Journal of Financial Economics 68 (2003) 47–73
JOURNAL OF Financial ECONOMICS
www.elsevier.com/locate/econbase

News related to future GDP growth as a risk factor in equity returns ☆

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Abstract

A model that includes a factor that captures news related to future Gross Domestic Product (GDP) growth along with the market factor can explain the cross-section of equity returns about as well as the Fama-French model can. Furthermore, the Fama-French factors HML and SMB appear to contain mainly news related to future GDP growth. When news related to future GDP growth is present in the asset-pricing model, HML and SMB lose much of their ability to explain the cross-section.

JEL Classification: G12

Keywords: Asset pricing; News; Future gdp; Gmm

☆ Early versions of this paper were circulated under the title "The Fama-French factors as proxies for fundamental economic risks." I would like to thank Geert Bekaert, Michael Brennan, Eugene Fama, Larry Glosten, Bob Hodrick, Peter Bossaerts, Ross Valkanov, and seminar participants at the Columbia Lunch Seminar, Deutsch Asset Management in New York, Federal Reserve Bank of New York, the 2000 Portuguese Finance Conference in Braga, the 2000 European Finance Association Meetings in London, the 2001 Western Finance Association Meetings in Arizona, Yale University, Purdue University, Washington University at St. Louis, and the Institute for quantitative Research in Finance (Q-Group) for useful comments. I am especially thankful to the referee, Tuomo Vuolteenaho, for many insightful comments that greatly improved the paper. Qing Li and Yuhang Xing provided excellent research assistance.

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0304-405X/02/$ - see front matter
PII: S0304-405X(02)00248-9

1. Introduction

Fama and French (1992) initiated one of the main research topics in asset pricing in the 1990s. Fama and French show that the Capital Asset Pricing Model (CAPM) cannot explain the cross-section of asset returns in the US. They propose an alternative model which includes, apart from the market factor, a factor related to book-to-market (B/M) which they call High-Minus-Low (HML), and a factor related to size (MV) called Small-Minus-Big (SMB). In a series of articles, Fama and French (1992, 1993, 1995, 1996) show that their model (the FF model henceforth) does a good job explaining average equity returns. Nevertheless, it still remains unknown whether their book-to-market and size-related factors have any economic interpretation. Recall that the size (Banz, 1981) and book-to-market (Rosenberg et al., 1985) effects are two well-known anomalies in the literature of the CAPM. Understanding the economic forces behind HML and SMB helps us also understand the sources of abnormal returns for these anomalies.

Fama and French (1993, 1995, 1996) also argue that HML and SMB act as state variables in the context of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM). If this is the case, HML and SMB should capture information about fundamental risk in the economy which affects the investment opportunity set. Liew and Vassalou (2000) show that HML and SMB can predict future economic growth. The current paper explores further this argument.

The contribution I make is twofold. First, news related to future Gross Domestic Product (GDP) growth explains part of the cross-sectional variation in average asset returns. Adding this factor to the CAPM significantly improves the ability of the model to price equities. Second, when news related to future GDP growth is present in the asset pricing model, HML and SMB have virtually no remaining incremental ability to explain the cross-section. In addition, the pricing errors produced by the proposed model have a similar pattern and size to those from the FF model.

News related to future GDP growth is unobservable. To model such news, I create a mimicking portfolio using both equity and fixed-income portfolios as base assets. The ability of the base assets to predict future GDP growth is demonstrated using both asymptotic theory and bootstrap simulations.

The asset pricing tests follow the stochastic discount factor approach. To avoid a generated-regressors problem in standard errors, the mimicking portfolio and the proposed asset pricing model are estimated simultaneously in one step using Hansen's (1982) Generalized Methods of Moments (GMM). This one-step estimation method is adapted from Cochrane (2001) who uses a similar procedure to correct for the generated-regressors problem in the context of the Fama-Macbeth (1973) methodology. By considering the moments that generate the mimicking portfolio at the same time as the moments of the asset pricing model, the standard errors for the coefficients of the asset pricing model are adjusted to reflect the fact that the mimicking portfolio is a generated factor.

The performance of the proposed model is compared to those of the CAPM and the FF model. For the purpose of comparison, the proposed model is also estimated in two steps. In the first step, I estimate the mimicking portfolio which is used subsequently as a factor in the asset pricing tests. The coefficient estimates from the one-step and two-step estimations are identical, although the standard errors differ. The two-step estimation is necessary because some of the statistics used for model comparisons and diagnostics require the use of specific weighting matrices that are difficult to accommodate in the one-step estimation.

I compute the Hansen and Jagannathan (1997) distance measure to compare the maximum pricing errors generated by the competing models. In addition, I test whether HML and SMB are important factors for pricing assets when news related to future GDP growth is present in the model. To test this hypothesis, I use a Wald test in the context of the one-step estimation and the Newey-West (1987a) ΔJ test in the context of the two-step estimation. I also test whether the parameter estimates of the models are stable over time using the Andrews (1993) supLM test. To evaluate whether the competing models can explain alternative sets of test assets, I use Cochrane's (1996) approach and scale returns by a conditioning variable. Finally, I investigate whether the performance of the models is robust to alternative data frequencies and specifically to the use of quarterly and monthly holding period returns.

The rest of the paper is organized as follows. Section 2 outlines the empirical methodology used in the estimation of the asset pricing models and describes in some detail the various tests performed. Section 3 discusses the data. Section 4 presents the methodology used to construct the mimicking portfolio and reports results on the ability of the base assets to predict future GDP growth. Section 5 contains the asset pricing results. Section 6 evaluates how sensitive my results are to the choice of base assets used for the construction of the mimicking portfolio, and Section 7 concludes with a summary of my findings.

2. Empirical methodology for the asset pricing tests

The empirical tests use the stochastic discount factor approach. It is well known that in the absence of arbitrage, there exists a stochastic discount factor (or pricing kernel) m such that every asset is correctly priced:

$$\mathrm{E}(Rm) = p, \tag{1}$$

where R is a $nx1$ vector of gross asset returns and p is a $nx1$ vector of asset prices. When R represents excess returns, then p is equal to zero. When R is simple returns, $p=1$.

I compare the proposed GDP factor model with the CAPM and the FF model. All these models are linear factor pricing models. Therefore, their pricing kernels can be expressed as linear combinations of the factors:

$$m = b_0 + f'b_1, \tag{2}$$

where f is a $kx1$ vector of factors, b_0 is a constant, and b_1 is a $kx1$ vector of coefficients.

Cochrane (1996) demonstrates the equivalence between a discount factor m being a linear function of factors and a factor-pricing model expressed in terms of betas and factor risk premiums. In particular,

$$\mathrm{E}(R) = R^0 p + \beta'\lambda, \tag{3}$$

where

$$R^0 = \frac{1}{\mathrm{E}(m)} = \frac{1}{b_0 + \mathrm{E}(f')b_1}$$

is the unconditional riskless rate or zero-beta rate, $\beta = \mathrm{cov}(r, f')\mathrm{var}(f)^{-1}$ are the projections of asset returns on the factors f, and $\lambda = -R^0\mathrm{cov}(f, f')b_1$ are the risk premiums.

To estimate the competing models, I employ the Generalized Methods of Moments (GMM) procedure of Hansen (1982). When I estimate the proposed model in one step, I stack the moment conditions of the mimicking portfolio on top of the moment conditions of the asset-pricing model. I then choose a matrix A that forces the moments identifying the mimicking-portfolio regression to be matched exactly. In particular, A has the form

$$A = \begin{bmatrix} I\,J_1 + J_2 & 0 \\ 0 & \gamma \end{bmatrix}, \tag{4}$$

where I is the identity matrix with J_1 denoting the number of base assets in the estimation of the mimicking portfolio and J_2 the number of control variables. In other words, to match the moment conditions of the mimicking portfolio exactly, I assign an identity matrix at the upper-left corner of matrix A. The approach used for the construction of the mimicking portfolio is detailed in Section 4.2.

To assign γ in matrix A, I first estimate the asset-pricing model in two steps by taking the mimicking portfolio as given. I then use the asymptotically optimal weighting matrix W from that estimation to define $K{=}D'\ W$, where D is the derivative matrix of the orthogonality conditions. K is then used as the $\gamma's$ in matrix A. This approach ensures that the coefficients for the mimicking portfolio and the asset pricing model are exactly the same as those from the two-step estimation. However, the standard errors will be different; they will be adjusted for estimation error in the construction of the mimicking portfolio.

