Industry return predictability: 
Does it matter out of sample?

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Abstract

We uncover extensive evidence of out-of-sample return predictability for industry portfolios, as well as substantial differences in the degree of return predictability across industries. To understand these differences, we develop an out-of-sample decomposition that separates predictability into beta and alpha shares, where the former corresponds to a conditional beta pricing model. A conditional version of the popular Fama-French three-factor model accounts for nearly all industry return predictability, with exposures to time-varying market and size risk premiums especially important for explaining differences in out-of-sample return predictability across industries. We also show that out-of-sample return predictability is economically important from an asset allocation perspective and can be exploited to improve portfolio performance for industry-rotation investment strategies.

JEL classifications: C22, C32, C53, G11, G12, G17

Keywords: Out-of-sample return predictability; Industry portfolios; Conditional beta pricing model; Fama-French factors; Alpha predictability; Industry-rotation portfolio
1. Introduction

Numerous studies report evidence of aggregate stock market return predictability based on a host of economic variables, and the emerging consensus is that aggregate returns contain a significant predictable component (e.g., Campbell, 2000). The considerable attention paid to aggregate market return predictability in the literature stems from its important economic implications (e.g., Cochrane, 2008). However, return predictability for components of the aggregate market also has important implications for, among other things, dynamic asset pricing models (e.g., Stambaugh, 1983; Campbell, 1987; Connor and Korajczyk, 1989; Ferson and Harvey, 1991; Kirby, 1998), the efficient allocation of capital across sectors, and sector-rotation asset allocation strategies. Despite these implications, component return predictability has received comparatively limited attention in the empirical literature.

To enhance our understanding of component return predictability, we extensively analyze return predictability for industry portfolios comprising the aggregate market in the present paper. An industry division is a natural parsing of the aggregate market, since industry portfolios are of keen interest to both researchers (e.g., Fama and French, 1997) and practitioners (e.g., the increasing popularity of industry ETFs). Other papers examining industry return predictability include Ferson and Harvey (1991, 1999) and Ferson and Korajczyk (1995), who, in addition to portfolios sorted on size and/or book-to-market value, regress 12 to 25 industry portfolio returns on a small set of economic variables that serve as predictors. However, these studies present only in-sample evidence of return predictability for a number of industry portfolios, and industry return predictability itself is not their primary focus. In contrast, we provide a thorough analysis of industry return predictability with four key ingredients.

First, we consider a large number of industries (33) and potential predictors (47). The list of potential predictors includes 14 economic variables from Goyal and Welch (2008), which represent

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1 Examples of studies and economic variables used as return predictors include the dividend-price ratio (Dow, 1920; Fama and French, 1988, 1989; Cochrane, 2008; Pástor and Stambaugh, 2009), earnings-price ratio (Campbell and Shiller, 1988, 1998), book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998), nominal interest rates (Fama and Schwert, 1977; Campbell, 1987; Breen, Glosten, and Jagannathan, 1989; Ang and Bekaert, 2007), inflation rate (Nelson, 1976; Fama and Schwert, 1977; Campbell and Vuolteenaho, 2004), term and default spreads (Campbell, 1987; Fama and French, 1989), corporate issuing activity (Baker and Wurgler, 2000; Boudoukh, Michaely, Richardson, and Roberts, 2007), consumption-wealth ratio (Lettau and Ludvigson, 2001), and stock market volatility (Guo, 2006; Ludvigson and Ng, 2007).
popular economic variables from the literature, as well as 33 lagged industry portfolio returns. Hong, Torous, and Valkanov (2007) find that lagged industry returns are useful for predicting the aggregate market return. In contrast to Hong, Torous, and Valkanov (2007), we investigate the extent to which economic variables and lagged industry returns predict returns across a large number of individual industries.

Second, given the potential fragility of in-sample return predictability evidence (e.g., Goyal and Welch, 2008), we focus on out-of-sample tests of industry return predictability. Our out-of-sample focus is also motivated by its relevance for investors, who must rely on real-time (i.e., out-of-sample) forecasts for asset allocation purposes. We form out-of-sample forecasts of individual industry portfolio returns based on a principal component approach in the spirit of Ludvigson and Ng (2007), who use such an approach to obtain significant evidence of aggregate market return predictability. A principal component approach is useful for tractably incorporating information from a large number of potential predictors. To compute principal component forecasts, we first identify a small number of common factors (i.e., principal components) that capture key comovements across the complete set of 14 economic variables and 33 lagged industry returns. Principal component return forecasts for each industry are then calculated from predictive regression models for industry returns in which the common factors appear as predictors. The historical average (or constant expected return) forecast serves as a natural benchmark, and we measure the ability of principal component forecasts to outperform historical average forecasts of industry returns using the Campbell and Thompson (2008) out-of-sample $R^2$ statistic in conjunction with the Clark and West (2007) test.

Third, we decompose out-of-sample return predictability into two portions attributable to conditional beta pricing model predictability and alpha predictability, respectively. As indicated above, component return predictability has important implications for asset pricing models, and our out-of-sample decomposition measures the degree to which a given conditional beta pricing model accounts for out-of-sample industry return predictability. The decomposition compares unrestricted and restricted principal component forecasts of industry returns, where the restricted forecasts impose a conditional beta pricing model. The portion of the out-of-sample $R^2$ statistic accounted for by the restricted forecast represents beta pricing model predictability, while the remaining portion captures alpha predictability. We perform our decomposition—which can be viewed as an out-of-sample counterpart to the in-sample decomposition in Ferson and Harvey (1991) and Ferson and

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2 An alternative combination forecast approach (e.g., Timmermann, 2006) yields similar results.
Korajczyk (1995)—for conditional versions of popular beta pricing models, namely, the CAPM and Fama and French (1993) three-factor model. Our out-of-sample decomposition also extends the analysis in Fama and French (1997) by examining whether conditional versions of the CAPM and Fama-French model can account for return predictability across industries.

Fourth, we analyze industry return predictability from an asset allocation perspective in the context of “130-30” industry-rotation portfolios. These portfolios employ weights of 1.3/5 (−0.3/5) for the five industries with the highest (lowest) expected returns (and zero weights on the remaining industries). We identify the industries with the highest and lowest expected returns using the principal component or historical average forecasts. Intuitively, if industry return predictability is economically important, 130-30 portfolios based on principal component forecasts, which utilize the predictive information in the economic variables and lagged industry returns, should outperform 130-30 portfolios based on historical average forecasts, which assume constant expected returns.

Previewing our results, out-of-sample tests uncover extensive evidence of return predictability in real time for industry portfolios. In particular, we find significant evidence of out-of-sample return predictability for 20 (26) of 33 industry portfolios at the 5% (10%) level based on the principal component forecasts. While there is widespread evidence of out-of-sample industry return predictability, the degree of predictability varies considerably across industries. For example, monthly out-of-sample $R^2$ statistics are relatively small or negative for some industries, such as mining, oil and gas extraction, tobacco products, petroleum and coal products, instruments and related products, and telephone communication, ranging from −0.49% to 0.01%. In contrast, out-of-sample return predictability is substantially stronger for other industries, such as construction; textiles; apparel; furniture; printing and publishing; stone, clay, and gas products; transportation equipment; miscellaneous manufacturing industries; radio and television broadcasting; and wholesale, with monthly out-of-sample $R^2$ statistics ranging from 2.27% to 5.44%. The monthly out-of-sample $R^2$ is 1.45% for the aggregate market return (which is statistically significant). Our results thus indicate that aggregate market return predictability is an amalgam of substantially varying degrees of return predictability across industries.

Out-of-sample decompositions reveal that conditional beta pricing models with time-varying risk premiums account for much of the out-of-sample predictability in industry returns. A conditional CAPM accounts for out-of-sample return predictability for 28 (25) of 33 industries at the 5% (10%) level, so that exposures to a time-varying aggregate market risk premium explain out-of-
sample return predictability for a clear majority of industries. In accord with the basic logic of the conditional CAPM, there is a positive cross-sectional relationship between the degree of out-of-sample industry return predictability and market betas. A conditional version of the Fama-French three-factor model explains out-of-sample return predictability for 32 (30) of 33 industries at the 5% (10%) level, and there is an especially strong positive relationship between the degree of out-of-sample industry return predictability and exposures to a time-varying risk premium corresponding to the Fama-French size factor. Overall, a conditional version of the popular Fama-French model effectively explains out-of-sample industry return predictability.

Our asset allocation exercises based on 130-30 industry-rotation portfolios point to significant economic gains for investors who exploit industry return predictability. Industry-rotation portfolios based on principal component forecasts of industry returns produce Sharpe ratios nearly twice as large as portfolios based on historical average forecasts. Investors also realize substantially higher utility when they rely on principal component forecasts compared to historical average forecasts. In addition, the industry-rotation portfolio based on restricted principal component forecasts that impose a conditional version of the Fama-French model outperforms the portfolio based on unrestricted principal component forecasts, reinforcing the success of the conditional Fama-French model in explaining industry return predictability.

The remainder of the paper is organized as follows. Section 2 outlines the econometric methodology, including construction of out-of-sample industry return forecasts, forecast evaluation, and the out-of-sample decomposition of industry return predictability. Section 3 describes the data and reports the out-of-sample test results. Section 4 reports performance results for industry-rotation investment strategies. Section 5 concludes.

2. Econometric methodology

This section describes the construction and evaluation of principal component and historical average forecasts of industry returns, as well as the out-of-sample decomposition of industry return predictability.

2.1. Forecast construction

The conventional framework for analyzing return predictability is a predictive regression model:

\[ r_{i,t+1} = a_i + b_i'x_t + e_{i,t+1}, \]  \hspace{1cm} (1)
where $r_{i,t+1}$ denotes the return on industry portfolio $i$ in excess of the risk-free interest rate from time $t$ to $t+1$, $x_t = (x_{1,t}, \ldots, x_{J,t})'$ is a $J$-vector of predictors, $a_i$ is an intercept term, $b_i$ is a $J$-vector of slope coefficients, and $\epsilon_{i,t+1}$ is a zero-mean disturbance term. It is straightforward to compute out-of-sample forecasts based on (1). For example, to form a forecast of $r_{i,t+1}$ utilizing information through $t$, we can use

$$\hat{r}_{i,t+1} = \hat{a}_{i,1:t} + \hat{b}_{i,1:t}'x_t,$$

(2)

where $\hat{a}_{i,1:t}$ and $\hat{b}_{i,1:t}$ are OLS estimates of the intercept and $J$-vector of slope coefficients, respectively, from the regression of $\{r_{i,s}\}_{s=2}^{t}$ on a constant and $\{x_s\}_{s=1}^{t-1}$. This approach encounters difficulties, however, when $J$ is large, that is, when there are a large number of potential predictors.

We could include all of the potential predictors in (2)—assuming there are a sufficient number of time-series observations—but this entails substantial in-sample “overfitting” that often results in poor out-of-sample performance (e.g., Goyal and Welch, 2008). Or, we could somewhat arbitrarily select a small number of the potential predictors to include in (2), but this possibly excludes substantial amounts of relevant information.

Rather than pursuing either of these strategies when $J$ is large, we employ a forecasting approach that tractably incorporates information from the large number of potential return predictors we consider; $J = 47$ in our applications. The basic idea is to use a small number of principal components to capture the important common fluctuations in the $J$ potential predictors. More specifically, to generate a principal component forecast of $r_{i,t+1}$ based on information through $t$, we begin by computing the first two principal components of $\{x_s\}_{s=1}^{t}$; let $\hat{z}_{s,1:t} = (\hat{z}_{1,s,1:t}, \hat{z}_{2,s,1:t})'$ for $s = 1, \ldots, t$ signify the vector of estimated time-$s$ principal components based on data from period 1 through $t$. We use the first two principal components, since the potential predictors we consider can (roughly) be separated into two categories (economic variables and lagged industry returns, described in detail in Section 3). We then use a predictive regression model based on the first two principal components to calculate a forecast of $r_{i,t+1}$:

$$\hat{r}^{PC}_{i,t+1} = \hat{a}^{PC}_{i,1:t} + \hat{b}^{PC}_{i,1:t}'\hat{z}_{t,1:t},$$

(3)

where $\hat{a}^{PC}_{i,1:t}$ and $\hat{b}^{PC}_{i,1:t}$ are the OLS estimates of the intercept and vector of slope coefficients, respectively, from the regression of $\{r_{i,s}\}_{s=2}^{t}$ on a constant and $\{\hat{z}_{s,1:t}\}_{s=1}^{t-1}$. Dividing the total sample of $T$ observations for the return and predictor series into an initial in-sample estimation period com-

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3Campbell and Thompson (2008), Goyal and Welch (2008), and Rapach, Strauss, and Zhou (2010) recently analyze out-of-sample forecasts based on (2) for the aggregate market portfolio.

