portfolios as test assets. The pricing factors of the MF model are changes in industrial production growth expectations (MYP), unexpected inflation (UI), changes in the aggregate survival probability (DSV), changes in the average level and the slope of the term structure of risk-free interest rate yields (ATS and STS, respectively), and changes in the exchange rate between the US dollar and a trade-weighted composite currency (FX). The pricing factors of the AMF model are the former factors plus the orthogonalized excess return of the market portfolio (RM*). The pricing factors of the FF model are the excess return of the market portfolio, the return of the SMB zero-investment portfolio, and the return of the HML zero-investment portfolio. The pricing factors of the C model are the former factors plus the return of the WML zero-investment portfolio. In the one-step GMM procedure, we stack the moment conditions of the mimicking portfolio onto the moment conditions of the asset pricing model and then use the weighting matrix *a* (shown in the Appendix A) to ensure that the coefficients obtained from this approach are exactly equal to those from a two-stage approach (see Appendix A). The one-step GMM approach corrects standard errors for the additional uncertainty induced through the generated regressor. The *J*-test is Hansen's (1982) test of the over-identifying restrictions, while the adjusted R^2 is obtained from an OLS regression of mean test asset returns onto the pricing factor betas. The sample period extends from January 1975 to April 2008.

In a similar way, controlling for the relation between BM and MYP might drive out the link between SMB and MYP.

While our results on the relations between the benchmark risk factors and UI or FX and those on the relations between WML and the macroeconomic fundamentals are entirely new to the literature, it is instructive to compare other results in our analysis with those from the prior literature. Our results contradict the prior literature in three main ways:

First, Liew and Vassalou (2000) and Kelly (2004) find a significantly positive relation between HML and MYP. In contrast, we report a negative relation in Table 5. We can account for the difference by observing that these two prior studies do not control for term structure risk. Our summary statistics reveal that MYP has a positive correlation with ATS and STS. When we drop ATS and STS, add RM and restrict our sample period to 1978–1996 (the sample period analyzed in these studies), the relation between HML and MYP turns positive.

Second, in contrast to our main findings, Hahn and Lee (2006) and Petkova (2006) obtain no evidence that SMB associates with term structure risk. We conjecture that this difference could be driven by correlation between ATS and STS, on the one hand, and MYP and FX, on the other. When we end our sample period in 2001,[11] include RM and drop MYP and FX, we also find an insignificant association between SMB and ATS.

Finally, Vassalou and Xing (2004) find a significantly negative relation between HML and DSV. In contrast, we find no significant association after controlling for other macroeconomic fundamentals. We conjecture that the findings in Vassalou and Xing (2004) are an artifact of the positive correlation between MYP and DSV. Dropping MYP from our MF model and truncating our sample period in 1999,[12] HML loads significantly and negatively on DSV.

While our remaining results confirm those reported in the literature, the above cases confirm the importance of controlling for correlation between macroeconomic fundamentals. Of course, while our MF model includes more macroeconomic fundamentals than those in prior studies, we acknowledge that it could also be incomplete, and thus vulnerable to a similar critique.

4.2. Unconditional pricing tests

We evaluate the cross-sectional pricing ability of the MF, FF and C models in this section. If the success of the FF and C models in pricing characteristic portfolios can be explained by the benchmark risk factor exposures serving as proxies for our macroeconomic exposures, then the macroeconomic exposures of the MF model should at least in theory perform similarly in pricing. On the other hand, if either the FF or C model outperforms the MF model, then the firm characteristics capture a richer set of information on priced factors than that captured by our macroeconomic fundamentals. This section analyzes unconditional test portfolios. In particular, we run our pricing tests on the 25 two-way sorted BM and size portfolios that are widely used in the literature. We also consider 64 three-way sorted BM, size and momentum portfolios, as a larger number of test assets with greater spreads in expected returns should increase explanatory power in the presence of measurement errors endemic in macroeconomic data. We estimate all models with the GMM to avoid a bias in standard errors (see Appendix A).

[11] The sample period used in Hahn and Lee (2006) and Petkova (2006) ends in 2001. Unfortunately, the start of their sample period is before ours.

[12] The sample period used in Vassalou and Xing (2004) ends in 1999. Unfortunately, the start of their sample period is before ours.