The estimation of the proposed model in one-step can be performed only using quarterly data, since GDP is available only at a quarterly frequency. To compute quarterly holding period returns, I compound the three monthly returns of each quarter.

The GMM estimate is formed by choosing b so as to minimize the objective function

$$J_t = g_T(b)' \cdot W \cdot g_T(b), \tag{5}$$

where $g_T(b)$ denotes the vector of sample pricing errors and W is the asymptotically optimal weighting matrix. When the asymptotically optimal weighting matrix is used, Hansen's test on the overidentifying restrictions of the model is given by

$$T \cdot J_T \sim \chi^2(\text{\# of moments} - \text{\# of parameters}). \tag{6}$$

When an arbitrary weighting matrix other than the asymptotically optimal one is used, the test becomes

$$\begin{aligned} &Tg_T(\hat{b})'\left[(I - d(ad)^{-1}a)S(I - d(ad)^{-1}a)'\right]^{-1} g_T(\hat{b}) \\ &\quad \sim \chi^2(\# \; of \; moments \; - \# \; of \; parameters), \end{aligned} \tag{7}$$

where $a \equiv p\lim a_T$ with a_T being the matrix that defines the linear combination of $g_T(b)$ that will be set to zero, and d is the population moment. Note that the above variance-covariance matrix is singular because the terms $I - d(ad)^{-1}a$ set some linear combinations of $g_T(b)$ to zero in order to estimate the parameters. Because the variance-covariance matrix is singular, it requires pseudo-inversion.

The overidentification tests of Eqs. (6) and (7) can easily fail to detect model misspecification (see Newey, 1985). For that reason, I supplement the evaluation of the models with the tests described below.

To perform model comparisons, I employ the Hansen and Jagannathan (1997) weighting matrix, $\mathrm{E}[RR']^{-1}$, which is the inverse of the second moments of asset returns, and compute the Hansen and Jagannathan (1997) distance, or HJ-distance as it is often called. This matrix is invariant across models and therefore suitable for model comparisons.

The HJ-distance δ is given by the square root of the minimized objective function. When an asset pricing model is not correct, then the stochastic discount factor y implied by this model does not belong to the set of stochastic discount factors m that can price the assets correctly. In that case, there is a strictly positive distance between y and m which is given by δ. An economically important interpretation of δ is that it represents the maximum pricing error for the set of assets. Campbell and Cochrane (2000) use this interpretation to evaluate the size of the pricing errors of competing models when these models are used to explain the cross-section of asset returns.

Jagannathan and Wang (1996) construct a distribution for the HJ-distance statistic. This statistic is the sum of n–k independently and identically distributed random variables with a $\chi^2(1)$ distribution, where n denotes the number of assets and k the number of parameters estimated. To determine its p-value, I simulate 100,000 of such $\chi^2(1)$ variables.

Section 5.4 provides graphical representation of the pricing errors for the competing models when they are estimated with monthly observations. The two standard-error band is calculated using Cochrane's (1996) derivation of the asymptotic variance of the pricing error.

I test for possible parameter instability and structural changes in the GMM estimates over the sample period examined using Andrews' (1993) supLM test. Suppose there is a change point at time $T\pi$. Using GMM, one can estimate the parameters for the sample between zero and $T\pi$, and then between $T\pi$ and T. It is also possible to impose the restriction that the parameters are the same in the two subperiods and use GMM to estimate the parameters for the whole sample period.

To test whether this restriction is true, one can apply the Wald, LR (Likelihood Ratio), or LM (Lagrange Multiplier) tests. The LM test is particularly easy to perform because it uses only the restricted estimates from the whole sample period GMM. To test whether there is a structural change in the parameters between $T\pi_1$ and $T\pi_2$, Andrews (1993) proposes the $\sup_{\pi\in[\pi_1,\pi_2]} LM(\pi)$ test. I adopt the interval [0.15, 0 0.85], which is the interval Andrews recommends when the change point is unknown. Note that it is not possible to use the whole sample, i.e., the interval [0,1], because the supLM will go to infinity when the interval does not have a positive distance from the endpoints. Andrews provides the critical values at the 1%, 5%, and 10% level for the distribution of the statistic. To compute the supLM test, I use the asymptotically optimal weighting matrix.

I also test whether the news related to future GDP growth model can summarize the information in HML and SMB. In other words, I test whether HML and SMB retain any incremental ability to explain the cross-section of asset returns in the presence of the GDP-related factor. To examine this hypothesis in the context of the one-step estimations, I perform a Wald test. The same hypothesis is re-examined in the context of the two-step estimations using Newey and West's (1987a) ΔJ statistic. Newey and West (1987a) show that the two test statistics are asymptotically equivalent under general assumptions about heteroskedasticity and serial correlation in the residuals. The ΔJ test involves the estimation of a model that includes the GDP-related factor along with HML and SMB. The weighting matrix from this (unrestricted) estimation is subsequently used to estimate a restricted model that excludes HML and SMB. If HML and SMB have no incremental ability to explain the cross-section, the J function of the restricted model should not rise much. The ΔJstatistic is defined as follows:

$$\Delta J = TJ(restricted) - TJ(unrestricted) \sim \chi^2(\#\ of\ restrictions). \tag{8}$$

In addition, I examine whether the performance of the models is robust to alternative sets of test assets using Cochrane's (1996) approach of scaled returns. Cochrane proposes the use of conditioning information to scale returns. One can multiply both sides of Eq. (1) by a conditioning variable. The resulting scaled returns can be interpreted as managed portfolios, where the manager adjusts portfolio weights according to the signal received from the conditioning variable. If a model is robust, it should also price the managed portfolios correctly. As conditioning information I use the term premium (TERMY), defined as the difference in the yields of a ten-year government bond and a one-year government bond. Fama and French (1989) show that TERMY tracks short-term business conditions. Therefore, scaling returns by TERMY is equivalent to observing a fund manager adjusting portfolio holdings according to the signal received from TERMY about the short-term business conditions. Hodrick and Zhang (2001) also scale returns by TERMY and show that none of the models they test can price the scaled returns correctly.

Finally, I examine whether the performance of the proposed models is sensitive to the data frequency. For that purpose, I re-estimate them using monthly data. The models that include the mimicking portfolio as a factor can be estimated only by using monthly data in a two-step procedure. Since the CAPM and the FF model are usually tested on monthly data, I will also compare the competing models on the basis of their monthly estimations. Note that the monthly estimations can accommodate the whole set of test assets, whereas the quarterly estimations cannot.

The set of test assets include the 25 Fama-French portfolios and the 30-day T-bill rate. The data span the period from 1953:1 to 1998:12. When the proposed model is estimated using quarterly observations, only 12 of the 25 FF portfolios are used as test assets. The number of observations in the quarterly tests is one-third those of the monthly tests. Using all 26 assets in the quarterly estimations would greatly compromise the behavior of the GMM estimator. To mitigate this problem, I select 12 portfolios that summarize well the properties of all the 25 Fama–French portfolios. In particular, I include the two extreme portfolios of the three smallest size quintiles plus the middle one, i.e., nine portfolios. I also include the two extreme portfolios and the middle one from the fifth (biggest) size quintile. In other words, the selection of portfolios emphasizes those that have proven harder to price, such as the small growth; set of test assets in the quarterly estimations includes also the *T*-bill rate. Table 1 presents the equity portfolios included in the monthly and quarterly estimations.

3. Data

The 25 US equity portfolios, constructed by Fama and French, are value-weighted and formed from the intersection of five size (MV) portfolios and five book-to-market (B/M) portfolios. The portfolios are rebalanced every June, using end-of-June MV information and six-month prior B/M information. The portfolios include NYSE, AMEX, and NASDAQ firms in COMPUSTAT, as well as firms hand-collected from the Moody's Industrial Manuals.[1]

To create the mimicking portfolio of news related to future GDP growth outlined in Section 4.2, I use eight portfolios as base assets. Six of the them are equity portfolios and two are fixed-income portfolios. The equity portfolios are the six value-weighted portfolios, constructed again by Fama and French, from the intersection of two Market Value (MV) and three B/M portfolios. These portfolios use the same assets as the 25 portfolios and they are rebalanced in the same way. However, they are created from a separate sorting of the assets. In the work of Fama and French (1993, 1995, 1996) and Davis, et al., (2000), these six portfolios are used to create the HML and SMB factors. The two fixed-income portfolios are the returns on DEF and TERM. DEF is defined as the difference between the return on long-term corporate bonds and long-term government bonds. Similarly, TERM is the difference between the return on 30-year government bonds and the short-term rate. The source for TERM and DEF is the 1999 Yearbook on Stocks, Bonds, Bills, and Inflation compiled by Ibbotson Associates.