4We obtain similar results when we include additional principal components.
posed of the first \( n_1 \) observations and an out-of-sample portion composed of the last \( n_2 = T - n_1 \) observations, we generate simulated real-time principal component forecasts of industry \( i \)'s excess return over these last \( n_2 \) observations: \( \{ \hat{\rho}_{i,t+1}^{PC} \}_{t=n_1}^{T-1} \). Ludvigson and Ng (2007) find significant evidence of in-sample and out-of-sample aggregate market return predictability using a principal component approach based on numerous macroeconomic and financial variables; we explore the value of a principal component approach for predicting industry portfolio returns.

The constant expected excess return (or random walk with drift) model is the relevant benchmark under the null hypothesis of no predictability, corresponding to \( b_i = 0 \) in (1). Following Campbell and Thompson (2008) and Goyal and Welch (2008), we simulate real-time forecasts based on the constant expected excess return model using the historical average of industry \( i \)'s excess return:

\[
\bar{r}_{i,t+1} = \left( \frac{1}{t} \right) \sum_{s=1}^{t} r_{i,s}. \tag{4}
\]

If the potential predictors contain information useful for forecasting industry returns, then principal component forecasts, which incorporate information from the predictors, should outperform historical average forecasts, which ignore such information.\(^5\)

### 2.2. Forecast evaluation

The Campbell and Thompson (2008) out-of-sample \( R^2 \) statistic provides a convenient metric for comparing principal component and historical average forecasts of industry returns. The out-of-sample \( R^2 \) statistic for industry \( i \) measures the reduction in mean square prediction error (MSPE) for the principal component forecast vis-à-vis the historical average forecast of industry \( i \)'s excess return:

\[
R_{i,OS}^2 = 1 - \frac{\sum_{t=n_1}^{T-1} (r_{i,t+1} - \hat{\rho}_{i,t+1}^{PC})^2}{\sum_{t=n_1}^{T-1} (r_{i,t+1} - \bar{r}_{i,t+1})^2}. \tag{5}
\]

When \( R_{i,OS}^2 > 0 \), the principal component forecast outperforms the historical average benchmark according to the MSPE metric.

We assess the statistical significance of \( R_{i,OS}^2 \) by testing the null hypothesis that the principal component and historical average forecasts have equal MSPE against the (one-sided) alternative

\(^5\)We also considered forecast combination as an alternative approach for incorporating information from a large number of potential predictors. This approach takes a weighted average of \( J \) individual bivariate predictive regression model forecasts, where each individual model contains a single potential predictor. Rapach, Strauss, and Zhou (2010) find that a combination approach substantially improves out-of-sample forecasts of the aggregate market return. The principal component and combination approaches perform similarly with respect to forecasting industry returns in our applications. For brevity, we thus do not report the combination forecast results. They are available upon request from the authors.
hypothesis that the historical average forecast has a higher MSPE; this corresponds to a test of
\( H_0: R_i^{2,\text{OS}} = 0 \) against \( H_1: R_i^{2,\text{OS}} > 0 \). We implement this test using the Clark and West (2007) 
\textit{MSPE-adjusted} statistic, which is a variant of the popular Diebold and Mariano (1995) and West 
(1996) statistic for testing equal MSPE between competing forecasts. Our reliance on the Clark 
and West (2007) statistic derives from the fact that we are ultimately comparing nested models, 
since the predictive regression model used in the principal component forecast reduces to the con-
stant expected return model under the null hypothesis of no predictability. While the Diebold and 
Mariano (1995) and West (1996) statistic has a standard asymptotic distribution when comparing 
non-nested forecasts, it has a non-standard distribution when comparing nested forecasts (Clark 
and McCracken, 2001; McCracken, 2007).\(^6\) The Clark and West (2007) \textit{MSPE-adjusted} statistic 
modifies the Diebold and Mariano (1995) and West (1996) statistic so that is has an asymptotic 
standard normal distribution and good finite-sample properties when comparing nested forecasts.

2.3. \textit{An out-of-sample decomposition of return predictability}

Studies such as Stambaugh (1983), Campbell (1987), Connor and Korajczyk (1989), Ferson 
lyze the theoretical and empirical implications of return predictability for conditional beta pricing 
models. This provides a framework for determining the extent to which exposures to time-varying 
systemic risk premiums, as captured by a conditional beta pricing model, account for industry 
return predictability. Return predictability beyond this represents alpha predictability, which cor-
responds to mispricing in the context of the conditional beta pricing model. We propose an out-
of-sample decomposition of return predictability into conditional beta pricing model and alpha 
predictability shares, respectively.\(^7\)

We can express the excess return for industry portfolio \( i \) as

\[
r_{i,t+1} = \alpha_i(x_t) + \beta_i' f_{i,t+1} + \epsilon_{i,t+1},
\]

where \( f_{i,t+1} = (f_{1,t+1}, \ldots, f_{K,t+1})' \) is a \( K \)-vector of portfolio-based factors capturing systemic risk, 
\( \beta_i = (\beta_{i,1,t}, \ldots, \beta_{i,K,t})' \) is a \( K \)-vector comprising industry \( i \)'s factor exposures, and \( \epsilon_{i,t+1} \) is a zero-
mean disturbance term. Assume that

\[
f_{i,t+1} = \lambda(x_t) + u_{i,t+1},
\]

\(^6\)As shown by Clark and McCracken (2001) and McCracken (2007), the Diebold and Mariano (1995) and West 
(1996) statistic can be severely undersized when comparing forecasts from nested models, leading to tests with very 
low power.

\(^7\)We thank Rossen Valkanov for encouraging us to pursue this line of inquiry.
where \( \hat{\lambda}(x_t) = (\lambda_1(x_t), \ldots, \lambda_K(x_t))^t \) is a \( K \)-vector of conditional expected returns for the portfolio-based factors and \( u_{t+1} = (u_{1,t+1}, \ldots, u_{K,t+1})^t \) is a \( K \)-vector of zero-mean disturbance terms. The dependence of \( \lambda \) on \( x_t \) allows for time-varying risk premiums. A conditional beta pricing model implies the following conditional expectation for \( r_{i,t+1} \):

\[
E(r_{i,t+1}|x_t) = \beta_{i,t}'E(f_{t+1}|x_t) = \beta_{i,t}'\lambda(x_t). \tag{8}
\]

Intuitively, according to the conditional beta pricing model, any predictability in industry \( i \)'s excess return emanates solely from the predictability of the risk factors in conjunction with the sensitivity of industry \( i \) to those factors—as given by \( \beta_{i,t}'\lambda(x_t) \)—implying that \( \alpha_i(x_t) = 0 \) in (6). Predictability in industry \( i \)'s excess return beyond what is produced by \( \beta_{i,t}'\lambda(x_t) \) represents alpha predictability, since it implies that \( \alpha_i(x_t) \neq 0 \). Insofar as (7) adequately captures systemic risk premiums, \( \alpha_i(x_t) \neq 0 \) corresponds to mispricing in industry \( i \).

Campbell (1987), Ferson and Harvey (1991, 1999), Ferson and Korajczyk (1995), and Kirby (1998) test the restrictions implied by conditional beta pricing models for the predictability of a variety of portfolio returns using in-sample tests and a small number of predictors. In addition, Ferson and Harvey (1991) and Ferson and Korajczyk (1995) estimate the fraction of in-sample return predictability captured by a conditional beta pricing model. Given our out-of-sample approach in the present paper, we propose a decomposition of the \( R_{i,OS}^2 \) statistic given in (5). This statistic measures the out-of-sample predictability of industry \( i \)'s excess return, and we apportion \( R_{i,OS}^2 \) into shares corresponding to a conditional beta pricing model and alpha predictability, respectively.

To perform the decomposition, we calculate a \textit{beta pricing-restricted} forecast of \( r_{i,t+1} \) based on (8). Forming such a forecast requires estimates of \( \beta_{i,t} \) and \( \hat{\lambda}(x_t) \) to plug into (8). When the betas are assumed constant (\( \beta_{i,t} = \beta_i \forall t \)), it is straightforward to estimate the elements of \( \beta_{i,t} \) by regressing \( \{r_{i,t}\}_{t=1}^T \) on \( \{f_t\}_{t=1}^T \) (without a constant).\(^8\) In light of (7), it is natural to estimate the elements of \( \lambda(x_t) \) using principal component forecasts of each element in \( f_{t+1} \) based on \( x_t \), in a manner analogous to the procedures described in Section 2.1, with \( r_{i,t+1} \) replaced by an element of \( f_{t+1} \). The beta pricing-restricted forecast of \( r_{i,t+1} \) based on (8) and information through period \( t \) is then given by

\[
\hat{r}_{i,t+1}^{\beta,PC} = \hat{\beta}_{i,t}'\hat{\lambda}^{PC}(x_t), \tag{9}
\]

where \( \hat{\beta}_{i,t} \) is the estimate of \( \beta_i \) based on information through \( t \) and \( \hat{\lambda}^{PC}(x_t) \) is a \( K \)-vector of principal component forecasts of the elements in \( f_{t+1} \).

\(^8\)Note that this avoids “look-ahead” bias, since we only use data available at the time of forecast formation in estimating \( \beta_i \).
It is less straightforward to compute a beta pricing-restricted forecast of $r_{t+1}$ when $\beta_{t,i}$ is not assumed constant and depends on $x_t$, especially given the large dimension of $x_t$ in our applications. With a small number of elements in $x_t$ and under the assumption that $\beta_{t,i} = \beta_{i,0} + \sum_{j=1}^J \beta_{i,j} x_{j,t}$, where $\beta_{i,0} = (\beta_{i,0,1}, \ldots, \beta_{i,0,K})'$ and $\beta_{i,j} = (\beta_{i,j,1}, \ldots, \beta_{i,j,K})'$ are $K$-vectors, we can estimate the elements of $\beta_{i,0}$ and $\beta_{i,j}$ using information through $t$ by regressing $\{r_{i,s}\}_{s=1}^T$ on $\{f_{j}\}_{j=1}^9$ and $\{f_t \otimes x_t\}_{t=1}^T$ (again without a constant, where $\otimes$ is the Kronecker product). When $J$ is large, however, this will likely lead to substantial overfitting (and is not even feasible if an inadequate number of observations are available, given the multitude of regressors). When betas are permitted to depend on $x_t$ and $J$ is large, we again use a principal component approach to estimate the betas:

$$\hat{\beta}_{PC} = \hat{\beta}_{i,0,t} + \hat{\beta}_{PC,t,1:t},$$

(10)

where the elements of the $K$-vector $\hat{\beta}_{PC,i,0,t}$ and $K \times 2$ matrix $\hat{\beta}_{PC,i,1:t}$ are generated by regressing $\{r_{i,s}\}_{s=1}^T$ on $\{f_{s}\}_{s=1}^T$ and $\{f_s \otimes z_{s,1:t}\}_{s=1}^T$. This principal component estimate of the vector of exposures is then used in place of $\hat{\beta}_{i,t}$ in (9).

The principal component forecast of $r_{i,t+1}$ in Section 2.1 does not impose a conditional beta pricing model, so that it constitutes an unrestricted forecast of industry $i$’s excess return based on the $J = 47$ predictors. In contrast to the beta pricing-restricted forecast, this unrestricted forecast permits both conditional beta pricing model and alpha predictability.