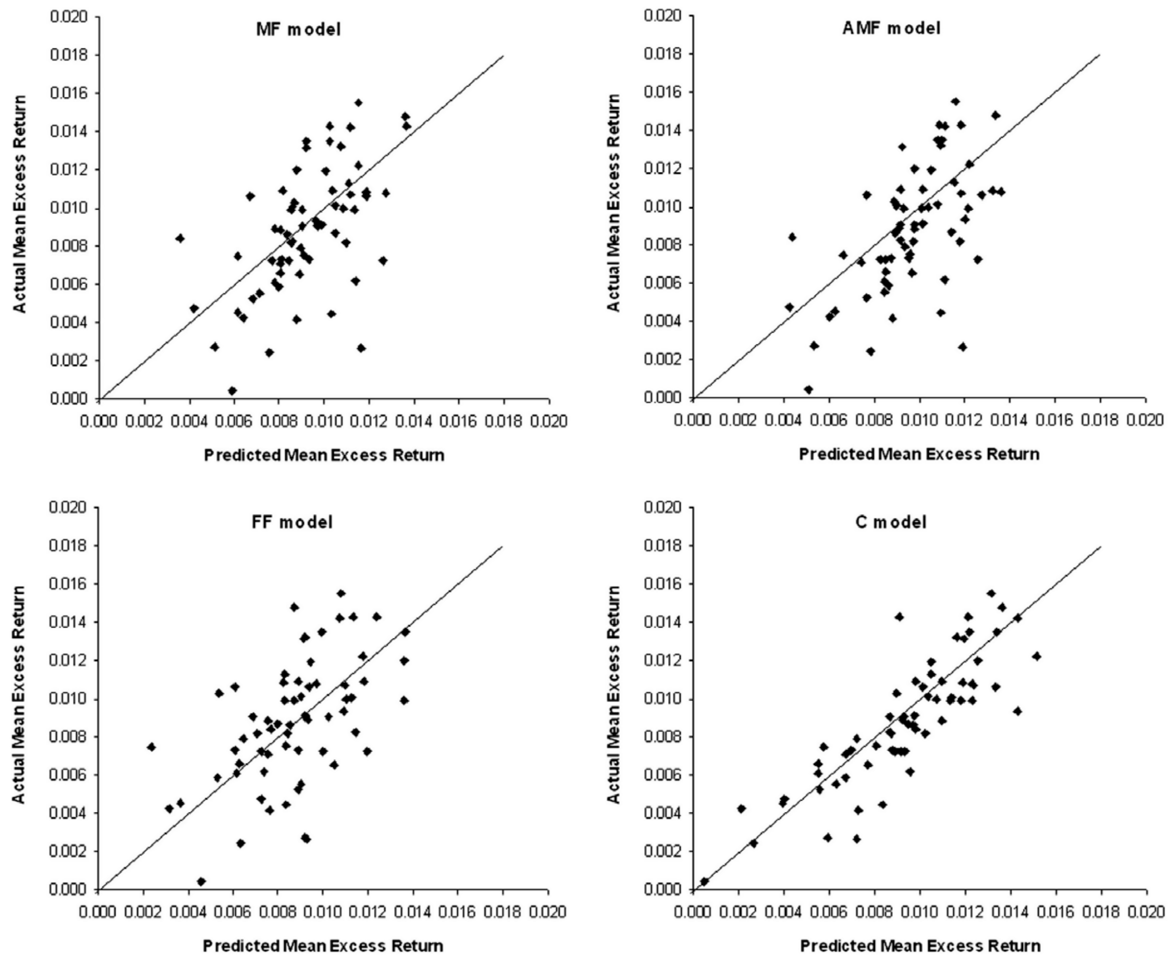

Fig. 2. In this figure, we show the model prediction versus the actual mean excess return of the 64 three-way sorted size, book-to-market, and momentum portfolios. The model prediction is obtained from the macroeconomic factor model (top left), the augmented macroeconomic factor model (top right), the Fama and French model (bottom left), or the Carhart model (bottom right).

Our results are in Table 6. We first report the relations between the relevant set of pricing factors and the stochastic discount factor. Significant coefficients indicate that, conditional on the other pricing factors of a model, a pricing factor helps to correctly price the test portfolios. Below the loadings on the stochastic discount factor, we show the estimated risk premia, which reveal whether each pricing factor is priced. To evaluate the pricing ability of each model, we also report Hansen's (1982) *J*-test and the adjusted R^2 from an OLS regression of mean portfolio returns on exposures. For the FF and C models, our results based on the 25 portfolios are close to those shown on the 64 portfolios. For the MF and AMF models, we find similar parameter estimates on both sets of test portfolios, but consistent with our expectations significance levels are lower for the smaller set of test portfolios. As a result, we only report the estimation outcomes from the larger set of 64 portfolios. Still, it is worthwhile highlighting that the abilities of the MF and FF models to price the 25 test assets are relatively similar. For example, the adjusted R^2s of the MF and the FF models are 42.5% and 54.5%, respectively, while that of the C model equals 71.6%.

Using the 64 test portfolios, several of the macroeconomic fundamentals capture variation in the stochastic discount factor, i.e., MYP, DSV, ATS, STS, and FX are all highly significant at conventional levels. However, a different set of pricing factors could command significant risk premia, as the macroeconomic fundamentals are highly correlated (Cochrane, 2001, pp. 260–262). Notwithstanding this argument, we find that the same macroeconomic fundamentals are priced. Augmenting the MF model by adding the orthogonalized market return (RM*) turns the loading on the stochastic discount factor and the risk premium of UI significant, while it renders the risk premium of STS insignificant. In addition, the risk premium on DSV is now less significant. The RM* factor itself obtains a significant stochastic discount factor loading and risk premium, and its inclusion in the MF model increases the adjusted R^2 from 30.9% to 35.9%.

The signs of the risk premia are in accordance with economic intuition. We have already shown that high (low) BM assets often have small (large) positive MYP betas and small (large) negative STS betas. In light of the more negative risk premium on MYP than on STS and the almost equal spread in exposures on these macroeconomic fundamentals, MYP can help to explain the average return spread between BM portfolios. Similarly, small (big) sized assets have large (small) positive DSV betas and small (large) negative ATS betas, with the spread in the DSV betas being much larger than that in the ATS betas. In combination with a positive risk premium, DSV can help to explain the average return spread in the size portfolios. Finally, high (low) momentum assets have small (large) positive DSV betas, large (small) negative STS betas and small negative (small positive) FX betas. As a result, the negative risk premium on STS drives up the average return prediction of a winners minus losers spread portfolio, while the positive risk premium on DSV drives down this prediction. As the effect induced through DSV is stronger than the effect induced through STS, the macroeconomic fundamentals seem unable to explain momentum.