[1] We thank Kenneth French for making the data available on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

Table 1
Test equity assets included in the monthly and quarterly model estimations
Asterisks denote the equity portfolios used as test assets in the monthly and quarterly estimations of the asset pricing models.

Size	Book-to-market	Monthly estimations	Quarterly estimations
1 (Small)	1 (Low)	*	*
	2	*	
	3	*	*
	4	*	
	5 (High)	*	*
2	1 (Low)	*	*
	2	*	
	3	*	*
	4	*	
	5 (High)	*	*
3	1 (Low)	*	*
	2	*	
	3	*	*
	4	*	
	5 (High)	*	*
4	1 (Low)	*	
	2	*	
	3	*	
	4	*	
	5 (High)	*	
5 (Big)	1 (Low)	*	*
	2	*	
	3	*	*
	4	*	
	5 (High)	*	*

The construction of the mimicking portfolio also makes use of control variables which are known for their ability to predict equity returns. These control variables include the default yield spread (DEFY), the term yield spread (TERMY), the 30-day T-bill rate (RF), and the variable CAY. DEFY is the yield spread between Moody's BAA and AAA corporate bonds. TERMY is the yield spread between ten-year government bonds and one-year government bonds. Data for DEFY and TERMY are obtained from the Federal Reserve Bank of St Louis. The variable CAY is a detrended wealth variable computed by Lettau and Ludvigson (2000). This variable represents deviations from a common trend found in consumption, asset wealth, and labor income. Lettau and Ludvigson show that the deviations are the result of movements in the consumption-aggregate wealth ratio. They also show that CAY is a powerful predictor of stock returns in short to medium horizons and provide details of its construction. Data for the 30-day T-bill rate are obtained from Ibbotson Associates.

The market portfolio is proxied by the value-weighted return of all firms included in the 25 portfolios. Seasonally adjusted GDP data are obtained from the CITIBASE.

Although equity and fixed-income data are available starting in 1926 and GDP data are available from 1947, the CAY variable can only be constructed from 1953 onwards. For that reason, our tests cover the period from 1953 to 1998. Fortunately, since I use a mimicking portfolio to capture news related to future GDP growth I can also perform the asset-pricing tests on monthly data, albeit in two steps. Therefore, the monthly tests make use of 540 observations whereas the quarterly ones use 180 observations.

4. The mimicking portfolio and the ability of the base assets to predict future GDP growth

A simple way to construct mimicking portfolios is to regress the macroeconomic variable of interest on a set of portfolio returns (base assets) as proposed in Breeden et al. (1989). The fitted value from the regression will contain the same information as the macroeconomic variable, but now this information will be expressed in terms of portfolio returns. Cochrane (1999) provides further discussion on the economic interpretation of mimicking portfolios.

Only innovations earn a risk premium in asset returns. Therefore, it is useful for our purposes to "filter" the information in the mimicking portfolio, so that it captures news mainly related to future GDP growth. One way to do that is by including in the right-hand-side (RHS) of the regression control variables which can predict the returns on the base assets. This variation to the simple mimicking-portfolio approach is presented in Lamont (2001).

One nice property of the use of mimicking portfolios to proxy economic variables is the following. The information captured in the portfolio about the economic variable is that which is reflected in the asset returns, and which can therefore affect the prices of assets. There is sometimes much more information about the economic variable which is not captured by the mimicking portfolio, but that is because this additional information may not be relevant for asset returns. Furthermore, the use of mimicking portfolios avoids problems related to measurement errors of economic variables.

Note that the use of a mimicking portfolio is necessary for the asset-pricing tests of this study. Recall that the aim is to capture *news related to future* GDP growth rather than expectations. But news related to future GDP growth is unobservable. Including in the stochastic discount factor information about expected future GDP growth or actual future GDP growth will not throw any light on whether news related to future GDP growth is priced. A plausible way to capture such information is to extract it from the returns of assets which are affected by it. This can be achieved through the construction of a mimicking portfolio.

4.1. The ability of the base assets to predict future GDP growth

Before I describe the construction of the mimicking portfolio, it is important to examine whether the eight base assets can actually predict future GDP growth.

The inference presented is based both on asymptotic theory and on 10,000 bootstrap simulations. In the bootstrap simulations, I use the coefficients of the linear regressions, the explanatory variables, and the residuals to generate 180 quarterly GDP growth rates defined between time t and $t+4$. Each of the 10,000 bootstraps draws a random sample, with replacement, of the 180 observations for the explanatory variables and the residuals. I then compute the artificial GDP growth rates under the null hypothesis that the coefficients on the base assets are zero. Subsequently, I regress the artificial GDP growth rates on the drawn explanatory variables and compute the Wald statistic on the coefficients of the base assets. This experiment is repeated 10,000 times. I then compare the actual value of the Wald statistic with the simulated ones and compute the empirical p-value. Because of multicollinearity among the explanatory variables, I test only for the joint significance of the coefficients of the base assets.

The results are shown in Table 2. The third, fourth, and fifth columns provide results from regressions of GDP growth four quarters ahead on the current returns of the eight base assets:

$$\mathrm{GDPGR}_{t,t+4} = a + cB_{t-1,t} + e_{t,t+4}, \tag{9}$$

where $\mathrm{GDPGR}_{t+4,t}$ denotes GDP growth between t and $t+4$, and B_{t} is the vector of the returns in the eight base assets between $t-1$ and t. Note that the six equity portfolio returns are in excess of the riskless rate RF. Therefore, all eight base assets represent zero-investment portfolios. Standard errors are corrected for serial correlation up to three lags and White's (1980) heteroskedasticity using the Newey-West (1987b) estimator.

The third column reports the results for the whole sample. Because of multicollinearity among the regressors, the individual coefficient estimates are hard to interpret. However, the adjusted R-square is 16.12%, suggesting that a significant proportion of variation in future GDP growth is forecast by the eight base assets. The asymptotic p-value for the chi-square test that the coefficients of the eight base assets are jointly zero is 0.0000. Furthermore, the empirical p-value is 0.0020. The results for the two subperiods are similar in the sense that the adjusted R-squares are again high and of the order of 18% and the asymptotic p-values for the chi-square tests are in both cases close to 0.000. However, the empirical p-values of the chi-square tests are large, and only in the case of the first subperiod can I reject the hypothesis that the coefficients are jointly zero at the 10% level. The empirical p-values are large because there are only 90 observations in each of the two subperiods and a large number of regressors. For that reason, the results for the whole period can be considered more reliable.

I also examine the extent to which the eight base assets contain important incremental information about future GDP growth. Given the large number of regressors, this test is performed only for the entire sample period. In particular, I

Table 2
The ability of size and B/M portfolios to predict future GDP growth
The base assets include six equity portfolios with different book-to-market (B/M) and size (MV) characteristics as well as the return on long-term government bonds minus the return on short-term government bonds (TERM) and the return on long-term corporate bonds minus the return on long-term government bonds (DEF). The returns of the six equity portfolios are in excess of the riskless rate. S MV stands for small MV whereas B MV stands for big MV. Similarly, L B/M, M B/M, and H B/M denote low, medium, and high B/M, respectively. The set of control variables includes a constant, the yield spread of long-term Treasury bonds minus the *T*-bill yield (TERMY), the yield spread of long-term corporate bonds minus the yield on long-term government bonds (DEFY), the detrended wealth (CAY), and the risk-free rate (RF). The variables TERMY, DEFY, and CAY are lagged by one period. The dependent variable is the annualized GDP growth over the next four quarters. *T*-values are reported below the coefficient estimates. Standard errors are corrected for White's (1980) heteroskedasticity and serial correlation up to three lags using the Newey-West (1987b) estimator. The *R*-squares are adjusted for degrees of freedom. The regressions use quarterly data, and the returns are continuously compounded and expressed in percentage terms. The $\chi^2(8)$ test examines the hypothesis that the coefficients of the base assets are jointly zero. The table reports both asymptotic *p*-values and empirical *p*-values derived from 10,000 bootstrap simulations. The column in bold refers to the estimates used for the construction of the mimicking portfolio.