Then, we are ready to decompose the $R^2_{i,OS}$ statistic in (5) by computing two subsidiary $R^2_{i,OS}$ statistics. The first is a modified version of (5) that measures the reduction in MSPE for a beta pricing-restricted forecast relative to the historical average forecast:

$$R^2_{i,OS} = 1 - \frac{\sum_{t=1}^{T-1} (r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_{t=1}^{T-1} (r_{i,t+1} - \bar{r}_{i,t+1})^2},$$

(11)

where $\hat{r}_{i,t+1}$ is given by (9), although we can use (10) in place of $\hat{\beta}_{i,t}$ in (9) to allow for time-varying betas. The $R^2_{i,OS}$ statistic gauges the extent of conditional beta pricing model out-of-sample predictability in industry $i$. The next statistic measures the decrease in MSPE for the unrestricted forecast compared to the beta pricing-restricted forecast:

$$R^2_{i,OS} = 1 - \frac{\sum_{t=1}^{T-1} (r_{i,t+1} - \tilde{r}_{i,t+1})^2}{\sum_{t=1}^{T-1} (r_{i,t+1} - \hat{r}_{i,t+1})^2},$$

(12)

The empirical evidence on time variation in betas is mixed. For example, Ferson and Harvey (1999) and Ang and Chen (2007) find evidence of significant time variation in factor exposures, while Ghysels (1998) and Lewellen and Nagel (2006) question the usefulness of time-varying betas for empirical asset pricing. Given the mixed empirical results, and the evidence in Fama and French (1997) of instabilities in betas for industry portfolios, we consider beta pricing-restricted forecasts that either assume constant betas or allow for betas that vary with $x_t$. 

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$R_{i,OS}^{2,\alpha}$ quantifies the degree of out-of-sample predictability beyond conditional beta pricing model predictability, thereby providing a measure of out-of-sample alpha predictability.\footnote{Since (11) and (12) entail nested forecast comparisons, we again use the the Clark and West (2007) MSPE-adjusted statistic to test the significance of $R_{i,OS}^{2,\beta}$ and $R_{i,OS}^{2,\alpha}$.}

Observe from (5), (11), and (12) that

$$R_{i,OS}^{2,\alpha} = 1 - \left[ \frac{\sum_{t=n_{1}}^{T-1} (r_{i,t+1} - \hat{r}_{i,t+1}^{PC})^2}{\sum_{t=n_{1}}^{T-1} (r_{i,t+1} - \bar{r}_{i,t+1})^2} \right] \left[ \frac{\sum_{t=n_{1}}^{T-1} (r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_{t=n_{1}}^{T-1} (r_{i,t+1} - \bar{r}_{i,t+1})^2} \right] = 1 - \left( \frac{1 - R_{i,OS}^{2,\beta}}{1 - R_{i,OS}^{2,\alpha}} \right). \quad (13)$$

Solving for $R_{i,OS}^{2}$ in (13), we have

$$R_{i,OS}^{2} = R_{i,OS}^{2,\beta} + R_{i,OS}^{2,\alpha} - R_{i,OS}^{2,\beta} R_{i,OS}^{2,\alpha}. \quad (14)$$

For “small” $R_{i,OS}^{2,\beta}$ and $R_{i,OS}^{2,\alpha}$, the cross-product term is approximately zero, so that

$$R_{i,OS}^{2} \approx R_{i,OS}^{2,\beta} + R_{i,OS}^{2,\alpha}. \quad (15)$$

Our approach thus (approximately) dichotomizes the measure of total out-of-sample predictability, $R_{i,OS}^{2}$, into two components corresponding to a conditional beta pricing model and alpha variation, $R_{i,OS}^{2,\beta}$ and $R_{i,OS}^{2,\alpha}$, respectively.

Observe that an out-of-sample approach should be especially useful in analyzing conditional beta pricing models. On an in-sample basis, there is a danger of overfitting a conditional model by simply including additional factors until we “explain” all of the predictability in industry returns. The additional factors may appear significant according to standard in-sample tests, although they do not capture actual economic relationships.\footnote{See, for example, Lo and MacKinlay (1990) and MacKinlay (1995) on this “data-snooping” problem in the context of unconditional tests of multi-beta pricing models.} Such in-sample overfitting, however, will often detract from out-of-sample forecasting performance. From this perspective, out-of-sample tests help to provide more reliable inferences regarding the ability of conditional multi-beta pricing models to explain industry return predictability.

3. Empirical results

This section first describes the data and then analyzes principal component forecasts of industry returns. It also provides decompositions of the $R_{i,OS}^{2}$ statistics based on conditional versions of the CAPM and Fama-French three-factor model.
3.1. Data

We analyze predictability for monthly returns on value-weighted industry portfolios, which are available from Kenneth French’s Data Library.\(^{12}\) We use monthly returns on 33 industry portfolios available from 1946:01–2008:12: AGRIC (Agriculture, Forestry, and Fishing), MINES (Mining), OIL (Oil and Gas Extraction), STONE (Nonmetallic Minerals Except Fuels), CNSTR (Construction), FOOD (Food and Kindred Products), SMOKE (Tobacco Products), TXTLS (Textile Mill Products), APPRL (Apparel and other Textile Products), WOOD (Lumber and Wood Products), CHAIR (Furniture and Fixtures), PAPER (Paper and Allied Products), PRINT (Printing and Publishing), CHEMS (Chemicals and Allied Products), PTRLM (Petroleum and Coal Products), RUBBR (Rubber and Miscellaneous Plastics Products), LETHR (Leather and Leather Products), GLASS (Stone, Clay, and Glass Products), METAL (Primary Metal Industries), MTLPR (Fabricated Metal Products), MACHN (Machinery, Except Electrical), ELCTR (Electrical and Electronic Equipment), CARS (Transportation Equipment), INSTR (Instruments and Related Products), MANUF (Miscellaneous Manufacturing Industries), TRANS (Transportation), PHONE (Telephone and Telegraph Communication), TV (Radio and Television Broadcasting), UTILS (Electric, Gas, and Water Supply), WHLSL (Wholesale), RTAIL (Retail Stores), MONEY (Finance, Insurance, and Real Estate), SRVC (Services).\(^{13}\)

As potential predictors of industry returns, we consider two sets of variables. The first is a group of 14 economic variables used by Goyal and Welch (2008):

- Dividend-price ratio (log), D/P: difference between the log of dividends paid on the S&P 500 index and log of prices (S&P 500 index), where dividends are measured using a one-year moving sum.
- Dividend yield (log), D/Y: difference between the log of dividends and log of lagged prices.
- Earnings-price ratio (log), E/P: difference between the log of earnings on the S&P 500 index and log of prices, where earnings are measured using a one-year moving sum.
- Dividend-payout ratio (log), D/E: difference between the log of dividends and log of earnings on the S&P 500 index.

\(^{12}\)The library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.
\(^{13}\)These are the industry mnemonics from the Data Library. Data are also available for GARBG (Sanitary Services), STEAM (Steam Supply), WATER (Irrigation Systems), GOVT (Public Administration), and OTHER (Almost Nothing). There are missing observations for these series, however, so we exclude them, as in Hong, Torous and Valkanov (2007).
• Book-to-market ratio, B/M: ratio of book value to market value for the Dow Jones Industrial Average.

• Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).

• Long-term yield, LTY: long-term government bond yield.

• Long-term return, LTR: return on long-term government bonds.

• Term spread, TMS: difference between the long-term yield and Treasury bill rate.

• Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.

• Default return spread, DFR: difference between long-term corporate bond and long-term government bond returns.

• Stock variance, SVAR: sum of squared daily returns on the S&P 500 index.

• Net equity expansion, NTIS: ratio of 12-month moving sums of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.

• Inflation, INFL: calculated from the CPI (all urban consumers); following Goyal and Welch (2008), since inflation rate data are released in the following month, we use $x_{j,t-1}$ but not $x_{j,t}$ for inflation in the time-$t$ information set.

These variables include many of the predictors of aggregate market returns from the literature. The valuation ratios (D/P, D/Y, E/P, and B/M) and interest rate variables (TBL, LTY, TMS, and DFY) are especially prominent in the literature on aggregate market return predictability. The data are monthly and described in more detail in Goyal and Welch (2008).\textsuperscript{14}

Lagged industry returns (the same industry returns described above) comprise the second set of predictors. Our inclusion of lagged industry returns as potential predictors is motivated by Hong, Torous, and Valkanov (2007), who provide evidence that lagged industry returns have statistically and economically significant predictive ability for aggregate market returns. Hong, Torous, and Valkanov (2007) develop a theoretical model with information-diffusion frictions along the lines of Merton (1987) and Hong and Stein (1999) that provides an explanation for the ability of lagged industry returns to predict aggregate market returns.

\textsuperscript{14}The data are available at http://www.bus.emory.edu/AGoyal/Research.html.
Table 1 reports summary statistics for excess returns for the 33 industry portfolios, as well as the 14 economic variables from Goyal and Welch (2008), for 1966:12–2008:12. This corresponds to the forecast evaluation period used in the out-of-sample tests. For reference, the table includes summary statistics for the excess return on the aggregate CRSP value-weighted market portfolio (MKT). Excess returns are computed relative to the CRSP risk-free rate. The second and ninth columns show that mean monthly industry excess returns range from 0.26% (APPRL) to 0.91% (SMOKE), while the standard deviations range from 4.18% (UTILS) to 8.31% (MINES). Most of the monthly Sharpe ratios fall between 0.05 and 0.10. FOOD, SMOKE, and PTRLM have the highest Sharpe ratios, from 0.13 to 0.14.

3.2. Out-of-sample industry excess return predictability

We reserve the first two decades (1946:01–1965:12) of the full-sample period as the initial in-sample estimation period, leaving 1966:01–2008:12 as the forecast evaluation period. In addition to industry excess returns, we compute forecasts of the aggregate market excess return for reference. Figure 1 depicts principal component excess return forecasts for each industry portfolio, as well as the aggregate market portfolio. The figure also portrays historical average forecasts (gray lines). Figure 1 shows that the principal component forecasts are, as expected, more volatile than the historical average forecasts, since the former incorporate information from the 47 predictors, whereas the latter do not.

While the principal component forecasts are more variable than the historical average forecasts, substantial differences in volatility also exist among the principal component forecasts themselves. For example, the principal component forecasts in Figure 1 for industries such as CNSTR, TXTL, APPRL, CHAIR, PRINT, MANUF, and WHLSL are considerably more variable than those for industries such as FOOD, SMOKE, CHEMS, PTRLM, INSTR, PHONE, and UTILS. These differences in forecast volatility among industries in Figure 1 indicate that the 47 predictors provide stronger signals for future excess returns in particular industries. The key issue is whether these stronger signals translate into out-of-sample forecasting gains or simply represent excessive noise in the forecasts that detracts from forecast accuracy. The $R^2_{i,OS}$ statistics, reported in Table 2, address this issue.

The second, fourth, and sixth columns of Table 2 report $R^2_{i,OS}$ statistics for the principal component forecasts. The aggregate market portfolio has an $R^2_{i,OS}$ of 1.45% in the second column, which is significant at the 5% level according to the Clark and West (2007) test. Of course, we anticipate
relatively small $R^2_{i, OS}$ statistics for monthly excess stock returns, since returns have a substantial un-
expected component. Nevertheless, a seemingly small degree of predictability can have important eco-
nomic implications (e.g., Kandel and Stambaugh, 1996; Xu, 2004). Campbell and Thompson (2008) argue that a monthly $R^2_{i, OS}$ of around 0.5% can represent significant economic predictability for U.S. aggregate market excess returns; the MKT $R^2_{i, OS}$ of 1.45% is well above this threshold.

Principal component forecasts of excess returns deliver positive $R^2_{i, OS}$ statistics for 28 of the 33 industries; 20 (26) of these $R^2_{i, OS}$ statistics are significant at the 5% (10%) level. The average $R^2_{i, OS}$ across the 33 industries is 1.36%, slightly below the $R^2_{i, OS}$ for the aggregate market. While there is evidence of out-of-sample predictability for a large number of industry returns based on the principal component forecasts, sizable differences in the degree of return predictability across industries emerge. For example, the $R^2_{i, OS}$ statistics for the principal component forecasts are less than 0.3% for nine industries, but above 2% for 10 other industries. The $R^2_{i, OS}$ of 1.45% for the aggregate market portfolio thus masks ample differences in return predictability for the individual industries comprising the market.