Our outcomes on the FF and C models are consistent with prior studies. All the FF and C benchmark factors strongly associate with the stochastic discount factor and also obtain significant risk premia. The significant risk premium on SMB reveals that the size effect has re-emerged in recent years. Our evaluation statistics (i.e., the adjusted R^2s and the *J*-tests) and Fig. 2 suggest that the MF and FF models cannot correctly capture variation in the equity prices of the 64 portfolios, with the MF model working slightly better than the FF model. The C model displays the best pricing ability, which is not surprising given that it features a momentum-related pricing factor.

Our empirical analysis indicates that foreign exchange rate risk can be important when pricing the cross-section of average equity returns, as FX loads significantly on the stochastic discount factor and also attracts a significant risk premium. In contrast, inflation risk becomes only important once we add the orthogonalized market return to the other pricing factors. Again, we find it illuminating to compare our asset pricing results with those obtained in the prior literature. Two major differences should be highlighted and explained:

First, Hahn and Lee (2006) and Petkova (2006) fail to obtain a significant risk premium on changes in aggregate default risk in their cross-sectional tests. In contrast, DSV commands a significantly positive risk premium in our tests. The difference can be explained by noting that prior studies use the credit spread as their proxy for default risk. In this context, the findings of Elton et al. (2001) are interesting. They suggest that the credit spread only partially reflects default risk. Our contingent claims analysis-based proxy appears more powerful in reflecting changes in default risk in our sample period.

Second, Petkova (2006) shows that economic growth risk, computed using a methodology similar to ours, does not command a significant risk premium in the presence of other pricing factors. We cannot confirm this finding. While MYP and DSV exhibit a high degree of correlation and carry important common information, exposures to both macroeconomic fundamentals significantly explain average returns, and both attract significant risk premia in our analysis.

4.3. Conditional pricing tests

Following earlier studies, we also consider the pricing ability of the unconditional pricing models on conditional assets, i.e., on assets with time-varying weights equivalent to dynamic trading strategies. To this end, we multiply the returns of the $(2 \times 2 \times 2)$ three-way sorted portfolios by an instrument set, which contains a constant, the aggregate dividend yield, the default yield spread, and the government bond term spread, to obtain 32 managed portfolios. In this way, the magnitude of the long and the short positions in the eight zero investment portfolios depends on the business cycle. More information on the definition of the instruments is offered in the footnote of Table 7. The instruments are lagged by two periods to avoid overlap with the test assets. We ensure that the assets' scale is roughly equal by subtracting 0.04 from the dividend yield and multiplying all instruments by 100. We find it important to compare the estimates, significance levels, and pricing ability of the models across alternative test portfolios to assess the robustness of our prior outcomes.

Our estimation outcomes reported in Table 7 and shown in Fig. 3 suggest that the MF model does slightly better than the FF

Table 7
Conditional cross-sectional tests of alternative asset pricing models.[a]

	Pricing factors											*J*-test	Adj. R^2
	MYP	UI	DSV	ATS	STS	FX	RM*	RM	SMB	HML	WML		
Macroeconomic factor (MF) model													
b-estimate (stochastic discount factor)	**−18.31**	**18.18**	**36.54**	**−50.61**	**−130.26**	**3.87**						25.67	80.4%
t-stat.	[−1.20]	[0.38]	[3.62]	[−3.49]	[−4.84]	[0.37]						(0.48)	
Risk premia ($\times 10^2$)	**−0.06**	**−0.01**	**0.18**	**-0.09**	**−0.20**	**0.07**							
t-stat.	[−1.20]	[−0.21]	[3.00]	[−2.11]	[−4.37]	[0.25]							
Augmented macroeconomic factor (AMF) model													
b-estimate (stochastic discount factor)	**−6.42**	**−25.32**	**49.55**	**−58.96**	**−200.90**	**0.96**	**−13.08**					25.06	80.3%
t-stat.	[−0.37]	[−0.41]	[4.77]	[−3.65]	[−5.53]	[0.07]	[−2.90]					(0.46)	
Risk premia ($\times 10^2$)	**−0.01**	**−0.05**	**0.29**	**-0.09**	**−0.32**	**0.00**	**−0.63**						
t-stat.	[−0.24]	[−1.11]	[5.30]	[−1.85]	[−4.89]	[−0.00]	[−2.84]						
Fama and French (FF) model													
b-estimate (stochastic discount factor)								**5.79**	**3.60**	**11.11**		25.65	78.0%
t-stat.								[6.95]	[2.46]	[8.73]		(0.64)	
Risk premia ($\times 10^2$)								**0.66**	**0.27**	**0.63**			
t-stat.								[4.37]	[1.71]	[6.04]			
Carhart (C) model													
b-estimate (stochastic discount factor)								**6.79**	**3.76**	**13.74**	**6.32**	24.32	89.6%
t-stat.								[8.88]	[3.51]	[10.04]	[5.34]	(0.66)	
Risk premia ($\times 10^2$)								**0.81**	**0.32**	**0.56**	**0.36**		
t-stat.								[5.16]	[1.67]	[5.13]	[3.08]		