		1953:Q1-1998:Q4	1953:Q1-1975:Q2	1975:Q3-1998:Q4	**1953:Q1-1998:Q4**
BASE ASSETS	S MV, L B/M	−0.011	−0.097	0.034	**−0.005**
		(−0.15)	(−0.91)	(0.47)	**(−0.11)**
	S MV, M B/M	0.009	0.101	−0.128	**0.008**
		(0.05)	(0.50)	(−0.64)	**(0.07)**
	S MV, H B/M	0.010	0.005	0.144	**0.014**
		(0.09)	(0.03)	(0.93)	**(0.15)**
	B MV, L B/M	−0.047	0.014	−0.102	**−0.048**
		(−0.77)	(0.15)	(−1.55)	**(−1.16)**
	B MV, M B/M	0.111	0.026	0.260	**0.054**
		(1.21)	(0.17)	(2.87)	**(0.81)**
	B MV, H B/M	0.051	0.112	−0.166	**0.034**
		(0.66)	(0.81)	(−1.94)	**(0.52)**
	DEF	0.333	0.178	0.555	**0.142**
		(3.06)	(1.27)	(2.91)	**(1.73)**
	TERM	0.044	0.102	0.107	**0.013**
		(1.14)	(1.15)	(2.13)	**(0.52)**
	Constant	2.771	2.969	2.616	**−18.905**
		(9.21)	(6.90)	(8.03)	**(−1.52)**
CONTROL VARIABLES	DEFY				**0.006**
					(2.65)
	TERMY				**0.001**
					(1.00)
	CAY				**0.373**
					(1.81)
	RF				**−1.888**
					(−4.35)
	Adj. R^2	16.12	18.58	18.78	**38.62**
	$\chi^2(8)$	43.91	35.06	27.54	**18.88**
	p-value	0.0000	0.0000	0.0006	**0.0155**
	Bootstrap (*p*-value)	0.0020	0.0654	0.1439	**0.0973**

run the regression:

$$\mathrm{GDPGR}_{t,t+4} = a + cB_{t-1,t} + k_1\mathrm{TERMY}_{t-2,t-1} + k_2\mathrm{DEFY}_{t-2,t-1} + k_3\mathrm{CAY}_{t-2,t-1} + k_4\mathrm{RF}_{t-1,t} + e_{t,t+4}. \quad (10)$$

The results from this regression are reported in column 6 of Table 2. The standard errors of the regression are again corrected for serial correlation up to three lags and White's(1980) heteroskedasticity. The adjusted R-square is 38.62% and the asymptotic p-value from the $\chi^2(8)$ test is 0.0155. The simulated p-value for the same test is 0.0974 suggesting again that the eight base assets jointly contain some information about future GDP growth at the 10% level of significance, even in the presence of the control variables. The results in column 6 are those used for the construction of the mimicking portfolio, and they appear in bold for that reason.

4.2. Construction of the mimicking portfolio

Following Lamont (2001), the regression model used is of the form:

$$\mathrm{GDPGR}_{t,t+4} = cB_{t-1,t} + kZ_{t-2,t-1} + e_{t,t+4}, \quad (11)$$

where $\mathrm{Z}_{t-2,t-1}$ denotes a set of control variables which have the ability to predict the returns on the base assets. The return on the mimicking portfolio is then equal to

$$\mathrm{TRB}_{t-1,t} = cB_{t-1,t} \quad (12)$$

In what follows, the mimicking portfolios are constructed using regression Eq. (10). In other words, the set of control variables includes a constant, TERMY, DEFY, CAY, and RF. All of these variables are known for their ability to predict asset returns. Note that the coefficients c in Eq. (10) do not need to add up to one because the base assets are zero-investment portfolios.

In regression Eq. (10), future GDP growth is assumed to be GDP growth over the next four quarters, and therefore, the implicit assumption is that asset returns reflect news about next year's GDP growth. This is a reasonable simplifying assumption because even if asset returns reflect news about future GDP growth over a longer horizon, one would expect that most of this news refers to next year's GDP growth.

Once the vector of coefficients c is estimated, I can construct a mimicking portfolio using either monthly or quarterly returns on the base assets. I will denote by MFTRALL the mimicking portfolio constructed using monthly returns on the eight base assets, whereas I will denote by QFTRALL the mimicking portfolio constructed using quarterly returns on the eight base assets.

Summary statistics for the simple returns on MFTRALL and QFTRALL are presented in Table 3. The means of the mimicking portfolios are positive. This means that if news related to future GDP growth is a factor that can explain part of the cross-sectional variation in returns, then its associated risk premium is positive. In addition, it is statistically significant. I also report the correlation coefficients of HML and SMB with MFTRALL and QFTRALL. The size of the coefficients imply that the mimicking portfolios share important information with the Fama-French

Table 3
Summary statistics for the mimicking portfolio
This table reports summary statistics for the mimicking portfolio of news related to future GDP growth constructed using quarterly data (QFTRALL) and monthly data (MFTRALL). The coefficients for the mimicking portfolio are estimated using the following regression

$$\mathrm{GDPGR}_{t,t+4} = a + cB_{t-1,t} + k_1\mathrm{TERMY}_{t-2,t-1} + k_2\mathrm{DEFY}_{t-2,t-1} + k_3\mathrm{CAY}_{t-2,t-1} + k_4\mathrm{RF}_{t-1,t} + e_{t,t+4}$$

and reported in Table 2 in bold. The mimicking portfolio is given by the sum of the products of the coefficients c with the returns on the base assets B. When quarterly holding period returns for B are used, the resulting mimicking portfolio is QFTRALL. Similarly, when monthly holding period returns are used for B, the mimicking portfolio is called MFTRALL. The summary statistics are computed using simple returns, not log returns. In the regression results, t-values are reported in parentheses below the coefficient estimates. They are corrected for White's (1980) heteroskedasticity and serial correlation up to three lags using the Newey-West (1987b) estimator.

Panel A

	QFTRALL	MFTRALL
Mean	0.172	0.058
t-value	4.02	4.25
Standard deviation	0.569	0.315
Correlation with SMB	0.425	0.291
Correlation with HML	0.280	0.290

Panel B: Regression of mimicking portfolio on SMB and HML

Dependent variable	Constant	SMB	HML	Adj. R^2
QFTRALL	0.001	0.051	0.039	28.76
	(3.06)	(7.63)	(4.40)	
MFTRALL	0.039	0.042	0.044	19.08
	(3.63)	(6.42)	(5.82)	

Panel C: Regression of SMB on mimicking portfolio

Constant	QFTRALL	MFTRALL	Adj. R^2
−0.428	4.031		18.30
(−0.97)	(7.93)		
−0.127		2.341	8.33
(−1.17)		(5.80)	

Panel D: Regression of HML on mimicking portfolio

Constant	QFTRALL	MFTRALL	Adj. R^2
0.798	2.326		6.87
(2.09)	(3.19)		
0.249		2.170	8.24
(2.45)		(5.03)	

factors. The same conclusion emerges from the bivariate regressions of MFTRALL and QFTRALL on SMB and HML. In the case of QFTRALL, the adjusted R-square is 28.76%, whereas for MFTRALL it is 19%.

Note that the fact that the correlation coefficients and the R-squares are much smaller than one does not imply that MFTRALL and QFTRALL cannot price assets similarly to the Fama-French factors. Recall that HML and SMB are constructed using empirical methods and are not designed to proxy or capture any particular economic factor. It is possible that only part of the information they contain is relevant for pricing risky assets. The relevant part may be the one correlated with the mimicking portfolios.

5. Empirical results

This section contains the results from GMM estimations of the competing models, as well as robustness tests for their performance. I test whether a model that includes QFTRALL or MFTRALL instead of HML and SMB can price assets equally well as the Fama-French model. I also examine, using a Wald test and the Newey-West ΔJ-test, whether HML and SMB retain their ability to price assets in the presence of the mimicking portfolio. I will show that the two models perform very similarly and, in the presence of the mimicking portfolio, HML and SMB lose much of their ability to price assets. I will interpret these results as implying that much of the priced information in SMB and HML is news related to future GDP growth.

5.1. One-step estimation of the proposed model

I will first present results from one-step estimations of a model that includes news about future GDP growth as a risk factor. The mimicking portfolio QFTRALL is estimated simultaneously with the asset pricing model following the procedure outlined in Section 2. As a result, the standard errors of the coefficients are adjusted for the fact that QFTRALL is a generated regressor.