To more readily observe differences in the degree of return predictability across industries, Figure 2 presents a bar graph of the sorted $R^2_{i, OS}$ statistics for the principal component forecasts. TXTLS, CHAIR, PRINT, CARS, APPRL, MANUF, WHLSL, GLASS, CNSTR, and TV are the industries with the highest degree of out-of-sample return predictability. Observe that these are also some of the industries in Figure 1 with the most volatile principal component forecasts. Evi-
dently, the greater volatility in these forecasts translates to greater return predictability, rather than simply excessive noise. Furthermore, Figure 2 shows that OIL, SMOKE, PHONE, MINES, PTRLM, INSTR, METAL, UTILS, CHEMS, PAPER, and FOOD are the industries with the least return predictability. These are some of the industries in Figure 1 with the least volatile principal component forecasts.

To glean further insight into the relationship between the degree of industry return predictability and principal component forecast volatility, Figure 3 displays a scatterplot of the industry $R^2_{i, OS}$ statistics in Table 2 and standard deviations of the principal component forecasts. The figure clearly shows a positive correlation between the industry $R^2_{i, OS}$ statistics and principal component forecast volatility. In addition, a cross-sectional regression of $R^2_{i, OS}$ on the principal component forecast standard deviation produces an OLS slope coefficient estimate of 3.46 and a corresponding White (1980) heteroskedasticity-consistent $t$-statistic of 8.01. The cross-sectional regression $R^2$ is a very sizable 59%. In sum, we see a strong connection between principal component industry return
forecast volatility and out-of-sample industry return predictability.

Given that we consider multiple tests in Table 2, which are almost surely dependent, we conduct a simulation experiment along the lines of Hong, Torous, and Valkanov (2007) to get a sense of whether the evidence of industry return predictability in Table 2 is spurious. In essence, we use a bootstrap procedure to generate a large number of pseudo samples of excess returns for each of the 33 industries under a constant expected excess return (no predictability) data-generating process for each industry.\footnote{The bootstrap procedure is described in detail in the Appendix.} For each pseudo sample, we compute $R^2_{i,OS}$ statistics and corresponding Clark and West (2007) $p$-values for each industry and record the number of industry $R^2_{i,OS}$ statistics that are significant at the 5% and 10% levels, respectively. We obtain at least 20 (26) significant industry $R^2_{i,OS}$ statistics at the 5% (10%) level in only one of 500 pseudo samples, or 0.20% of the pseudo samples, strongly suggesting that the evidence of industry return predictability in Table 2 is not spurious.

### 3.3. Decomposing the $R^2_{i,OS}$ statistics

In this section, we decompose the $R^2_{i,OS}$ statistics reported in Table 2 into two components attributable to conditional beta pricing model and alpha predictability, respectively, as described in Section 2.3. We consider decompositions based on conditional versions of the canonical CAPM and popular Fama-French three-factor model.

#### 3.3.1. Conditional CAPM

We first examine whether a conditional CAPM based on principal component forecasts can account for the out-of-sample industry excess return predictability documented in Section 3.2. Consider principal component forecasts under the assumption of constant betas. Based on (9), the CAPM-restricted principal component forecast of industry $i$’s excess return is given by

$$\hat{r}^{\text{CAPM,PC}}_{i,t+1} = \hat{\beta}_{i,t}^{\text{CAPM}} \hat{\lambda}^{\text{PC,CAPM}}(x_t),$$

(16)

where $\hat{\beta}_{i,t}^{\text{CAPM}}$ is an estimate of industry $i$’s market beta based on data from 1946:01 through month $t$ and $\hat{\lambda}^{\text{PC,CAPM}}(x_t) = \hat{r}^{\text{PC,MKT},t+1}$ is the principal component forecast of the excess return on the aggregate market portfolio (already computed in Section 3.2). To allow for time-varying betas when forming the CAPM-restricted principal component forecasts, we replace $\hat{\beta}_{i,t}^{\text{CAPM}}$ in (16) with $\hat{\beta}_{i,t}^{\text{CAPM,PC}}$ based on (10).
The second and seventh (third and eighth) columns of Table 3 report $R_{i,OS}^{2,\beta}$ ($R_{i,OS}^{2,\alpha}$) statistics for CAPM-restricted principal component forecasts with constant betas. As shown in Section 2.3, the $R_{i,OS}^{2,\beta}$ and $R_{i,OS}^{2,\alpha}$ statistics approximately sum to the corresponding $R_{i,OS}^{2}$ statistic in Table 2. Recall from (11) that $R_{i,OS}^{2,\beta}$ measures the reduction in MSPE for the CAPM-restricted principal component forecast relative to the historical average forecast. The second and seventh columns of Table 3 indicate that the CAPM-restricted principal component forecast delivers positive $R_{i,OS}^{2,\beta}$ statistics for 29 of 33 industries, and 26 (27) of these statistics are significant at the 5% (10%) level. CAPM-restricted principal component forecasts thus outperform historical average forecasts for the clear majority of industries.

According to the logic of the conditional CAPM, industries with larger market exposures will have more volatile expected returns. Relative to the constant expected return model, industries with larger exposures should thus display greater out-of-sample return predictability in the form of higher $R_{i,OS}^{2,\beta}$ statistics. Evidence in support of this is found in Figure 4, which portrays a scatterplot of the industry $R_{i,OS}^{2,\beta}$ statistics for the CAPM-restricted principal component forecasts and the time-series averages of $\hat{\beta}_{CAPM}^{\beta}$ in (16) for each industry. Figure 4 shows that the $R_{i,OS}^{2,\beta}$ statistics and average betas are positively related. For example, CNSTR, the industry with the highest average market beta (near 1.3), is among the industries with the highest $R_{i,OS}^{2,\beta}$ statistics, while PHONE, the industry with the lowest average market beta (near 0.55), is among the industries with the lowest $R_{i,OS}^{2,\beta}$ statistics. Furthermore, a cross-sectional regression of $R_{i,OS}^{2,\beta}$ on the time-series average of $\hat{\beta}_{CAPM}^{\beta}$ yields an OLS slope coefficient estimate of 2.99 with a heteroskedasticity-consistent t-statistic of 4.80.

Industry exposures to the market portfolio help to explain differences in return predictability across industries. However, are CAPM-restricted principal component forecasts sufficient for explaining the out-of-sample industry return predictability detected in Section 3.2? The $R_{i,OS}^{2,\alpha}$ statistics in the third and eighth columns of Table 3, which measure the percent reduction in MSPE for the unrestricted principal component forecasts relative to the CAPM-restricted principal component forecasts, address this issue. Fifteen of the 33 $R_{i,OS}^{2,\alpha}$ statistics are positive, signaling that the unrestricted forecasts outperform the CAPM-restricted forecasts according to the MSPE metric. Five (eight) of the 15 positive $R_{i,OS}^{2,\alpha}$ statistics are significant at the 5% (10%) level, meaning that we find significant evidence of out-of-sample alpha predictability for 15%–25% of the 33 industries. TXTLS, APPRL, CHAIR, PRINT, GLASS, CARS, and MANUF all have $R_{i,OS}^{2,\alpha}$ statistics near or above 0.5%. Observe that each of these industries also have statistically significant and
sizable $R^2_{i,OS}$ statistics, so that out-of-sample return predictability is composed both of important conditional CAPM and alpha components for these industries. Recall that these are also among the industries with the most volatile principal component forecasts in Figure 1. These relatively volatile forecasts appear to capture fluctuations in expected returns related to both conditional CAPM and alpha out-of-sample predictability.\footnote{Observe that there are also a few industries, such as OIL and INSTR, with substantially negative $R^2_{i,OS}$ statistics. For these industries, out-of-sample predictability is improved by using CAPM-restricted instead of unrestricted principal component forecasts, reflecting the idea that out-of-sample forecasting performance can be improved by imposing economically meaningful restrictions on forecasting models.}

The fourth and ninth (fifth and tenth) columns of Table 3 report $R^2_{i,OS}$ ($R^2_{i,OS}$) statistics for CAPM-restricted principal component forecasts that allow for time-varying betas. Allowing for industry market betas to vary with the 47 predictors does little to affect the results. For example, the average $R^2_{i,OS}$ across industries is 1.36% for the principal component forecasts with time-varying betas, which is almost identical to the constant beta forecast average of 1.38%. Nearly all of the 29 industries that have positive $R^2_{i,OS}$ statistics for the CAPM-restricted principal component forecasts with constant betas also have positive $R^2_{i,OS}$ statistics for forecasts with time-varying betas, and 26 (27) of these statistics are significant at the 5% (10%) level in both cases. The $R^2_{i,OS}$ statistics are also more or less similar across principal component forecasts with constant and time-varying betas, and five (nine) industries have significant $R^2_{i,OS}$ statistics at the 5% (10%) level with time-varying betas, compared to five (eight) for constant betas. The bottom line is that time-varying betas do not improve out-of-sample return predictability relative to constant betas, so that time-varying betas cannot explain the out-of-sample alpha predictability exhibited by a conditional CAPM with constant betas.\footnote{This result parallels recent in-sample findings in Lewellen and Nagel (2006). Using a novel procedure for measuring time variation in CAPM betas, they show that allowing for such variation does not account for the momentum and value premium anomalies evident in the CAPM with constant betas.}

Overall, interpreting the results in Table 3 depends on whether one views the glass as mostly full or still partly empty. On the one hand, we cannot reject the null hypothesis that a conditional CAPM sufficiently explains out-of-sample return predictability—evidenced by insignificant $R^2_{i,OS}$ statistics—for a strong majority of industries (28 of 33 at the 5% level). In addition, there is a significantly positive relationship between the $R^2_{i,OS}$ statistics and industry portfolios’ market exposures, in line with the logic of the CAPM. On the other hand, a number of industries (five of 33 at the 5% level) display significant out-of-sample alpha predictability, suggesting that the conditional CAPM alone omits relevant factors for explaining industry return predictability. We next investigate whether a conditional version of the popular Fama-French three-factor model can
explain the out-of-sample predictability of industry returns unaccounted for by the conditional CAPM.\(^\text{18}\)

### 3.3.2. Conditional Fama-French three-factor model

The Fama-French multi-beta pricing model expands the set of risk factors to include \(r_{SMB,t}\) and \(r_{HML,t}\), where \(r_{SMB,t}\) and \(r_{HML,t}\) are returns on the well-known size (“small minus big” or SMB) and value (“high minus low” or HML) portfolio-based factors, respectively.\(^\text{19}\) A sizable empirical literature indicates that these factors capture important risk premiums in the cross section of average returns not accounted for by the excess return on the aggregate market portfolio alone. In addition, studies such as Liew and Vassalou (2000) and Vassalou (2003) link the Fama-French factors to macroeconomic conditions and business-cycle fluctuations. We examine whether the inclusion of size and value factors improves upon the conditional CAPM’s ability to explain out-of-sample industry return predictability.

The Fama-French three-factor model (FF)-restricted principal component forecast of industry \(i\)’s excess return can be expressed as

\[
\hat{r}_{FF,PC}^{i,t+1} = \hat{\beta}_{FF}^{i,t} \hat{\lambda}_{FF}(x_t),
\]

where

\[
\hat{\beta}_{FF}^{i,t} = (\hat{\beta}_{MKT}^{i,t}, \hat{\beta}_{SMB}^{i,t}, \hat{\beta}_{HML}^{i,t})
\]

is a vector of industry \(i\)’s estimated factor betas based on data from 1946:01 through month \(t\) and

\[
\hat{\lambda}_{FF}(x_t) = (\hat{\lambda}_{MKT,t+1}, \hat{\lambda}_{SMB,t+1}, \hat{\lambda}_{HML,t+1})
\]

is a vector of principal component factor forecasts. We allow for time-varying betas by replacing \(\hat{\beta}_{FF}^{i,t}\) with \(\hat{\beta}_{FF,PC}^{i,t}\) in (17), where \(\hat{\beta}_{FF,PC}^{i,t}\) is based on (10).