[a] In this table, we show the stochastic discount factor and risk premia estimations for the macroeconomic factor (MF) model, an augmented macroeconomic factor (AMF) model, the Fama and French (FF) model and the Carhart (C) model. We use 32 conditional (managed) portfolios as test assets, i.e., eight three-way sorted book-to-market, size and momentum benchmark portfolios, plus the same portfolios multiplied by the dividend yield on the S&P 500 stock index, the yield spread between Baa and Aaa-rated corporate bond portfolios, and the yield spread between long-term and short-term government bond portfolios. All instruments are lagged by two months. The pricing factors of the MF model are changes in industrial production growth expectations (MYP), unexpected inflation (UI), changes in the aggregate survival probability (DSV), changes in the average level and the slope of the term structure of risk-free interest rate yields (ATS and STS, respectively), and changes in the exchange rate between the US dollar and a trade-weighted composite currency (FX). The pricing factors of the AMF model are the former factors plus the orthogonalized excess return of the market portfolio (RM*). The pricing factors of the FF model are the excess return of the market portfolio, the return of the SMB zero-investment portfolio, and the return of the HML zero-investment portfolio. The pricing factors of the C model are the former factors plus the return of the WML zero-investment portfolio. In the one-step GMM procedure, we stack the moment conditions of the mimicking portfolio onto the moment conditions of the asset pricing model and then use the weighting matrix *a* (shown in the Appendix A) to ensure that the coefficients obtained from this approach are exactly equal to those from a two-stage approach (see Appendix A). The one-step GMM approach corrects standard errors for the additional uncertainty induced through the generated regressor. The *J*-test is Hansen's (1982) test of the over-identifying restrictions, while the adjusted R^2 is obtained from an OLS regression of mean test asset returns onto the pricing factor betas. The sample period extends from January 1975 to April 2008.

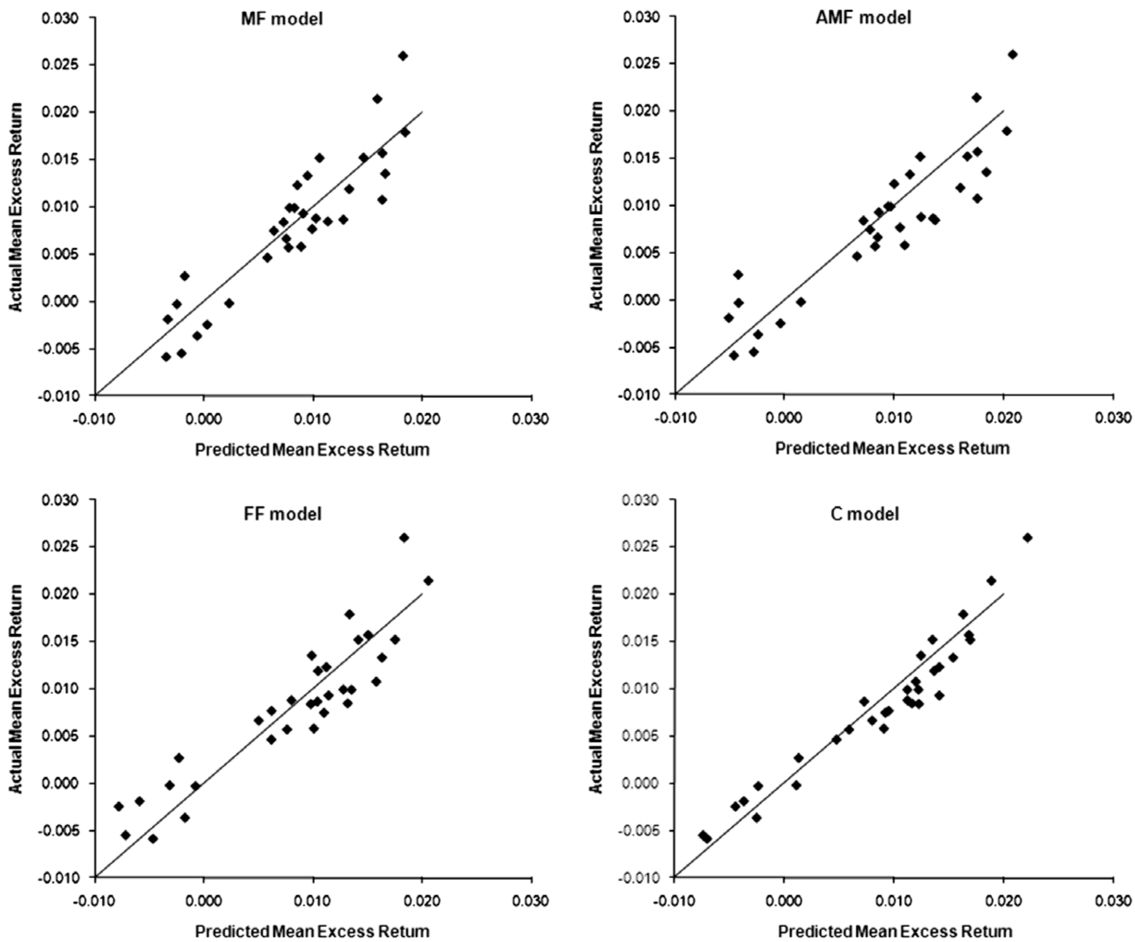

Fig. 3. In this figure, we show the model prediction versus the actual mean excess return of the 32 conditional portfolios. The model prediction is obtained from the macroeconomic factor model (top left), the augmented macroeconomic factor model (top right), the Fama and French model (bottom left), or the Carhart model (bottom right).