Table 4 presents the results when unscaled returns are used. Panel A reports the coefficient estimates and the *t*-values for the base assets of the mimicking portfolio. Note that the coefficients are identical to those reported in Table 2, but the *t*-values differ. The *p*-value of the $\chi^2(8)$ test is 0.0126, suggesting again that the eight base assets contain jointly important information about future GDP growth.

In Panel B of Table 4, I report the asset pricing results for a factor model that includes only a constant and QFTRALL. The *t*-values in parentheses are those obtained from the one-step estimation, whereas those in square brackets are the ones obtained from the two-step estimation. In the two-step estimation, the mimicking portfolio is estimated first and then used as a factor in the asset-pricing tests.

Note that the premium attached to QFTRALL is statistically significant independently of whether the standard error is obtained from the one-step or two-step estimation. The over-identification test from the one-step estimation has a *p*-value of 0.0391 which means that the model can be rejected at the 5% level of significance. The Wald (b) test examines whether the coefficients *b* of the asset pricing model are jointly zero. Its associated *p*-value is zero. The Wald (SMB&HML) test examines whether the inclusion of SMB and HML in the pricing kernel can improve the ability of the model to price equities. The *p*-value of 0.44

Table 4

Estimation of mimicking portfolio and asset pricing models in one-step: quarterly data, unscaled returns QFTRALL is the quarterly mimicking portfolio of news related to future GDP growth constructed using the coefficient estimates in Panel A. RMRF is the excess return on the market portfolio. T-values in parentheses are calculated using standard errors obtained from the one-step estimations. T-values in square brackets are from standard errors obtained from the two-step estimation, where the mimicking portfolio is estimated in the first step, and the asset pricing model in the second. The Wald's (SMB&HML) statistic tests the hypothesis that the risk premiums of SMB and HML are jointly zero. p-Wald (b) is the p-value of the Wald test that $b=0$.

Panel A: Coefficients on the base assets

	Coefficient	t-value
S MV, L B/M	−0.005	−0.11
S MV, M B/M	0.008	0.07
S MV, H B/M	0.014	0.15
B MV, L B/M	−0.048	−1.16
B MV, M B/M	0.054	0.79
B MV, H B/M	0.034	0.51
DEF	0.142	1.74
TERM	0.013	0.52

p-value of joint significance test on the coefficients of base assets: 0.0126

Panel B: The QFTRALL factor model

	Constant	QFTRALL	
Coefficient	1.096	−62.305	
(t-value)	(15.21)	(−2.20)	
[t-value]	[22.57]	[−3.95]	
Premium		0.002	
(t-value)		(2.20)	
[t-value]		[3.95]	
	Over-identification test	p-Wald (b)	Wald (SMB&HML)
	20.483		1.613
(p-value)	(0.0391)	(0.0000)	(0.4465)

Panel C: The RMRF and QFTRALL factor model

	Constant	QFTRALL	RMRF
Coefficient	1.075	−76.096	1.308
(t-value)	(12.45)	(−1.50)	(0.53)
[t-value]	[21.51]	[−3.29]	[0.88]
Premium		0.002	0.016
(t-value)		(1.97)	(1.63)
[t-value]		[4.04]	[2.48]
	Over-identification test	p-Wald (b)	Wald (SMB&HML)
	19.460		4.828
(p-value)	(0.0348)	(0.0000)	(0.0895)

implies that in the presence of QFTRALL, SMB and HML lose their ability to price equities.

Panel C reports the results of a model that includes both the excess return on the market portfolio (RMRF) and QFTRALL as factors. Again the risk premium on QFTRALL is statistically significant, although only marginally so at the 5% level, when the standard error is obtained from the one-step estimation. The magnitude of the risk premium does not change when RMRF is included in the pricing kernel. The risk premium for RMRF is only marginally significant at the 10% level in the one-step estimation. The over-identification test has a p-value of 0.0348 rejecting the model again at the 5% level. The Wald (SMB&HML) test has a p-value of 0.0895, and therefore, the hypothesis that HML and SMB have incremental information about equity returns, over and above that in QFTRALL and RMRF, can be rejected only at the 10% level.

The results of Table 4 show that news related to future GDP growth is important for pricing equities. In the presence of this information, SMB and HML lose much of their ability to explain the cross-section. Table 5 confirms these findings by presenting results from testing the models using scaled returns by TERMY.

Panel A of Table 5 is identical to Panel A of Table 4 because the composition of the mimicking portfolio is invariant to scaling the test assets returns by a conditioning variable. Panels B and C confirm that QFTRALL is priced and the premium is statistically significant at the 5% level in both cases based on the standard error from the one-step estimation. The market factor is also priced at the 5% level. The over-identification tests cannot reject either of the two models that include QFTRALL as a factor. In addition, the Wald (SMB&HML) tests have large p-values. Therefore, the hypothesis that HML and SMB have no incremental information about the cross-section once QFTRALL is present in the model cannot be rejected at conventional levels of significance.

5.2. Comparison of competing models using monthly data

In this section, I compare the models that include the mimicking portfolio of news related to future GDP growth with the CAPM and the FF model using monthly data.

To compare the performance of the competing models, I compute the Hansen-Jagannathan distance measure which translates into the maximum annualized pricing error generated by each of the models. To compute the HJ-distance, I need to use the Hansen-Jagannathan weighting matrix. In addition, I compute Andrews' (1993) supLM test to examine whether the parameters of the model are stable over time. To compute this statistic, I need to estimate the models using the asymptotically optimal weighting matrix. Therefore, the computation of both the HJ-distance and the supLM test require the estimation of the proposed models in two steps.

To estimate the proposed models in two steps, I first construct the mimicking portfolio following the methodology described in Section 4.2. I then use GMM to estimate the asset pricing model that includes the mimicking portfolio as a factor.

Table 5
Estimation of mimicking portfolio and asset pricing models in one-step: quarterly data, scaled returns by TERMY.
TERMY is the yield spread of long-term Treasury bonds minus the *T*-bill yield. QFTRALL is the quarterly mimicking portfolio of news related to future GDP growth constructed using the coefficient estimates in Panel A. RMRF is the excess return on the market portfolio. *T*-values in parentheses are calculated using standard errors obtained from the one-step estimations. *T*-values in square brackets are from standard errors obtained from the two-step estimation, where the mimicking portfolio is first estimated and used subsequently as a factor in the asset pricing tests. The Wald (SMB&HML) statistic tests the hypothesis that the risk premiums of SMB and HML are jointly zero. *p*-Wald (b) is the p-value of the Wald test that *b=0*.

Panel A: Coefficients on the base assets

	Coefficient	*t*-value
S MV, L B/M	−0.005	−0.11
S MV, M B/M	0.008	0.07
S MV, H B/M	0.014	0.15
B MV, L B/M	−0.048	−1.16
B MV, M B/M	0.054	0.79
B MV, H B/M	0.034	0.51
DEF	0.142	1.74
TERM	0.013	0.52

p-value of joint significance test on the coefficients of base assets: 0.0126

Panel B: The QFTRALL factor model

	Constant	QFTRALL	
Coefficient	1.120	−98.18	
(*t*-value)	(10.78)	(−2.03)	
[*t*-value]	[18.73]	[−4.92]	
Premium		0.003	
(*t*-value)		(2.03)	
[*t*-value]		[4.92]	
	Over-identification test	*p*-Wald (b)	Wald (SMB&HML)
	11.884		0.715
(*p*-value)	(0.3724)	(0.0000)	(0.6992)

Panel C: The RMRF and QFTRALL factor model

	Constant	QFTRALL	RMRF
Coefficient	1.135	−90.134	−1.017
(*t*-value)	(9.22)	(−1.60)	(−0.32)
[*t*-value]	[13.97]	[−3.63]	[−0.44]
Premium		0.003	0.036
(*t*-value)		(2.45)	(2.38)
[*t*-value]		[4.51]	[2.88]
	Over-identification test	*p*-Wald (b)	Wald (SMB&HML)
	11.653		2.110
(*p*-value)	(0.3090)	(0.0000)	(0.3482)

Table 6 presents a summary of the results from estimating the competing models using monthly, unscaled returns. Since the CAPM and the FF model are widely tested in previous studies using monthly data, I do not report the coefficient estimates here, in order to conserve space. I report only the statistics used for the comparison of the models.