As a prelude to reporting out-of-sample decompositions of the \(R_{i,OS}^2\) statistics using the FF-restricted forecasts, we note that the \(R_{i,OS}^2\) statistics for the principal component forecasts of returns

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\(^{18}\)Simulation experiments indicate that the evidence of significant beta pricing model and alpha predictability in Table 3 is not spurious. To assess the \(R_{i,OS}^2\) statistics in the second and seventh columns of Table 3, we simulated industry returns under the null hypothesis of constant expected excess returns for each industry. At least 26 (27) of the \(R_{i,OS}^2\) statistics were significant at the 5% (10%) level for only one (eight) of 500 pseudo samples, or 0.20% (1.60%) of the pseudo samples. With respect to the \(R_{i,OS}^2\) statistics in the third and eighth columns of Table 3, we simulated industry returns for a CAPM data-generating process (see the Appendix), and none of 500 pseudo samples produced at least five (eight) significant \(R_{i,OS}^2\) statistics at the 5% (10%) level.

\(^{19}\)Data for these factors are from Kenneth French’s Data Library.
on the SMB and HML portfolio-based factors are 4.53% and −0.88%, respectively. (The former is significant at the 5% level.) According to the $R^2_{i,\text{OS}}$ statistics, there is thus substantial out-of-sample predictability for SMB, but not HML. Our out-of-sample decomposition provides insight into whether the significant predictability of SMB helps to explain industry return predictability.

Table 4 reports decompositions of the $R^2_{i,\text{OS}}$ statistics in Table 2 for FF-restricted principal component forecasts with constant betas given in (17). Observe that 31 of the 33 $R^2_{i,\beta}$ statistics are positive (see the second and seventh columns of Table 4), and 26 (29) of these statistics are significant at the 5% (10%) level. A conditional multi-beta pricing model based on the three Fama-French factors thus delivers significantly more accurate forecasts than the historical average benchmark for a large proportion of industries.

Analogous to the logic of the conditional CAPM, and insofar as the conditional Fama-French model captures time-varying expected returns, we expect stronger out-of-sample return predictability for industries with greater (absolute) factor exposures. Regressing the $R^2_{i,FF}$ statistics from second and seventh columns of Table 4 on the time-series averages of the three factor exposures for each industry yields the estimated cross-sectional relationship,

$$R^2_{i,\beta} = -0.43 + 0.90\hat{\beta}^{\text{MKT}}_{i,t} + 2.69\hat{\beta}^{\text{SMB}}_{i,t} + 0.42\hat{\beta}^{\text{HML}}_{i,t}, \quad R^2 = 37\%,$$

where $\hat{\beta}^l_{i,t}$ is the time-series average of the $\hat{\beta}^l_{i,t}$ estimates ($l = \text{MKT}, \text{SMB}, \text{HML}$) and heteroskedasticity-consistent $t$-statistics are given in brackets.\textsuperscript{20} Equation (20) indicates that $R^2_{i,\beta}$ is positively related to exposures to all three size factors. The $t$-statistic is a substantial 4.17 for exposures to the size factor, although the $t$-statistics are not significant at conventional levels for exposures to the other two factors.

Recall from Table 3 that five of the 33 industry portfolios exhibited significant $R^2_{i,\alpha}$ statistics at the 5% level based on the conditional CAPM with constant betas. When we augment the conditional beta pricing model with the Fama-French size and value factors in the third and eighth columns of Table 4, only one of these $R^2_{i,\alpha}$ statistics remains significant. In particular, among the industries with significant $R^2_{i,\alpha}$ statistics at the 5% level in the third and eighth columns of Table 3, TXTLS, CHAIR, PRINT, and MANUF are no longer significant in the corresponding columns of Table 4. The conditional Fama-French model thus accounts for the out-of-sample alpha predictability evidenced in the conditional CAPM for these industries. The out-of-sample predictability of the size factor in conjunction with the results in (20) suggest that exposures to a time-varying size

\textsuperscript{20}We use the absolute value for $\bar{\hat{\beta}}^{\text{SMB}}_{i,t}$ and $\bar{\hat{\beta}}^{\text{HML}}_{i,t}$ in (20), since some of these time-series averages are negative. All of the average market exposures are positive.
risk premium are particularly important for improving the performance of the conditional CAPM. Only one industry, CARS, still displays statistically significant out-of-sample alpha predictability for the FF-restricted forecasts with constant betas. Using a 10% level, only three industries exhibit significant out-of-sample alpha predictability in the third and eighth columns of Table 4, compared to eight in the corresponding columns of Table 3.\footnote{Simulation experiments indicate that the significant evidence of beta pricing model predictability according to the \( R_i^{2,\beta} \) statistics in the second and seventh columns of Table 4 is not spurious. In 500 pseudo samples generated under the null hypothesis of constant expected excess returns for all industries, zero (six) of the pseudo samples produced at least 26 (29) or more significant \( R_i^{2,\beta} \) statistics at the 5% (10%) level, or 0% (1.20%) of the pseudo samples. With respect to alpha predictability and the \( R_i^{2,\alpha} \) statistics in the third and eighth columns of Table 4, we simulated industry returns based on the Fama-French model. For 500 pseudo samples, 47 (six) yielded at least one (three) significant \( R_i^{2,\alpha} \) statistic(s) at the 5% (10%) level, or 9.40% (1.20%) of the pseudo samples.}

The fourth and ninth (fifth and tenth) columns of Table 4 report \( R_{i,OS}^{2,\beta} \) (\( R_{i,OS}^{2,\alpha} \)) statistics for FF-restricted principal component forecasts that allow for time-varying factor exposures. Actually, allowing for time-varying betas often leads to a deterioration in FF-restricted principal component forecasts. For example, two (seven) of the \( R_{i,OS}^{2,\alpha} \) statistics are significant at the 5% (10%) level in the fifth and tenth columns of Table 4, compared to one (three) in the third and eighth columns. The FF-restricted forecasts with time-varying betas likely introduce too many additional parameters to estimate, thereby detracting from forecasting performance vis-\-á-vis FF-restricted forecast with constant betas.

In sum, the results in Table 4 show that a conditional version of the Fama-French three-factor model with constant betas goes a very long way toward accounting for out-of-sample return predictability in industry portfolios. From this perspective, the glass is essentially full with respect to accounting for out-of-sample industry return predictability. We reiterate that an out-of-sample approach is particularly useful for establishing the relevance of the conditional Fama-French model for explaining industry return predictability. This model augments the conditional CAPM with additional factors, so that the conditional Fama-French model would likely fare poorly in out-of-sample tests if it introduces largely extraneous factors, especially when trying to explain returns on portfolios not formed on the basis of size and value sorts. The fact that the FF-restricted principal component forecasts are successful in explaining out-of-sample return predictability across industries thus constitutes strong support for the conditional Fama-French model.
3.3.3. Additional Results

A conditional version of the Fama-French model with constant betas accounts for out-of-sample return predictability in nearly all industries. To further evaluate the sources of industry return predictability, we consider variations of the Fama-French model. In particular, we consider beta pricing-restricted principal component forecasts (with constant betas) based on four variants of the Fama-French model:

- Conditional Carhart (1997) model (FF+MOM). This is a conditional version of the Carhart (1997) four-factor model. This model augments the Fama-French model with a portfolio-based factor defined as the return on a zero-investment portfolio that is long (short) in stocks with the highest (lowest) returns over the previous year, designed to capture the momentum effect documented by Jegadeesh and Titman (1993).\(^{22}\)

- Conditional Pástor and Stambaugh (2003) model (FF+LIQ). This is a conditional version of a four-factor model that augments the Fama-French model with a portfolio-based factor defined as the return on a zero-investment portfolio that goes long (short) in relatively illiquid (liquid) stocks.\(^{23}\) Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Liu (2006) recently provide empirical evidence that a liquidity factor helps to explain the cross section of average returns for a variety of portfolios.

- Conditional two-factor model (MKT+SMB).

- Conditional one-factor model (SMB).

The FF+MOM and FF+LIQ models augment the Fama-French model with momentum and liquidity factors, respectively. Momentum and liquidity are leading candidates for priced risk factors in stock returns. The two-factor model omits HML from the Fama-French model. We consider this model because, as reported above, the HML principal component forecast does not outperform the historical average forecast. We thus expect that excluding this factor from the conditional Fama-French model will have little effect on accounting for industry return predictability. The final model, SMB, isolates the role of the size factor. Using the methodology from Section 2.3, we form beta pricing-restricted principal component forecasts based on each of these four models. For the FF+MOM and FF+LIQ models, we compute principal component forecasts of the momentum

\(^{22}\)Momentum factor data are from Kenneth French’s Data Library.

\(^{23}\)Liquidity factor data are from Lúboš Pastor’s web page at http://faculty.chicagobooth.edu/lubos.pastor/research/.
and liquidity factors to go along with the principal component forecasts of the aggregate market, size, and value factors. Industry $R_{i,OS}^{2,\alpha}$ statistics corresponding to beta pricing-restricted forecasts based on each model are reported in Table 5.  

The second and seventh columns of Table 5 show that the inclusion of a momentum factor has little effect on the pattern of out-of-sample alpha predictability across industries. Only one (three) of the $R_{i,OS}^{2,\alpha}$ statistics is (are) significant at the 5% (10%) level, matching the number of significant $R_{i,OS}^{2,\alpha}$ statistics for the conditional Fama-French model in Table 4. It is perhaps not surprising that the two models produce such similar results in terms of out-of-sample alpha predictability, since the conditional Fama-French model already accounts for nearly all of the out-of-sample predictability in industry returns. Furthermore, the momentum factor itself is not predictably, with an $R_{i,OS}^{2}$ of −0.11%.

The principal component forecast for the liquidity factor has a sizable $R_{i,OS}^{2}$ of 3.80%, indicating relatively strong predictability for the liquidity factor. Nevertheless, augmenting the conditional Fama-French model with a liquidity factor has little effect on the $R_{i,OS}^{2,\alpha}$ statistics (see the third and eighth columns of Table 5). Two (three) of the $R_{i,OS}^{2}$ statistics are significant at the 5% (10%) level, compared to one (three) for the conditional Fama-French model. The similar results for the two models are perhaps again not surprising, since the conditional Fama-French model already explains so much of industry return predictability.

The results for the conditional MKT+SMB model in the fourth and ninth columns of Table 5 indicate that excluding the HML factor from the conditional Fama-French model has little effect. CARS (FOOD and CARS) have significant $R_{i,OS}^{2,\alpha}$ statistics at the 5% (10%) level for both the conditional MKT+SMB and Fama-French models. While it is significant at the 10% level for the Fama-French model, the $R_{i,OS}^{2,\alpha}$ for TXTLS is actually insignificant at the 10% level for the MKT+SMB model, although the statistics are similar in magnitude. Recall that the HML principal component forecast has an $R_{i,OS}^{2}$ statistic of −0.88%, helping to explain the insensitivity of the performance of the conditional Fama-French model to the inclusion of the HML factor. While including the HML factor has little effect, the results in the fifth and tenth columns of Table 5 show that it is important to include the aggregate market factor, since 13 (18) of the $R_{i,OS}^{2,\alpha}$ statistics are significant at the 5% (10%) level for the conditional SMB model. Overall, the results in Table 5 underscore the leading roles played by exposures to time-varying aggregate market and size risk premiums in explaining industry return predictability.

\[^{24}\text{For brevity, we do not report the } R_{i,OS}^{2,\beta} \text{ statistics. They are available upon request from the authors.}\]
4. Industry-rotation investment strategies

Asset allocation provides another perspective for assessing the economic significance of out-of-sample industry return predictability. Studies such as Kandel and Stambaugh (1996), Barberis (2000), Hong, Torous, and Valkanov (2007), and Campbell and Thompson (2008) analyze the importance of aggregate market return predictability for asset allocation, while Avramov (2004) and Avramov and Chordia (2006) investigate the relevance of component return predictability for portfolio management. Along the lines of these studies, we measure gains for investors who utilize principal component forecasts of industry returns when forming portfolios.