model and somewhat worse than the C model in pricing the 32 test portfolios. The links between the macroeconomic fundamentals and the stochastic discount factor and the risk premia are often close to those found from the unconditional test assets. Two notable exceptions are that the loadings of MYP and FX on the stochastic discount factor and their risk premia are no longer significant. The differences in significance are very likely driven by smaller spreads in average returns on the test portfolios, and thus lower statistical power. With regards to the AMF model, RM* again loads significantly on the stochastic discount factor and also obtains a significant risk premium. Surprisingly, however, the sign of the RM* estimates has changed. Our estimation outcomes on the FF and C models are almost equal to those found previously. An important difference is that, for both models, SMB no longer commands a significant risk premium at the 95% confidence level, indicating that the characteristic-factor models also suffer from the lower spreads in average portfolio returns. Overall, all models seem fairly capable of correctly pricing the 32 conditional portfolios.

4.4. Incremental pricing ability of HML, SMB, and WML

Our earlier results are informative about the relative pricing performance of the three models. An alternative perspective is to consider the incremental pricing ability of the FF and C benchmark factors when added to the MF (or AMF) model. If the FF and C factors do not contain incremental information, the macroeconomic fundamentals should drive out their significant risk premia. In Table 8, we thus report the outcomes from model specification tests and tests of incremental pricing ability. The model specification tests indicate that the stochastic discount factor loadings of the macroeconomic fundamentals are always jointly significant and that the Hansen–Jagannathan (HJ) distance always rejects the MF and AMF models at conventional levels.

Our tests of incremental pricing ability reveal that neither the benchmark factors specified by the FF model nor those specified by the C model contain incremental information beyond our macroeconomic fundamentals when pricing BM and size-sorted assets. Focusing first on the unconditional models, if we add HML and SMB or HML, SMB and WML to the macroeconomic fundamentals, the risk premia on the FF benchmark factors or the C benchmark factors are jointly insignificant on the 25 portfolios. Our evidence hence suggests that the macroeconomic fundamentals adequately capture risks associated with BM and size. We can draw the same conclusions when we consider the AMF model. Further, when we analyze three-way sorted portfolios, i.e., the 64 unconditional portfolios or the 32 conditional portfolios, then the macroeconomic fundamentals can never drive out the significant risk premia of the FF or C benchmark factors. We conclude that HML and SMB or HML, SMB and WML contain information not captured by the macroeconomic fundamentals that is necessary to correctly price portfolios reflecting risks associated with BM, size and momentum.

Table 8
Model specification and comparison tests.[a]

		Test portfolios		
		25 portfolios	64 portfolios	32 managed portfolios
Panel A: Macroeconomic factor (MF) model				
Joint test factor loadings on sdf	χ^2 (# restrictions)	**13.78**	**79.94**	**36.77**
(All *b* parameters = 0)	*p*-value	*(0.03)*	*(0.00)*	*(0.00)*
Joint test SMB and HML premia	χ^2 (# restrictions)	**3.45**	**27.27**	**15.19**
(RP_{SMB} and $RP_{HML} = 0$)	*p*-value	*(0.18)*	*(0.00)*	*(0.00)*
Joint test SMB, HML, and WML premia	χ^2 (# restrictions)	**6.46**	**50.98**	**20.08**
(RP_{SMB}, RP_{HML}, and $RP_{WML} = 0$)	*p*-value	*(0.09)*	*(0.00)*	*(0.00)*
HJ statistic	Sum of (n-#) i.i.d. $\chi^2(1)$	**0.347**	**0.577**	**0.474**
	p-value	*(0.00)*	*(0.00)*	*(0.00)*
Panel B: Augmented macroeconomic factor (AMF) model				
Joint test factor loadings on sdf	χ^2 (# restrictions)	**13.94**	**67.00**	**66.11**
(All *b* parameters = 0)	*p*-value	*(0.05)*	*(0.00)*	*(0.00)*
Joint test SMB and HML premia	χ^2 (# restrictions)	**3.08**	**28.57**	**15.42**
(RP_{SMB} and $RP_{HML} = 0$)	*p*-value	*(0.21)*	*(0.00)*	*(0.00)*
Joint test SMB, HML, and WML premia	χ^2 (# restrictions)	**3.99**	**45.15**	**21.35**
(RP_{SMB}, RP_{HML}, and $RP_{WML} = 0$)	*p*-value	*(0.26)*	*(0.00)*	*(0.00)*
HJ statistic	Sum of (n-#) i.i.d. $\chi^2(1)$	**0.340**	**0.577**	**0.461**
	p-value	*(0.00)*	*(0.00)*	*(0.00)*

[a] In this table, we show test statistics used to evaluate the macroeconomic factor (MF) model (Panel A) and the augmented macroeconomic factor (AMF) model (Panel B). Our three sets of test assets are the 25 two-way sorted book-to-market and size portfolios, the 64 three-way sorted book-to-market, size, and momentum portfolios, and the 32 conditional (managed) portfolios. The first Wald statistic (joint test factor loadings on sdf) tests whether all factor loadings on the stochastic discount factor of the asset pricing model are jointly equal to zero. The next two Wald statistics test whether the risk premia (RP) on the benchmark factors, namely SMB and HML for the FF model (joint test SMB and HML premia) or SMB, HML and WML for the C model (joint test SMB, HML and WML premia), are jointly equal to zero if added to the other pricing factors of the MF model and the AMF model. Finally, we report the HJ distance and its empirical *p*-value. The sample period extends from January 1975 to April 2008.