Hansen's *J*-test on the overidentifying restrictions of each model rejects all four models examined. The competing models are also rejected on the basis of the HJ-distance test, implying that none of them can price the 26 assets correctly. Recall that the 26 assets are the 25 Fama-French equity portfolios plus the 30-day T-Bill rate. The HJ-distance for the CAPM is 0.418 compared to 0.358 for the FF model and 0.38 for the models that include MFTRALL as a factor. As can be seen from the plotted pricing errors in Fig. 1, the difference in the maximum annualized pricing errors of the FF model and the model that includes MFTRALL and RMRF comes mainly from the mispricing of the three smallest growth portfolios (11, 21, and 31). In fact, the proposed model prices large capitalization portfolios slightly better than the FF model. It also prices all assets, except the smallest growth portfolio (11) better than the CAPM.

The ΔJ-test examines whether the inclusion of HML and SMB in the pricing kernel improves the performance of the model. In the case of the CAPM, it is clear

Table 6

Comparison of competing models: monthly data, unscaled returns

J-test refers to Hansen's (1982) test on the overidentifying restrictions of the model. HJ-distance is the Hansen-Jagannathan (1997) distance measure. *p*-Wald (b) is the *p*-value of the Wald test that $b=0$.The ΔJ-test is the Newey-West (1987a) test of whether HML and SMB contain incremental ability to explain asset prices. The supLM test is Andrews' (1993) test of parameter stability. The results in Panels C and D are generated from a two-step estimation where the mimicking portfolio MFTRALL is first constructed and then used as a factor in the asset pricing tests.

Panel A: Capital Asset Pricing Model (CAPM)					
	J-test	HJ-distance	*p*-Wald(b)	ΔJ-test	Sup LM
	54.745	0.418		20.259	13.636**
(*p*-value)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	
Panel B: The Fama-French (FF) model					
	J-test	HJ-distance	*p*-Wald(b)		Sup LM
	46.208	0.358			14.793**
(*p*-value)	(0.0019)	(0.0000)	(0.0000)		
Panel C: The MFTRALL factor model					
	J-test	HJ-distance	*p*-Wald(b)	ΔJ-test	Sup LM
	48.763	0.3817		3.110	13.086
(*p*-value)	(0.0020)	(0.0000)	(0.0000)	(0.2112)	
Panel D: The RMRF and MFTRALL factor model					
	J-test	HJ-distance	*p*-Wald(b)	ΔJ-test	Sup LM
	48.518	0.381		6.834	8.643
(*p*-value)	(0.0014)	(0.0000)	(0.0000)	(0.0774)	

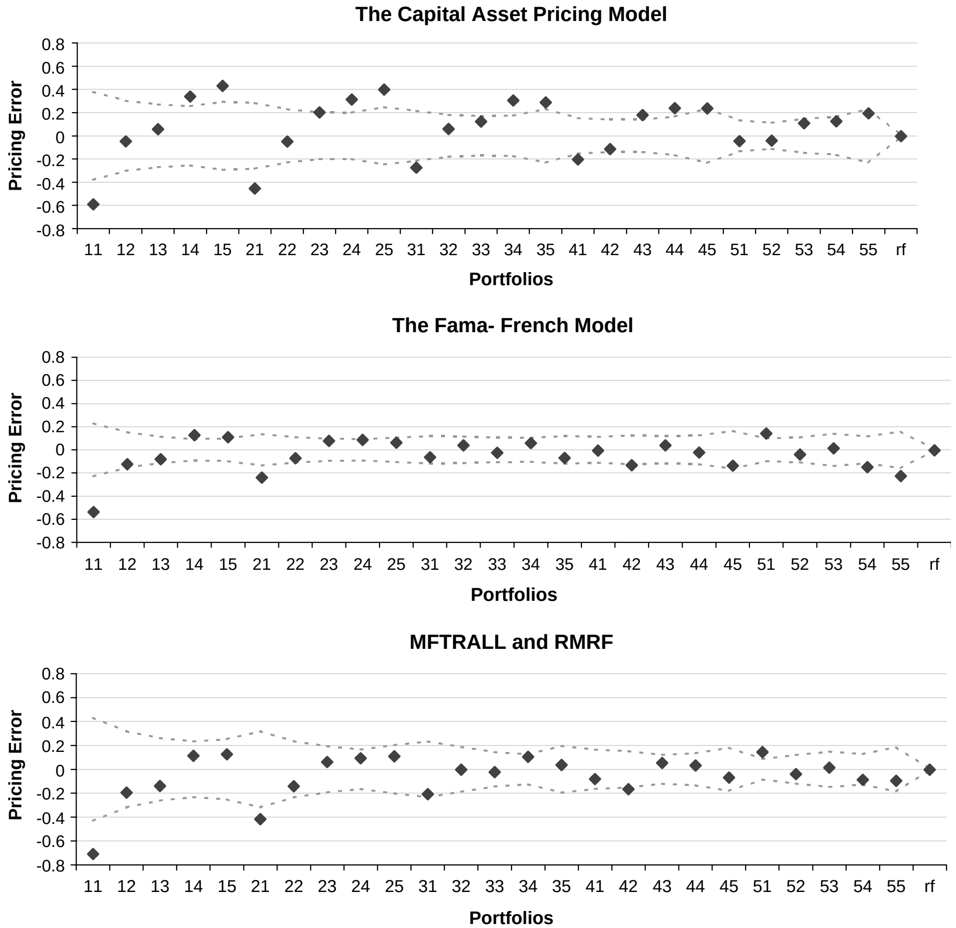

Fig. 1. Pricing errors for competing models unscaled returns and monthly observations. The test asset returns are the excess, over the risk-free rate, returns of the 25 Fama-French portfolios, and the T-Bill rate. The period covered is from 1953:1 through 1998:12. The portfolios on the x-axis are indexed so that the first digit refers to the size quintile whereas the second digit refers to the B/M quintile. For instance, 11 denotes the smallest size lowest B/M portfolio, whereas 55 denotes the biggest size highest B/M portfolio. The return on the T-Bill rate is denoted by rf. The diamonds are the pricing errors. The other two lines are the two standard error bands.

that the improvement is significant. The p-value of the statistic is 0.0000. This result emphasizes the extent to which the FF model constitutes an improvement over the CAPM. In the case of the models that include MFTRALL as a factor, the incremental contribution of SMB and HML is less clear. The p-value of the ΔJ-test in Panel C is 0.2112, suggesting again that in the presence of MFTRALL in the model, SMB, and HML lose all their ability to explain asset prices. The HJ-distance for the model that includes MFTRALL, SMB and HML is 0.373 compared to 0.382 when only MFTRALL is included. Therefore, the inclusion of SMB and HML in the pricing kernel has a trivial effect on the ability of the model to price assets. When SMB and HML are added to a model that includes both MFTRALL and the market factor, the ΔJ-test has a p-value of 0.0774. In that case, the HJ-distance is reduced to 0.370. Again, the reduction is not economically very important, but it implies that there is some remaining information in HML and SMB that can further improve the pricing of assets. The results on the ΔJ-test are consistent with the results on the Wald (SMB&HML) tests reported in Table 4.

The proposed model can also price well the returns on the TERM and DEF portfolios. It underprices TERM by 24 basis points per annum (bppa) and DEF by 68 bppa. Note that the FF model underprices TERM by one hundred bppa and DEF by only six bppa. Furthermore, the CAPM underprices TERM by 70 bppa and overprices DEF by 26 bppa. It appears that the mimicking portfolio includes important information about the yield curve which is not present in the market or the SMB and HML factors. However, SMB and HML appear to contain important information about DEF which is not captured by the mimicking portfolio. Some of the Wald (SMB&HML) and ΔJ-tests reported in Section 5 indicate that even in the presence of the mimicking portfolio, SMB and HML retain some information which is important for asset pricing, although this information is significant only at the 10% level. It is possible that this information is related to default risk. However, exploring this hypothesis is beyond the scope of the current study.

The supLM statistic reveals that the parameters of the CAPM and the FF model are unstable. This result implies that the CAPM and FF model are unsuitable to be used out-of-sample. This is not true for the models that include MFTRALL. Both specifications examined pass the supLM test.