An informative context for analyzing the value of industry return predictability for investors is a “130-30” industry-rotation portfolio. 130-30 portfolios are increasing in popularity and provide an accessible alternative to more passive long-only strategies for many investors (e.g., Lo and Patel, 2008). Specifically, we consider an investment strategy that first uses information through month \( t \) to identify the five industries with the highest forecasted returns and the five industries with the lowest forecasted returns for month \( t + 1 \). The 130-30 industry-rotation portfolio then employs equal weights of \( 1.3/5 \) (\(-0.3/5\)) for the five industries with the highest (lowest) forecasted returns and zero weights for the remaining industries for month \( t + 1 \).\(^{25}\) This portfolio thus rotates toward (away from) industries with relatively high (low) expected returns. We assess the economic value of industry return forecasts by comparing the performances of 130-30 industry-rotation portfolios formed from different sets of industry return forecasts.

Table 6 reports a variety of performance measures for 130-30 industry-rotation portfolios based on historical average, unrestricted, CAPM-restricted, and FF-restricted forecasts of industry excess returns for 1966:01–2008:12.\(^{26}\) For reference, we also report performance measures for a portfolio that passively holds the aggregate market. This buy-and-hold market portfolio has an average monthly excess return of 0.34% and a Sharpe ratio of 0.08. The second column of Table 6 shows that the portfolio based on the unrestricted principal component forecasts has a higher average monthly excess return than the portfolio based on the historical average forecasts (0.83% versus 0.43%). The portfolio based on the unrestricted forecasts is only slightly more volatile, so that the Sharpe ratio nearly doubles (0.14 versus 0.08) in the fourth column. The substantially higher Sharpe ratio for the unrestricted forecasts vis-à-vis the historical average forecasts in Table 6 in-

\(^{25}\)Our results are not very sensitive to the size of the groups. For example, we obtain similar results for portfolios that employ weights of \( 1.3/3 \) (\(-0.3/3\)) for the three industries with the highest (lowest) forecasted returns.

\(^{26}\)FF-restricted forecasts perform very similarly to beta pricing-restricted forecasts based on a conditional Fama-French model that excludes the HML factor. We omit the results for the latter model for brevity.
dicates sizable economic gains from exploiting industry return predictability, since the portfolio based on unrestricted principal component forecasts that incorporate information from 47 potential predictors outperforms the portfolio based on historical average forecasts that assume constant expected returns.

Observe from the fourth column of Table 6 that the portfolio based on the CAPM-restricted principal component forecasts has a Sharpe ratio equal to that of the portfolio based on the historical average forecasts. From this perspective, the CAPM-restricted forecasts thus fail to outperform the historical average forecasts and are substantially outperformed by the unrestricted forecasts. In contrast, the portfolio formed from the FF-restricted principal component forecasts delivers a Sharpe ratio of 0.15, which is slightly above the ratio for the unrestricted forecasts. The decompositions of the unrestricted forecasts in Table 4 demonstrate the ability of the conditional Fama-French model to explain out-of-sample industry return predictability in terms of $R^2_{i,OS}$ statistics; analogously, the similar Sharpe ratios for the unrestricted and FF-restricted forecasts in Table 6 demonstrate this in terms of portfolio performance.

Following Hong, Torous, and Valkanov (2007), we also measure portfolio performance for an investor with utility $U(1+R_{p,t})$, where $R_{p,t}$ is the portfolio return, $U(x) = x^{1-\gamma}/(1-\gamma)$, and $\gamma$ is the coefficient of relative risk aversion. For a given portfolio, we calculate utility for each month during 1966:01–2008:12, take the average, and invert it to compute the certainty equivalent return (CER).\footnote{That is, we compute the CER as $[(1-\gamma)\bar{U}]^{1/(1-\gamma)} - 1$, where $\bar{U}$ is average utility.} The fifth column of Table 6 reports the CER for an investor with $\gamma = 3$. The annualized CER is 5.12% for an investor who relies on the historical average forecasts. This is somewhat below the CER for an investor who holds the aggregate market portfolio (5.89%) and only around half of the CER for an investor who utilizes the unrestricted principal component forecasts (9.26%). Again, economically sizable gains accrue to an investor who exploits industry return predictability through the unrestricted principal component forecasts. An investor who uses the CAPM-restricted principal component forecasts only realizes a CER of 4.30%. In contrast, the FF-restricted principal component forecasts generate the highest CER in Table 6 (9.93%), approximately 60 basis points higher than the unrestricted forecasts, further demonstrating the capacity of the conditional Fama-French model to account for out-of-sample industry return predictability.

Finally, we compute Lo’s (2008) active ratio for each of the 130-30 portfolios. Under a standard set of stationarity assumptions, Lo (2008) decomposes the expected portfolio return into two
components:

\[ E(R_{p,t}) = \sum_{i=1}^{N} E(w_{i,t}R_{i,t}) = \sum_{i=1}^{N} Cov(w_{i,t}, R_{i,t}) + \sum_{i=1}^{N} E(w_{i,t})E(R_{i,t}), \tag{21} \]

where \( w_{i,t} \) \( (R_{i,t}) \) is the time-\( t \) weight (return) on asset \( i \),

\[ \sum_{i=1}^{N} Cov(w_{i,t}, R_{i,t}) = \delta_p \tag{22} \]

represents the portfolio’s active component, and

\[ \sum_{i=1}^{N} E(w_{i,t})E(R_{i,t}) = \nu_p \tag{23} \]

represents the passive component. The active ratio is then defined as

\[ \theta_p = \frac{\delta_p}{\delta_p + \nu_p}. \tag{24} \]

Intuitively, \( \theta_p \) measures the portfolio’s timing ability. If a portfolio has a \( \theta_p \) of zero, then the same expected return could be realized by simply passively holding the individual assets in accord with the portfolio’s average weights. When \( \theta_p > 0 \), the portfolio displays timing acumen in the sense of temporarily increasing (decreasing) allocations to assets during periods of higher-than-average (lower-than-average) returns. When \( \theta_p < 0 \), a higher expected return would prevail by avoiding the portfolio’s timing attempts entirely and passively holding the individual assets using the portfolio’s average weights. From our standpoint, we are interested in determining the extent to which principal component forecasts display timing ability in the context of the 130-30 industry-rotation portfolios.

To estimate the active ratio for a given portfolio, we compute sample versions of the moments in (22)–(23) for the time series of portfolio weights and asset returns and plug these sample moments into (24). Lo (2008) provides a GMM-based \( t \)-statistic for (24). The last column of Table 6 reports active ratio estimates for the 130-30 industry-rotation portfolios. The active ratio is significantly negative for the historical average forecasts \(-20.69\%\). Since the historical average forecasts assume constant expected returns, there is relatively little rotation among industries; the negative active ratio indicates that the limited rotation that does take place actually lowers the portfolio’s return. The unrestricted principal component forecasts produce an active ratio of nearly 24\%, which is clearly significant. We thus observe significantly enhanced timing for a portfolio that exploits return predictability relative to a portfolio that assumes constant expected returns, again highlighting the relevance of out-of-sample industry return predictability for investors.
The CAPM-restricted and FF-restricted forecasts deliver significant active ratios of 14.58% and 38.19%, respectively. The former is below and the latter above the active ratio for the unrestricted forecasts. The substantial positive active ratio for the FF-restricted forecasts is yet another piece of evidence supporting the usefulness of the conditional Fama-French model for explaining industry return predictability.

5. Conclusion

We investigate out-of-sample return predictability for 33 industry portfolios based on a principal component approach that incorporates information from a broad range of potential predictors. Four major findings emerge from our analysis. First, excess returns are significantly predictable on an out-of-sample basis for a clear majority of industries. Second, while significant out-of-sample industry return predictability is widespread, there are substantial differences in the degree of return predictability across industries, with industries such as TXTLS, CHAIR, PRINT, CARS, APPRL, MANUF, and WHLSL exhibiting the strongest degree of return predictability. Third, an out-of-sample decomposition shows that a conditional version of the popular Fama-French three-factor model accounts for nearly all of industry return predictability. In particular, exposures to time-varying market and size premiums appear central to understanding differences in return predictability across industries. Fourth, incorporating out-of-sample industry return predictability can substantially improve the performance of 130-30 industry-rotation portfolios, demonstrating the economic significance of industry return predictability from an asset allocation perspective.

Our results have a number of important implications. The widespread evidence of return predictability across industries indicates that numerous industries are characterized by time-varying expected returns—and thus a time-varying cost of capital. Efficiently allocating capital across industries requires that investment decisions reflect variations in the cost of capital over time. It would be interesting in future research to examine if industry investment expenditures are systematically related to fluctuations in industry expected returns as measured by our approach.

Furthermore, the ability of a conditional version of the Fama-French model to account for differences in return predictability across industries suggests that the model’s factors capture important sources of systemic risk. In particular, we find that the out-of-sample predictability of the aggregate market and size factors in conjunction with industry exposures to these factors effectively explains industry return predictability. In light of this, it is natural to interpret the predictable fluctuations in the aggregate market and size factors as key time-varying macroeconomic risk pre-
miums. The fact that we find support for the conditional Fama-French model using out-of-sample tests, as well as portfolios not sorted on size and value, provides strong support for this interpretation.

Finally, our results have implications for establishing the appropriate benchmarks for managed portfolios employing sector-rotation strategies. For example, a mutual fund could temporarily earn higher-than-average returns by allocating large shares to industries with relatively high time-varying expected returns. These higher-than-average returns, however, are not necessarily unexpected or “abnormal” when industry returns are predictable. In general, it would be interesting in future research to test whether mutual funds, especially those specializing in industry-rotation strategies, earn abnormal returns after accounting for the predictability in industry returns documented in the present paper.
Appendix

This appendix describes the bootstrap procedures used in the numerical simulations. For the simulations in Section 3.2 corresponding to Table 2, we generate 500 pseudo samples of size $T = 756$ (matching the size of the 1946:01–2008:12 sample) for the $N = 33$ industry excess returns. Since the historical average forecast serves as the benchmark for the $R_{i,OS}^2$ statistic, the pseudo samples are generated under the null hypothesis of constant expected excess returns (no predictability) for each industry. Let $r_t = (r_{1,t}, \ldots, r_{N,t})'$ denote the $N$-vector of time-$t$ industry excess return observations and concatenate the $T$ industry excess return vectors into an $N \times T$ matrix, $R = (r_1, \ldots, r_T)$. We construct a time-$t$ $N$-vector of pseudo observations for industry excess returns as $r^*_t$, where $r^*_t$ is a randomly drawn $N$-vector from the columns of $R$. By drawing an entire column from $R$, we retain the contemporaneous correlation structure in the original data. After making $T$ random draws (with replacement) from the columns of $R$, we can construct an $N \times T$ matrix of pseudo industry excess return observations under the assumption of no predictability: $R^* = (r^*_1, \ldots, r^*_T)$. We use this procedure to simulate 500 pseudo samples. For each pseudo sample, we calculate historical average and principal component forecasts for each industry, where the latter are based on recursively estimated principal components from the original sample, so that the procedure can be viewed as a fixed-regressor bootstrap. We also calculate industry $R_{i,OS}^2$ statistics and corresponding Clark and West (2007) $p$-values for each pseudo sample, storing the number of $p$-values in each pseudo sample that are less than 5% and 10%, respectively. We then count the number of pseudo samples with 20 (26) or more $p$-values less than 5% (10%), where 20 (26) corresponds to the number of significant $R_{i,OS}^2$ statistics significant at the 5% (10%) level in Table 2.