Overall, our results suggest that the success of the FF model in pricing BM and size-sorted test assets stems from its ability to capture exposures to the macroeconomic factors in our MF model. First, the pricing ability of the MF and the FF models are comparable on characteristic portfolios and on alternative portfolios. Second, when we use BM and size test portfolios the macroeconomic fundamentals render the risk premia of the FF benchmark factors insignificant. At the same time, the C model outperforms both the MF and AMF models, as well as the FF model. The failure of the MF model to completely capture momentum risks could indicate that momentum also relates to firm-specific risk factors (e.g., Li et al., 2008) or non-risk factors (e.g., Asem, 2009).

5. Robustness tests

Our analysis is complicated by the fact that proxy variables often only imprecisely measure the true macroeconomic fundamentals explaining variation in equity returns and prices. One manifestation of this problem is that macroeconomic proxy variables normally relate more weakly to the cross-section of average equity returns than return-based pricing factors, as, e.g., HML, SMB and WML (see the discussion in Cochrane, 2001). A reason for the weaker relation is that, as a result of reporting lags, it is often unclear at which point in time macroeconomic news is incorporated into equity prices. Further, macroeconomic data are subject to subsequent revisions, e.g., when the definition of a macroeconomic indicator changes, implying that investors at the time perceived different shocks to the macroeconomic fundamentals than those suggested by the revised data. Finally, macroeconomic proxy variables are often summary measures of broader phenomena. For example, in our study we attempt to capture the whole term structure of interest rates through the average level and slope of the term structure. The imprecise nature of the macroeconomic data implies that it is important to verify that our main conclusions are not driven by our choice of proxy variables. In this section, we hence analyze whether popular alternative proxy variables used in the literature to represent our macroeconomic fundamentals can yield findings different from those shown in our main tests.[13]

5.1. MYP

(1) We re-compute the mimicking portfolio using real-time data from the Federal Reserve Bank of Philadelphia. The real-time data feature the realizations of the industrial production index as experienced by market participants at the time. Our findings reveal that our previous conclusions continue to hold, although the relations between HML and STS and between SMB and ATS are now weaker and only significant at the 90% confidence level. (2) If the ability of the base assets to reflect news varies over time, then our assumption of constant mimicking portfolio weights could be problematic. As a result, we also compute MYP using recursive out-of-sample windows of initially 120 observations. As data on several of our base assets starts in January 1975, these tests use a sample period stretching from January 1985 to April 2008. Although we are unable to adjust standard errors for the additional uncertainty induced through MYP in this setting, our unadjusted results reveal that SMB no longer reflects interest rate risk, while FX no longer attracts a significant risk premium. On the other hand, there is now a significant relation between HML and DSV and between WML and MYP. Of course, if factor exposures and risk premia vary over time, then these differences might be driven by the change in the sample period. Other findings are qualitatively similar.

(3) Another potential concern is that the mimicking portfolio simply proxies for the market portfolio, one of its base assets. We therefore replace the market portfolio with (a) three character-

[13] We thank our referee for motivating this analysis. Note that we only shortly summarize the main findings from our robustness checks in this section. A more detailed description including tables can be obtained upon request.

istic portfolios sorted on dividend yields and (b) four industry portfolios from Kenneth French's website.[14] The factor loadings on HML are −2.33 (t-statistic of −2.00) and −2.49 (t-statistic of −2.96), respectively. In both cases, the MYP risk premium is significant at the 90% confidence level or better (t-statistics of −1.87 and −2.24, respectively). Other findings remain qualitatively similar. (4) As a further check, if MYP simply proxies for the market portfolio, we should be able to replace it with the market portfolio and still find similar results. Our evidence reveals that the spread in the market portfolio exposures across the BM deciles is, at best, weak (from 1.18 to 0.83). In combination with an estimated market risk premium of 0.80%, the market portfolio *reduces* the expected return prediction on a BM spread portfolio (BM10-BM1) by 0.22%. As MYP increases the expected return prediction on a BM spread portfolio by 0.47%, these pricing factors cannot be equivalent.

5.2. UI

We also construct UI from recursive out-of-sample windows of initially ten years. As the correlation coefficient between our in-sample and our out-of-sample estimate of UI is approximately 0.95, none of our main findings are substantially affected.