Table 7 presents comparative tests of the models when they are estimated using monthly data and scaled returns by TERMY. In this case, Hansen's J-test cannot reject any of the models examined. In addition, the p-values of the HJ-distances for the four models indicate that I cannot reject at the 1% level the hypothesis that the models price the assets correctly. The HJ-distance for the FF model is 0.292, compared to 0.299 for the model in Panel D. Furthermore, examination of the plotted pricing errors in Fig. 2 reveals that the pricing errors generated by the FF model and the model that includes MFTRALL and RMRF (Panel D) are very similar in magnitude. The ΔJ -tests cannot reject the hypothesis that in the presence of MFTRALL in the model, SMB and HML lose all their ability to price assets. In fact, adding SMB and HML in the model reduces the HJ-distance trivially to 0.292. Note that when returns are scaled by TERMY, the supLM test cannot detect instability in the parameters of any of the models examined.

6. How sensitive is the performance of the proposed model to the choice of base assets in the mimicking portfolio?

The proposed model can be motivated by a rational ICAPM where investors are concerned about future GDP growth and wish to hedge their risk exposure to this

Table 7

Comparison of competing models: monthly data, scaled returns by TERMY

The returns are scaled by TERMY, the yield spread on long-term government bonds minus the short-term T-bill rate. The *J*-test refers to Hansen's (1982) test on the overidentifying restrictions of the model. HJ-distance is the Hansen-Jagannathan (1997) distance measure. *p*-Wald(b) is the *p*-value of the Wald test that *b=0*.The ΔJ-test is the Newey-West (1987a) test of whether HML and SMB contain incremental ability to explain asset prices. The supLM test is Andrews' (1993) test of parameter stability. The results in Panels C and D are generated from a two-step estimation where the mimicking portfolio MFTRALL is first constructed and then used as a factor in the asset pricing tests.

	J-test	HJ-distance	*p*-Wald(b)	ΔJ-test	Sup LM
Panel A: Capital Asset Pricing Model (CAPM)					
	26.867	0.320		19.173	3.919
(*p*-value)	(0.3107)	(0.0363)	(0.0000)	(0.0001)	
Panel B: The Fama-French (FF) model					
	27.026	0.292			7.485
(*p*-value)	(0.2102)	(0.0479)	(0.0000)		
Panel C: The MFTRALL factor model					
	29.957	0.318		2.416	5.429
(p-value)	(0.1862)	(0.0278)	(0.0000)	(0.2987)	
Panel D: The RMRF and MFTRALL factor model					
	27.720	0.299		1.238	6.159
(*p*-value)	(0.2265)	(0.0613)	(0.0000)	(0.5385)	

state variable. To do that, they can purchase insurance from the asset markets by shorting the mimicking portfolio of news related to future GDP growth. A similar interpretation of ICAPM is provided in Brennan et al. (2001). Their analysis implies that HML and SMB are priced because they can predict changes in the investment opportunity set, which is given by the slope (Sharpe ratio) and position (short-term interest rate) of the instantaneous capital market line. In the current study, HML and SMB appear to be priced for the same reason. The interpretation I provide here is that changes in the investment opportunity set are described by news related to future GDP growth. Clearly, the two interpretations are related.

As Cochrane (2001, p. 167) notes, the mimicking portfolio is special because it represents "the purest way of hedging against or profiting from state variable risk exposure." The mimicking portfolio can also be used in asset pricing models instead of the true factor, since it contains the same pricing information. To construct the mimicking portfolio one should project the risk factor on the payoff space of all assets. However, it is not possible to regress the risk factor on thousands of assets. Typically, one chooses a small number of portfolios that includes a large percentage of the available assets.

In the present study, I chose eight portfolios that cover the equity and fixed income markets. In this section, I evaluate how sensitive my results are to the choice

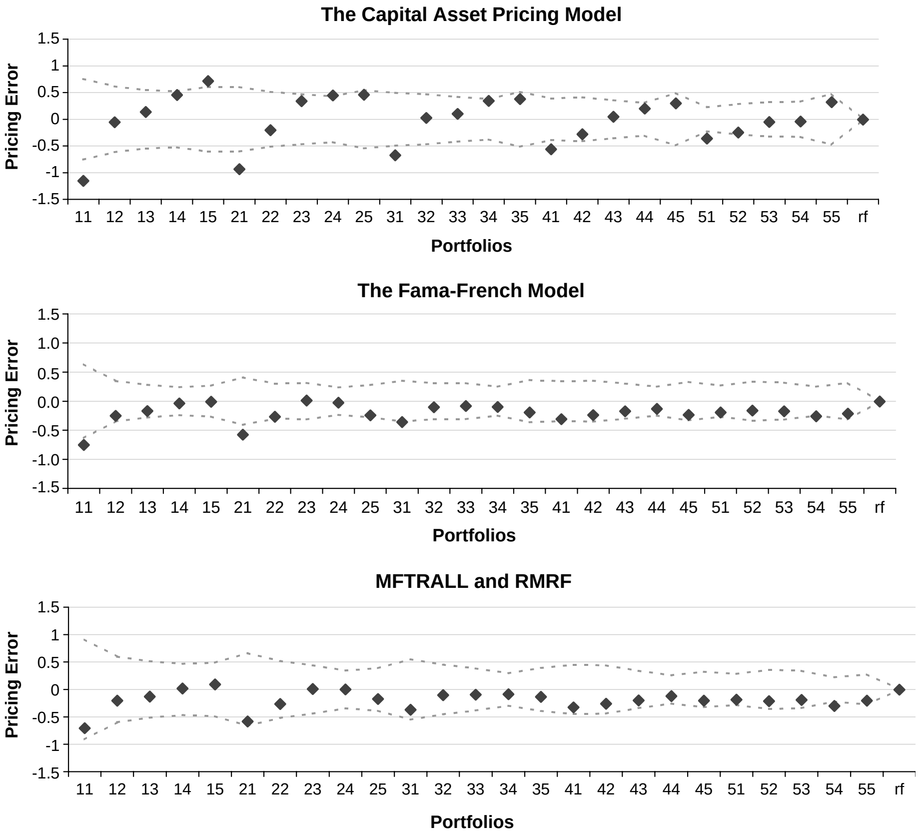

Fig. 2. Pricing errors of competing models when returns are scaled by TERMYusing monthly observations. The test asset returns are the excess, over the risk-free rate, returns of the 25 Fama-French portfolios, and the T-Bill rate. Returns are now scaled by TERMY, which is defined as the difference in the yields of a ten-year government bond and the T-Bill. The period covered is from 1953:1 through 1998:12. The portfolios on the x-axis are indexed so that the first digit refers to the size quintile whereas the second digit refers to the B/M quintile. For instance, 11 denotes the smallest size lowest B/M portfolio, whereas 55 denotes the biggest size highest B/M portfolio. The return on the T-Bill rate is denoted by RF. The diamonds are the pricing errors. The other two lines are the two standard error bands.

of base assets. This is important for the following reason. The equity base assets are the same six portfolios that Fama and French use for the construction of SMB and HML. It is therefore important to examine whether the mimicking portfolio derives its ability to price assets uniquely from these six portfolios. In other words, I would like to know whether the mimicking portfolio could continue to eliminate the information in SMB and HML when the six Fama-French equity portfolios are excluded from the set of base assets. This is not obvious since a mimicking portfolio constructed using only fixed-income base assets may have a low Sharpe ratio, and therefore, it may be unable to price the size- and B/M-sorted portfolios correctly.

To gain an understanding of how much information the equity and fixed-income base assets contribute to the mimicking portfolio, I perform the following experiment. I construct two mimicking portfolios. The first one, QFIX, includes only TERM and DEF in the set of base assets. The second one, QEQ, includes only the six equity portfolios as base assets. Both of them are otherwise constructed using the methodology of Section 4.2. I test whether QFIX and QEQ can price assets using both one-step and two-step estimations. Note that neither QFIX nor QEQ represent "the purest way to hedge or profit" (Cochrane, 2001, p.167) from exposure to news about future GDP growth because they are constructed using only part of all the available assets. They merely provide an idea of the contribution of priced information that equity and fixed-income base assets have to the mimicking portfolios of Section 5.

Table 8 presents the results for the mimicking portfolio QFIX using unscaled returns.[2] Panels B and C reveal that the risk premium attached to the mimicking portfolio is again statistically significant. Furthermore, the Wald (SMB&HML) tests of Panels B and C show that in the presence of QFIX in the asset pricing model, SMB and HML have no ability to explain the cross-section. This is an important result, since this mimicking portfolio does not include information from the equity market, yet it eliminates all the priced information in SMB and HML. The ΔJ-tests computed from two-step estimations confirm the results of the Wald (SMB&HML) tests. Furthermore, the HJ-distance for the model that includes QFIX and RMRF is 0.388. Note that when the FF model is estimated using quarterly data, the HJ-distance is 0.397. In addition, the supLM tests imply that the models that include QFIX as a factor have stable parameters. In other words, even if all information in equities about news on future GDP growth is excluded from the asset pricing tests, the mimicking portfolio still carries a statistically significant risk premium and contains all the priced information in SMB and HML. Therefore, the performance of the models presented in Section 5 cannot be attributed to the inclusion of the six equity portfolios in the set of base assets of the mimicking portfolio.