We perform two sets of simulations for the $R_{i,OS}^{2,\beta}$ and $R_{i,OS}^{2,\alpha}$ statistics based on the CAPM-restricted principal component forecasts in Table 3 (see footnote 18). The first set of simulations corresponds to the $R_{i,OS}^{2,\beta}$ statistics. Since the historical average forecast again serves as the benchmark for the $R_{i,OS}^{2,\beta}$ statistic, we use the same procedure described above to generate pseudo observations of industry excess returns under the null hypothesis of constant expected excess returns for each industry. We simulate 500 pseudo samples; for each pseudo sample, we compute historical average and CAPM-restricted principal component (with constant betas) forecasts, $R_{i,OS}^{2,\beta}$ statistics, and Clark and West (2007) $p$-values for each industry. The CAPM-restricted principal component forecasts are computed using recursively estimated principal components and excess market returns from the original sample. We store the number of $p$-values less than 5% and 10%,
respectively, for each pseudo sample and count the number of pseudo samples with 26 (27) or more p-values less than 5% (10%), where 26 (27) is the number of $R_{i, OS}^2$ statistics significant at the 5% (10%) level in Table 3.

The second set of simulations corresponds to the $R_{i, OS}^2, \beta_i, OS$ statistics in Table 3. For the $R_{i, OS}^2, \alpha_i, OS$ statistic, the CAPM-restricted principal component forecast serves as the baseline, so that we generate pseudo observations of industry excess returns under the CAPM. Let $\hat{\beta} = (\hat{\beta}_1, \ldots, \hat{\beta}_N)'$ represent the $N$-vector of OLS estimates of the market betas for all of the industries based on the 1946:01–2008:12 sample. The $N \times T$ matrix of OLS residuals for the CAPM can then be denoted by $\hat{E}_{CAPM} = R - \hat{\beta} r_{MKT}'$. After drawing with replacement from the columns of $\hat{E}_{CAPM}$, gathering the draws in the $N \times T$ matrix $E_{CAPM}^*$, and re-centering $E_{CAPM}^*$ so that the mean of each row of $E_{CAPM}^*$ is zero, we construct an $N \times T$ matrix of pseudo observations for the industry excess returns as $R_{CAPM}^* = \hat{\beta} r_{MKT}' + E_{CAPM}^*$. We simulate 500 pseudo samples; for each pseudo sample, we compute CAPM-restricted and unrestricted principal component forecasts, $R_{i, OS}^2, \alpha_i, OS$ statistics, and Clark and West (2007) p-values for each industry, storing the number of industries with p-values less than 5% and 10%, respectively, for each pseudo sample. The CAPM-restricted principal component forecasts are again computed using recursively estimated principal components and excess market returns from the original sample. We count the number of pseudo samples with five (eight) or more p-values less than 5% (10%), since there are five (eight) $R_{i, OS}^2, \alpha_i, OS$ statistics that are significant at the 5% (10%) level in Table 3.

The two sets of simulations for the $R_{i, OS}^2, \beta_i, OS$ and $R_{i, OS}^2, \alpha_i, OS$ statistics in Table 4 (see footnote 21) use procedures similar to those for the $R_{i, OS}^2, \beta_i, OS$ and $R_{i, OS}^2, \alpha_i, OS$ statistics in Table 3. The procedures are modified in obvious ways to account for the additional factors in the Fama-French model vis-à-vis the CAPM.
References


Clark, T.E., McCracken, M.W., 2001. Tests of equal forecast accuracy and encompassing for


Table 1
Summary statistics, monthly industry portfolio excess returns, 1966:01–2008:12

The table reports summary statistics for the 1966:01–2008:12 forecast evaluation period for excess returns on 33 value-weighted industry portfolios from Kenneth French’s Data Library. MKT is the CRSP value-weighted aggregate market portfolio. Excess returns are computed relative to the CRSP risk-free rate. ρ is the autocorrelation coefficient. Average corresponds to the average across the 33 industry portfolios.

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<tr>
<th>Industry portfolio</th>
<th>Mean (%)</th>
<th>Std. dev. (%)</th>
<th>Min. (%)</th>
<th>Max. (%)</th>
<th>Sharpe ratio</th>
<th>ρ</th>
<th>Industry portfolio</th>
<th>Mean (%)</th>
<th>Std. dev. (%)</th>
<th>Min. (%)</th>
<th>Max. (%)</th>
<th>Sharpe ratio</th>
<th>ρ</th>
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<td>0.17</td>
<td>TV</td>
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<td>0.18</td>
</tr>
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<td>−0.01</td>
<td>UTILS</td>
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<td>18.22</td>
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<td>0.06</td>
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<td>WHLSL</td>
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<td>−0.07</td>
<td>MONEY</td>
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<td>−22.40</td>
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<td>0.13</td>
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<td>RUBBR</td>
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<td>−32.78</td>
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<td>0.07</td>
<td>0.08</td>
<td>SRVC</td>
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<td>27.88</td>
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<td>0.12</td>
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Table 2
\( R_{i,OS}^2 \) statistics (in percent), out-of-sample industry portfolio excess return forecasts, 1966:01–2008:12

The table reports the Campbell and Thompson (2008) out-of-sample \( R^2 \) statistic, \( R_{i,OS}^2 \) (in percent), for principal component forecasts of industry portfolio excess returns. MKT is the CRSP value-weighted aggregate market portfolio. \( R_{i,OS}^2 \) measures the percent reduction in mean square prediction error for the principal component forecast relative to the historical average forecast. The principal component forecast is generated from a recursively estimated predictive regression model based on the first two principal components of 14 economic variables and 33 lagged industry returns. Statistical significance of \( R_{i,OS}^2 \) is based on the Clark and West (2007) MSPE-adjusted statistic corresponding to \( H_0: R_{i,OS}^2 = 0 \) against \( H_1: R_{i,OS}^2 > 0 \). * and ** indicate significance at the 10% and 5% levels, respectively. Average corresponds to the average \( R_{i,OS}^2 \) across the 33 industry portfolios. # > 0, # sig.(5%), and # sig.(10%) signify the number of industry \( R_{i,OS}^2 \) statistics that are positive, significant at the 5% level, and significant at the 10% level, respectively.

<table>
<thead>
<tr>
<th>Industry portfolio</th>
<th>(1) ( R_{i,OS}^2 ) (%)</th>
<th>(2) ( R_{i,OS}^2 ) (%)</th>
<th>(3) ( R_{i,OS}^2 ) (%)</th>
<th>(4) ( R_{i,OS}^2 ) (%)</th>
<th>(5) ( R_{i,OS}^2 ) (%)</th>
</tr>
</thead>
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<tr>
<td>AGRIC</td>
<td>1.09**</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>MINES</td>
<td>−0.10</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>OIL</td>
<td>−0.49</td>
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<td></td>
</tr>
<tr>
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<tr>
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<tr>
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<td>3.30**</td>
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</tr>
<tr>
<td>WOOD</td>
<td>0.77**</td>
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<tr>
<td>CHAIR</td>
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<tr>
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<tr>
<td># sig.(5%)</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># sig.(10%)</td>
<td>26</td>
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</table>
The table reports decompositions of the $R_{i,t}^{2,\beta}$ statistics in the second, fourth, and sixth columns of Table 2 into $R_{i,t}^{2,\beta}$ and $R_{i,t}^{2,\alpha}$. $R_{i,t}^{2,\beta}$ measures the percentage point reduction in MSPE for the CAPM-restricted principal component industry excess return forecast relative to the historical average industry excess return forecast. The CAPM-restricted principal component forecast employs a principal component MKT forecast—generated from a recursively estimated predictive regression model based on the first two principal components of 14 economic variables and 33 lagged industry returns—and recursively estimated betas for each industry. $R_{i,t}^{2,\alpha}$ measures the percentage point reduction in MSPE for the unrestricted principal component industry excess return forecast relative to the CAPM-restricted principal component industry excess return forecast. The unrestricted principal component forecast is generated from a recursively estimated predictive regression model based on the first two principal components of the 14 economic variables and 33 lagged industry returns. Statistical significance of $R_{i,t}^{2,\beta}$ ($R_{i,t}^{2,\alpha}$) is based on the Clark and West (2007) MSPE-adjusted statistic corresponding to a test of $H_0$: $R_{i,t}^{2,\beta} = 0$ ($R_{i,t}^{2,\alpha} = 0$) against $H_1$: $R_{i,t}^{2,\beta} > 0$ ($R_{i,t}^{2,\alpha} > 0$). * and ** indicate significance at the 10% and 5% levels, respectively. The CAPM-restricted forecasts in the second, third, seventh, and eighth (fourth, fifth, ninth, and tenth) columns assume constant (time-varying) betas. Average corresponds to the average $R_{i,t}^{2,\beta}$ or $R_{i,t}^{2,\alpha}$ across the 33 industry portfolios. # > 0, # sig.(5%), and # sig.(10%) signify the number of industry $R_{i,t}^{2,\beta}$ or $R_{i,t}^{2,\alpha}$ statistics that are positive, significant at the 5% level, and significant at the 10% level, respectively.

<table>
<thead>
<tr>
<th>Industry portfolio</th>
<th>$R_{i,t}^{2,\beta}$ (%</th>
<th>$R_{i,t}^{2,\alpha}$ (%)</th>
<th>$R_{i,t}^{2,\beta}$ (%)</th>
<th>$R_{i,t}^{2,\alpha}$ (%)</th>
<th>Industry portfolio</th>
<th>$R_{i,t}^{2,\beta}$ (%</th>
<th>$R_{i,t}^{2,\alpha}$ (%)</th>
<th>$R_{i,t}^{2,\beta}$ (%)</th>
<th>$R_{i,t}^{2,\alpha}$ (%)</th>
</tr>
</thead>
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<td>1.32**</td>
<td>0.24</td>
<td>GLASS</td>
<td>2.06**</td>
<td>0.53</td>
<td>2.07**</td>
<td>0.51</td>
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<tr>
<td>MINES</td>
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<td>0.35**</td>
<td>-0.45</td>
<td>METAL</td>
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<td>-0.50</td>
<td>0.64**</td>
<td>-0.59</td>
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<td>-1.18</td>
<td>0.61**</td>
<td>-1.11</td>
<td>MTLPR</td>
<td>1.57**</td>
<td>-0.01</td>
<td>1.53**</td>
<td>0.03</td>
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<td>1.83**</td>
<td>-0.36</td>
<td>MACHN</td>
<td>1.00**</td>
<td>-0.50</td>
<td>0.97**</td>
<td>-0.47</td>
</tr>
<tr>
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<td>0.18</td>
<td>2.04**</td>
<td>0.29**</td>
<td>ELCTR</td>
<td>0.75**</td>
<td>-0.33</td>
<td>0.65**</td>
<td>-0.23</td>
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<tr>
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<td>0.23</td>
<td>-0.01</td>
<td>0.39**</td>
<td>CARS</td>
<td>2.75**</td>
<td>0.78**</td>
<td>2.84**</td>
<td>0.69**</td>
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<td>-0.45</td>
<td>0.03</td>
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<td>-0.02</td>
<td>1.99**</td>
<td>-0.02</td>
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<td>2.35**</td>
<td>3.19**</td>
<td>2.32**</td>
<td>MANUF</td>
<td>2.54**</td>
<td>0.49**</td>
<td>2.57**</td>
<td>0.47**</td>
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<tr>
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<td>2.91**</td>
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<td>-0.31</td>
<td>1.39**</td>
<td>-0.31</td>
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<tr>
<td>WOOD</td>
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<td>0.94**</td>
<td>-0.17</td>
<td>PHONE</td>
<td>-0.09</td>
<td>-0.30</td>
<td>-0.13</td>
<td>-0.26</td>
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<td>1.23**</td>
<td>2.60**</td>
<td>1.27**</td>
<td>TV</td>
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<td>-0.10</td>
<td>2.35**</td>
<td>-0.08</td>
</tr>
<tr>
<td>PAPER</td>
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<td>0.62**</td>
<td>-0.30</td>
<td>UTILS</td>
<td>0.10</td>
<td>0.16</td>
<td>-0.02</td>
<td>0.28</td>
</tr>
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<td>PRINT</td>
<td>3.23**</td>
<td>0.46**</td>
<td>3.16**</td>
<td>0.53**</td>
<td>WHLSL</td>
<td>2.46**</td>
<td>0.31**</td>
<td>2.55**</td>
<td>0.22**</td>
</tr>
<tr>
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<td>0.34</td>
<td>-0.08</td>
<td>0.36</td>
<td>RTAIL</td>
<td>1.19**</td>
<td>-0.21</td>
<td>1.22**</td>
<td>-0.24</td>
</tr>
<tr>
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<td>0.18</td>
<td>-0.34</td>
<td>0.28</td>
<td>MONEY</td>
<td>1.16**</td>
<td>-0.32</td>
<td>1.13**</td>
<td>-0.28</td>
</tr>
<tr>
<td>RUBBR</td>
<td>1.35**</td>
<td>0.04</td>
<td>1.42**</td>
<td>-0.03</td>
<td>SRVC</td>
<td>1.48**</td>
<td>-0.67</td>
<td>1.49**</td>
<td>-0.68</td>
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<td>1.49**</td>
<td>-0.02</td>
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</table>