5.3. DSV

Although our proxy variable derived from Merton's (1974) contingent claims analysis should reflect changes in aggregate default risk more accurately than others based on bond data (see, Elton et al., 2001), we also check whether our main outcomes continue to hold under these alternative proxy variables. To this end, we first replace DSV with the spread between the return of a high-yield corporate bond portfolio and the return of a long-term government bond portfolio. Probably due to a mismatch in duration, the new proxy variable is strongly correlated with our interest rate variables (correlation of 0.50 with ATS and of 0.25 with STS). As these strong links are likely a sign of measurement error in the our alternative proxy and not of natural relations between aggregate default risk and interest rates, we orthogonalize the new proxy variable with respect to interest rates. Using the new proxy variable instead of DSV, all of our main conclusions continue to hold, except that FX no longer loads on WML at conventional levels (p-value of 0.13). In contrast, when we proxy for changes in aggregate default risk through the change in the yield spread between a high-yield corporate bond portfolio and a long-term government bond portfolio (orthogonalized with respect to the interest rate variables), our conclusions are not affected.

5.4. ATS and STS

Most other studies use one and not two proxy variables to capture news on the term structure. As a result, we investigate whether it is important to approximate the term structure through both its average level and through its slope by including either ATS or STS in our tests. Our outcomes reveal that HML and WML only reflect changes in the slope of the term structure (STS), i.e., the absence of STS fails to render the loading of ATS on HML or WML significant. In contrast, SMB only captures changes in the average level of the term structure (ATS). Other time-series relations, risk premia and significance levels are close to those shown before.

[14] In an earlier version of our study, we have chosen the eight three-way sorted benchmark portfolios as alternative base assets. However, as there is a mechanical relation between these base assets and the benchmark factors (i.e., the benchmark factors are a linear combination of the benchmark portfolios), we have replaced the benchmark portfolios by characteristic portfolios less strongly related to the benchmark factors.

5.5. FX

(1) We first replace the nominal version of the broad foreign exchange rate index with its inflation-adjusted counterpart. This modification does not affect our findings. (2) Next, as only FX can be forecasted with a positive adjusted R^2 in the out-of-sample VAR tests, we replace FX with the residual from an MA(1) model. We use an MA(1) model, as only the first autocorrelation of FX is significantly different from zero. Again, our main findings continue to hold.

Overall, our main conclusions seem largely robust with respect to our choice of macroeconomic proxy variables at the 90% confidence level or better. However, we agree that we only consider alternative proxy variables and not necessarily efficient measures of the true macroeconomic fundamentals. Hence, one cannot completely rule out that the relations between the benchmark factors and the true macroeconomic fundamentals are different from those reported in our study.

6. Conclusion

Several recent studies illustrate that the success of the Fama and French (1993) model in pricing characteristic-sorted portfolios is attributable to its ability to capture information on macroeconomic risk factors. However, as most of these studies analyze one macroeconomic fundamental or at best a narrow set of them (e.g., see, Vassalou, 2003; Vassalou and Xing, 2004; Hahn and Lee, 2006; Petkova, 2006), their empirical findings are not completely unambiguous. We contribute to this literature through a multivariate analysis based on a more comprehensive set of macroeconomic fundamentals. Our model controls for correlation between macroeconomic fundamentals considered in the prior literature, and it adds to them unexpected inflation and shocks to a compound US dollar exchange rate. Further, we examine for the first time the relation between the momentum-based factor WML (see, Carhart, 1997) and macroeconomic fundamentals. Finally, we follow the advice of Fama (1996) and deal with the confounding impact of the market return on the other pricing factors by orthogonalizing it with respect to the macroeconomic fundamentals.

Our analysis reveals that macroeconomic fundamentals exhibit strong contemporaneous links, and that changes in economic growth expectations and the term structure Granger-cause several of the other macroeconomic fundamentals. We also show that the macroeconomic fundamentals seem more elementary than the benchmark risk factor. Next, our empirical tests confirm much of the evidence reported in prior studies. For example, we show that BM conveys useful information about term structure risk, and size about default risk. However, we also obtain results that directly contradict prior research. Specifically, BM does not proxy for default risk exposure after controlling for term structure risk. Furthermore, BM reflects exposure to economic growth risk with the opposite sign to that reported in the prior literature. Similarly, size conveys information about term structure risk. We also report results entirely new to the literature. For example, we find that WML is significantly associated with default, term structure and foreign exchange rate risks.

In various cross-sectional pricing tests, we first document that the majority of the macroeconomic fundamentals command significant risk premia. More importantly, we find that, on three-way sorted BM, size, and momentum portfolios, the MF model can compete with the FF model in terms of pricing ability, but not with the C model. The pricing performance of the models is more similar when we use alternative portfolios, such as, e.g., conditional portfolios. When considering BM and size-sorted portfolios, the macroeconomic fundamentals render the risk premia on the FF benchmark factors and the C benchmark factors insignificant. In contrast, they cannot render the risk premia on either set of benchmark factors insignificant when we run our tests on three-way sorted BM, size and momentum portfolios. As a result, the ability of the C model to price momentum-sorted portfolios cannot be explained by our macroeconomic fundamentals.

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Appendix A. GMM methodology

We choose a methodology equivalent to that of Vassalou (2003) to correct standard errors for the additional uncertainty induced through the generated regressor MYP. More specifically, we use Hansen's (1982) GMM to estimate the asset pricing models in this study. In the tests in Table 4, we stack the moment conditions of the mimicking portfolio model onto those of the time-series asset pricing model. Since these systems are exactly identified, i.e., the number of moment conditions equals the number of parameters, the OLS parameter estimates obtained from estimating the time-series regressions separately also constitute the optimal parameter estimates from the GMM systems. Notwithstanding this, the GMM estimations take the dependence of the time-series regression outcomes on the mimicking portfolio estimations into account. In other words, standard errors are corrected for the presence of the generated regressor (MYP). Moreover, the GMM system estimations also allow us to perform Wald tests on the (average) differences between exposures across the time-series regressions.