Finally, Table 9 presents the results from asset pricing tests that include QEQ as a factor. Again, these tests are performed both in one and two steps, using quarterly unscaled returns. The risk premium on QEQ in Panel B is once again statistically significant, although smaller in magnitude than that of QFIX or QFTRALL. When the model includes both QEQ and the market factor, the risk premium on QEQ is statistically significant only at the 10% level. The Wald (SMB&HML) tests cannot reject the hypothesis that SMB and HML contain no information about the cross-section. However, the ΔJ-test from the two-step estimation rejects the hypothesis at the 10% level. The HJ-distance for the model that includes QEQ and RMRF is 0.442 and is reduced to 0.395 when SMB and HML are added to the model. Recall that when the models are estimated using quarterly data, the HJ-distance for the FF model is 0.397. Furthermore, it is equal to 0.440 for the model that includes RMRF and QFTRALL in the pricing kernel, whereas it is as high as

[2] The results for scaled returns by TERMY for the models that include QFIX and QEQ as factors are consistent with those for the unscaled returns. To conserve space, we do not present them here.

Table 8

Estimation of mimicking portfolio and asset pricing models in one-step when the mimicking portfolio is constructed on the basis of only fixed-income assets: quarterly data, unscaled returns

QFIX is a mimicking portfolio of news related to future GDP growth constructed using only equity portfolios as base assets: RMRF is the excess return on the market portfolio. T-values in parentheses are calculated using standard errors obtained from the one-step estimations. T-values in square brackets are from standard errors obtained from the two-step estimation. The Wald (SMB&HML) statistic tests the hypothesis that the risk premiums of SMB and HML are jointly zero. p-Wald (b) is the p-value of the Wald test that $b=0$. HJ-distance is the Hansen-Jagannathan (1997) distance measure. The ΔJ-test is the Newey-West (1987a) test of whether HML and SMB contain incremental ability to explain asset prices. The supLM test is Andrews' (1993) test of parameter stability. The HJ-distance, ΔJ-tests, and supLM tests are generated from a two-step estimation where the mimicking portfolio QFIX is first constructed and then used as a factor in the asset pricing tests.

Panel A: Coefficients on the base assets

	Coefficient	t-value
DEF	0.203	2.95
TERM	0.041	1.93

p-value of joint significance test on the coefficients of base assets: 0.0048

Panel B: The QFIX factor model

	Constant	QFIX	
Coefficient	1.055	−300.276	
(t-value)	(14.71)	(−2.13)	
[t-value]	[14.54]	[−2.89]	
Premium		0.003	
(t-value)		(2.14)	
[t-value]		[2.89]	
	Over-identification test	p-Wald(b)	Wald (SMB&HML)
	13.483		1.05
(p-value)	(0.2629)	(0.0000)	(0.5906)
	HJ-distance	ΔJ-test	SupLM
	0.407	1.175	5.60
(p-value)	(0.4064)	(0.5555)	

Panel C: The RMRF and QFIX factor model

	Constant	QFIX	RMRF
Coefficient	1.005	−386.726	2.036
(t-value)	(9.54)	(−1.90)	(0.77)
[t-value]	[9.62]	[−2.26]	[0.78]
Premium		0.004	0.017
(t-value)		(1.92)	(1.08)
[t-value]		[2.37]	[1.46]
	Over-identification test	p-Wald(b)	Wald (SMB&HML)
	11.17		0.03
(p-value)	(0.3441)	(0.0000)	(0.9841)
	HJ-distance	ΔJ-test	SupLM
	0.3882	0.7910	5.325
(p-value)	(0.6970)	(0.8516)	

Table 9
Estimation of mimicking portfolio and asset pricing models in one-step when mimicking portfolio is constructed using only equity base assets: quarterly data, unscaled returns

QEQ is a mimicking portfolio of news related to future GDP growth constructed using only the six Fama-French portfolios as base assets. RMRF is the excess return on the market portfolio. T-values in parentheses are calculated using standard errors obtained from the one-step estimations. T-values in square brackets are from standard errors obtained from the two-step estimation. The Wald (SMB&HML) statistic tests the hypothesis that the risk premiums of SMB and HML are jointly zero. p-Wald (b) is the p-value of the Wald test that b=0. HJ-distance is the Hansen-Jagannathan (1997) distance measure. The ΔJ-test is the Newey-West (1987a) test of whether HML and SMB contain incremental ability to explain asset prices. The supLM test is Andrews' (1993) test of parameter stability. The HJ-distance, ΔJ-tests, and supLM tests are generated from a two-step estimation where the mimicking portfolio QEQ is first constructed and then used as a factor in the asset pricing tests.

Panel A: Coefficients on the base assets

	Coefficient	t-value
S MV, L B/M	−0.012	−0.26
S MV, M B/M	0.014	0.12
S MV, H B/M	0.018	0.19
B MV, L B/M	−0.049	−1.17
B MV, M B/M	0.054	0.78
B MV, H B/M	0.035	0.52

p-value of joint significance test on the coefficients of base assets: 0.0409

Panel B: The QEQ factor model

	Constant	QEQ	
Coefficient	1.118	−69.036	
(t-value)	(14.32)	(−2.19)	
[t-value]	[20.69]	[−4.07]	
Premium		0.002	
(t-value)		(2.19)	
[t-value]		[4.07]	
	Over-identification test	p-Wald(b)	Wald (SMB&HML)
	19.37		1.82
(p-value)	(0.0547)	(0.0000)	(0.4028)
	HJ-distance	ΔJ-test	SupLM
	0.443	4.154	6.691
(p-value)	(0.0042)	(0.1253)	

Panel C: The RMRF and QEQ factor model

	Constant	QEQ	RMRF
Coefficient	1.100	−85.569	1.467
(t-value)	(12.22)	(−1.56)	(0.57)
[t-value]	[20.10]	[−3.64]	[1.04]
Premium		0.002	0.016
(t-value)		(1.90)	(1.54)
[t-value]		[4.11]	[2.54]
	Over-identification test	p-Wald(b)	Wald (SMB&HML)
	18.09		4.56
(p-value)	(0.0535)	(0.0000)	(0.1022)
	HJ-distance	ΔJ-test	SupLM
	0.442	4.857	6.348
(p-value)	(0.0029)	(0.0882)	

0.518 for the CAPM. Finally, the supLM test reveals that the parameters of the models are again stable.

The conclusion that emerges from the tests of this section is that news related to future GDP growth is an important factor for explaining the cross-section of asset prices, regardless of whether the base assets include equities, fixed-income, or both. Furthermore, the ability of the mimicking portfolio to contain virtually all the priced information of SMB and HML is not dependent of the inclusion of the six Fama-French equity portfolios in the base assets of the mimicking portfolio. In fact, the model performs slightly worse when the mimicking portfolio is constructed using the six equity portfolios, and it becomes less able to absorb all the priced information in SMB and HML. In other words, the ability of the model to price equities cannot be attributed to the use of the six Fama-French equity portfolios in the construction of the mimicking portfolio.

7. Conclusions

This paper shows that news related to future GDP growth is an important factor for explaining the cross-section of book-to-market and size portfolios. A model that includes this factor along with the excess return on the market portfolio can explain returns about as well as the Fama-French model, although its stochastic discount factor includes one less free parameter than the FF model. Furthermore, our analysis reveals that much of the information in HML and SMB is news related to future GDP growth. In the presence of the GDP news-related factor in the asset pricing model, SMB and HML lose most to all of their ability to explain returns.

The performance of the proposed model is robust to changes in data frequency or the use of scaled returns. Its parameters are stable over time, which is not the case for the CAPM and the FF model in the monthly unscaled returns estimations. Furthermore, the performance of the model is robust to the exclusion of some GDP-related information from the mimicking portfolio. So long as the mimicking portfolio captures news related to future GDP growth, it can price the cross-section about as well as the FF model, even if it does not represent the purest way to capture this information.

The paper provides an economic interpretation, based on empirical evidence, for the ability of HML and SMB to explain the cross-section of asset returns.

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