The cross-sectional tests in Tables 5 and 6 are estimated using a similar approach. In this case, one complicating fact is that the stochastic discount factor estimations are overidentified, i.e., the number of moment conditions exceeds the number of parameters. Separately estimating the mimicking portfolio weights and then the stochastic discount factor loadings will thus lead to differences in outcomes relative to the one-step GMM approach. However, we can ensure identical outcomes by forcing the GMM estimations to minimize the following linear combination of the moment conditions:

$$a = \begin{bmatrix} I_{BA+CV} & 0 \\ 0 & \frac{\partial g_T}{\partial b'} W \end{bmatrix},$$

where I_{BA+CV} is an identity matrix of dimension equal to the number of base assets and control variables, $\frac{\partial g_T}{\partial b'}$ is the derivative vector of the moment conditions with respect to the parameters and w is a weighting matrix. If we set w to the same matrix as used in the two-stage approach, then the usage of a in the GMM system approach ensures equivalent outcomes. We choose the inverse of the spectral density matrix as w in the GMM estimations, which we approximate via the positive definite matrix suggested by Newey and West (1987) with $l = 12$.

It should be noted that the choice of matrix a does not produce a statistically optimal weighting of the moment conditions, i.e., it does not lead to parameter estimates with the lowest possible asymptotic variance. In contrast, we choose an optimal weighting matrix for the moment conditions of the asset pricing model in the absence of the mimicking portfolio estimation. The moment conditions of the mimicking portfolio are equally weighted. The underlying idea is to prevent the mimicking portfolio estimation to have an impact on the relative weighting of the test assets in the asset pricing model estimation, as this might unduly affect our parameter estimates.

We assess an asset pricing model's validity through Hansen's (1982) J-test. Using the inverse of the spectral density matrix as w, we can compute this statistic in case of the FF and C model as follows:

$$Tg_T(b)'S^{-1}g_T(b) \sim \chi^2 \text{ (\# of moments } - \text{ \# of parameters)}, \tag{4}$$

where T is the sample size, $g_T(b)$ stands for the vector of moment conditions evaluated at the parameter estimates, and S^{-1} constitutes the estimated inverse of the spectral density matrix. For the MF and AMF model, we need to use a more general formula, as in this case we do not optimally weigh the moments in the estimation. This formula can be written as:

$$Tg_T(b)'[(I - d(ad)^{-1}a)S(I - d(ad)^{-1}a)^{-1})']^{-1}g_T(b) \\ \sim \chi^2 \text{ (\# of moments } - \text{ \# of parameters)}, \tag{5}$$

where d is the derivative of the moment conditions with respect to the parameters. In case of the MF and AMF model, we focus only on the evaluation of the moment conditions related to the asset pricing model, i.e., we completely ignore the mimicking portfolio estimation.

After we have estimated the loadings on the stochastic discount factor, we can compute the risk premia on the pricing factors and their significance levels in the following way:

$$0 = p_t^p = E_t[m_{t+1}R_{t,t+1}^p] = E_t[(1 - b'f_{t+1})R_{t,t+1}^p], \tag{6}$$

$$= E_t[R_{t,t+1}^p] - b'E_t[f_{t+1}R_{t,t+1}^p]. \tag{7}$$

Taking unconditional expectations and using the definition of covariance:

$$0 = E[R_{t,t+1}^p] - b'E[f_{t+1}R_{t,t+1}^p], \tag{8}$$

$$= E[R_{t,t+1}^p] - b'E[f_{t+1}]E[R_{t,t+1}^p] - b'cov[f_{t+1}, R_{t,t+1}^p], \tag{9}$$

$$= (1 - b'E[f_{t+1}])E[R_{t,t+1}^p] - b'var(f_{t+1})var(f_{t+1})^{-1} \\ \times cov[f_{t+1}, R_{t,t+1}^p]. \tag{10}$$

Rearranging:

$$E[R_{t,t+1}^p] = \frac{b'var(f_{t+1})}{1 - b'E[f_{t+1}]} var(f_{t+1})^{-1}cov[f_{t+1}, R_{t,t+1}^p], \tag{11}$$

$$= \lambda\beta^p, \tag{12}$$

where $\lambda = (1 - b'E[f_{t+1}])^{-1}b'var(f_{t+1})$ and $\beta^p = var(f_{t+1})^{-1}cov[f_{t+1}, R_{t,t+1}^p]$. We can thus see that the risk premia are a nonlinear function of the b estimates. To obtain the significance levels of the risk premia, we use the delta method. The delta method states that the variance of a vector of functions of b, $f(b)$, equals $f_b(b)'var(b)f_b(b)$, where $f_b(b)$ is a matrix containing the derivatives of $f(b)$ with respect to b. Using the product rule of matrix calculus, we can easily show that this derivative equals:

$$\frac{\partial\lambda}{\partial b} = \frac{var(f_{t+1})(1 - b'E[f_{t+1}]) + E[f_{t+1}]b'var(f_{t+1})}{(1 - b'E[f_{t+1}])^2}. \tag{13}$$

We obtain the variance of the b estimates using the one-step GMM procedure.

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