Average 1.38 -0.02 1.36 0.01
# > 0 29 15 27 15
# sig.(5%) 26 5 26 5
# sig.(10%) 27 8 27 9
Table 4

$R_{t,OS}^4$ decompositions for industry portfolio excess returns based on a conditional Fama-French three-factor model, 1966:01–2008:12

The table reports decompositions of the $R_{t,OS}^4$ statistics in the second, fourth, and sixth columns of Table 2 into $R_{t,OS}^{2,β}$ and $R_{t,OS}^{2,α}$. $R_{t,OS}^{2,β}$ measures the percentage point reduction in MSPE for the Fama-French three-factor model (FF)-restricted principal component industry excess return forecast relative to the historical average industry excess return forecast. The FF-restricted principal component forecast employs principal component MKT, SMB, and HML forecasts—generated from recursively estimated predictive regression models based on the first two principal components of 14 economic variables and 33 lagged industry returns—and recursively estimated betas for each industry. $R_{t,OS}^{2,α}$ measures the percentage point reduction in MSPE for the unrestricted principal component industry excess return forecast relative to the FF-restricted principal component industry excess return forecast. The unrestricted principal component forecast is generated from a recursively estimated predictive regression model based on the first two principal components of the 14 economic variables and 33 lagged industry returns. Statistical significance of $R_{t,OS}^{2,β}$ ($R_{t,OS}^{2,α}$) is based on the Clark and West (2007) MSPE-adjusted statistic corresponding to a test of $H_0$: $R_{t,OS}^{2,β} = 0$ ($R_{t,OS}^{2,α} = 0$) against $H_1$: $R_{t,OS}^{2,β} > 0$ ($R_{t,OS}^{2,α} > 0$). * and ** indicate significance at the 10% and 5% levels, respectively. The FF-restricted forecasts in the second, third, seventh, and eighth (fourth, fifth, ninth, and tenth) columns assume constant (time-varying) betas. Average corresponds to the average $R_{t,OS}^{2,β}$ or $R_{t,OS}^{2,α}$ across the 33 industry portfolios. # > 0, # sig.(5%), and # sig.(10%) signify the number of industry $R_{t,OS}^{2,β}$ or $R_{t,OS}^{2,α}$ statistics that are positive, significant at the 5% level, and significant at the 10% level, respectively.

<table>
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<th>Industry portfolio</th>
<th>Constant betas $R_{t,OS}^{2,β}$ (%)</th>
<th>Time-varying betas $R_{t,OS}^{2,β}$ (%)</th>
<th>$R_{t,OS}^{2,α}$ (%)</th>
<th>$R_{t,OS}^{2,α}$ (%)</th>
<th>Constant betas $R_{t,OS}^{2,β}$ (%)</th>
<th>Time-varying betas $R_{t,OS}^{2,β}$ (%)</th>
<th>$R_{t,OS}^{2,α}$ (%)</th>
<th>$R_{t,OS}^{2,α}$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGRIC</td>
<td>1.32**</td>
<td>−0.23</td>
<td>1.24**</td>
<td>−0.15</td>
<td>GLASS</td>
<td>2.47**</td>
<td>0.10</td>
<td>2.34**</td>
</tr>
<tr>
<td>MINES</td>
<td>0.34 −0.44</td>
<td>0.02 −0.11</td>
<td>0.22**</td>
<td>−0.16</td>
<td>METAL</td>
<td>1.13**</td>
<td>0.43</td>
<td>0.10</td>
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<tr>
<td>OIL</td>
<td>0.76** −1.26</td>
<td>0.76** −1.26</td>
<td>1.48**</td>
<td>0.08</td>
<td>MTLPR</td>
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<td>MACHN</td>
<td>0.66**</td>
<td>−0.24</td>
<td>0.52**</td>
</tr>
<tr>
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<td>0.66**</td>
<td>−0.24</td>
<td>ELCTR</td>
<td>1.04**</td>
<td>0.97</td>
<td>−0.10</td>
</tr>
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<td>2.73**</td>
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<td>CARS</td>
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<td>0.84**</td>
<td></td>
</tr>
<tr>
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<td>−2.21</td>
<td>INSTR</td>
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<td>−2.00</td>
<td></td>
</tr>
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<td>4.48** 1.01*</td>
<td>3.22**</td>
<td>−0.21</td>
<td>MANUF</td>
<td>3.04**</td>
<td>−0.02</td>
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<td>0.88**</td>
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<td>0.06</td>
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<tr>
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<td>0.29</td>
<td>−0.68</td>
<td>PHONE</td>
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<td>−0.62</td>
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</tr>
<tr>
<td>CHAIR</td>
<td>3.57** 0.27</td>
<td>2.98** 0.88*</td>
<td>2.28**</td>
<td>−0.01</td>
<td>TV</td>
<td>2.08**</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td>PAPER</td>
<td>0.66** −0.34</td>
<td>0.46** −0.13</td>
<td>0.46</td>
<td>−0.20</td>
<td>UTILS</td>
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<td>0.93*</td>
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</tr>
<tr>
<td>PRINT</td>
<td>3.56** 0.12</td>
<td>3.46** 0.23*</td>
<td>2.65**</td>
<td>0.12</td>
<td>WHLSL</td>
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</tr>
<tr>
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<td>0.26** 0.02</td>
<td>0.16** 0.12</td>
<td>1.21**</td>
<td>−0.23</td>
<td>RTAIL</td>
<td>0.95**</td>
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<td>0.97** −1.04</td>
<td>0.96**</td>
<td>−0.11</td>
<td>MONEY</td>
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<td>0.17</td>
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<tr>
<td>RUBBR</td>
<td>1.38** 0.01</td>
<td>1.34** 0.06*</td>
<td>0.55**</td>
<td>0.27</td>
<td>SRVC</td>
<td>0.66**</td>
<td>0.16</td>
<td></td>
</tr>
<tr>
<td>LETHR</td>
<td>2.13** −0.67</td>
<td>2.43** −0.98</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Average            | 1.55 −0.19                         | 1.42 −0.06                           |                     |                     |                                     |                                     |                     |                     |
| # > 0              | 31                                | 13                                  | 30                  | 17                  |                                     |                                     |                     |                     |
| # sig.(5%)         | 26                                | 1                                  | 23                  | 2                   |                                     |                                     |                     |                     |
| # sig.(10%)        | 29                                | 3                                  | 27                  | 8                   |                                     |                                     |                     |                     |
Table 5
\( R^2_{i,OS} \) statistics for industry portfolio excess returns based on various conditional beta pricing models, 1966:01–2008:12

The table reports \( R^2_{i,OS} \) statistics (in percent). \( R^2_{i,OS} \) measures the percentage point reduction in MSPE for the unrestricted principal component industry excess return forecast relative to the beta pricing-restricted principal component industry excess return forecast. The beta pricing-restricted principal component forecast employs principal component factor forecasts—generated from recursively estimated predictive regression models based on the first two principal components of 14 economic variables and 33 lagged industry returns—and recursively estimated betas for each industry. The column headings indicates the factors included, where FF indicates MKT, SMB, and HML. The unrestricted principal component forecast is generated from a recursively estimated predictive regression model based on the first two principal components of the 14 economic variables and 33 lagged industry returns. Statistical significance of \( R^2_{i,OS} \) is based on the Clark and West (2007) MSPE-adjusted statistic corresponding to a test of \( H_0: R^2_{i,OS} = 0 \) against \( H_1: R^2_{i,OS} > 0 \). * and ** indicate significance at the 10% and 5% levels, respectively. Average corresponds to the average \( R^2_{i,OS} \) across the 33 industry portfolios. # > 0, # sig.(5%), and # sig.(10%) signify the number of industry \( R^2_{i,OS} \) statistics that are positive, significant at the 5% level, and significant at the 10% level, respectively.

| Industry portfolio | FF+ | FF+ | MKT+ | SMB | | Industry portfolio | FF+ | FF+ | MKT+ | SMB |
|--------------------|-----|-----|------|-----| | | | | | |
| AGRIC              | −0.21 | −0.43 | −0.23 | 0.45 | | GLASS              | 0.08 | 0.05 | 0.22 | 0.69** |
| MINES              | −0.32 | −0.45 | −0.36 | −0.12 | | METAL              | −0.21 | −0.12 | −0.45 | −0.46 |
| OIL                | −0.94 | −1.24 | −1.13 | −0.37 | | MTLPR              | 0.09 | 0.00 | 0.09 | 0.94** |
| STONE              | −0.77 | −0.81 | −0.74 | 0.32 | | MACHN              | −0.32 | −0.39 | −0.50 | −0.34 |
| CNSTR              | −0.12 | −0.20 | −0.17 | 0.32 | | ELCTR              | −0.23 | −0.30 | −0.19 | 0.24 |
| FOOD               | 0.56** | 0.48** | 0.38* | 1.51** | | CARS               | 0.50** | 0.75** | 0.76** | 1.31** |
| SMOKE              | 0.40* | −0.08 | 0.21 | 1.26** | | INSTR               | −1.84 | −2.15 | −2.20 | −2.48 |
| TXTLS              | 0.52 | 0.98* | 0.75 | 1.08* | | MANUF              | −0.25 | −0.22 | −0.13 | 0.34* |
| APPRL              | −0.24 | −0.07 | −0.14 | 0.43 | | TRANS              | 0.14 | −0.14 | −0.02 | 0.38 |
| WOOD               | −0.13 | 0.12 | −0.10 | −0.08 | | PHONE              | −0.52 | −0.69 | −0.51 | −0.13 |
| CHAIR              | 0.13 | 0.37 | 0.20 | 0.53* | | TV                  | −0.01 | 0.13 | −0.07 | 1.45** |
| PAPER              | −0.28 | −0.29 | −0.37 | −0.63 | | UTILS              | −0.19 | 0.24 | 0.12 | 0.97*** |
| PRINT              | 0.07 | 0.30 | 0.10 | 0.96** | | WHLSL              | 0.21 | 0.02 | 0.04 | 0.93** |
| CHEMS              | 0.13 | 0.23 | −0.10 | 0.51* | | RTAIL              | −0.08 | −0.16 | −0.27 | 0.23 |
| PTRLM              | −0.85 | −0.80 | −0.65 | 0.95** | | MONEY              | −0.08 | −0.02 | −0.13 | 0.70** |
| RUBBR              | −0.01 | −0.16 | 0.02 | 0.25* | | SRVC                | 0.25 | 0.16 | 0.18 | 1.20** |
| LETHR              | −0.44 | −0.58 | −0.57 | 0.02 | | | | | |
| Average            | −0.15 | −0.17 | −0.18 | 0.41 | | | | | |
| # > 0              | 12 | 13 | 12 | 25 | | # sig.(5%)         | 1 | 2 | 1 | 13 | | # sig.(10%)        | 3 | 3 | 2 | 18 |
Table 6
130-30 industry-rotation portfolio performance, 1966:01–2008:12

The table reports portfolio performance measures for 130-30 portfolios based on various forecasting models of industry portfolio excess returns. The 130-30 portfolio uses weights of 1.3/5 (−0.3/5) for the five industries with the highest (lowest) forecasted excess returns and zero for all other industries. Mean and standard deviation (in percent) are computed for portfolio returns in excess of the CRSP risk-free rate. CER is the certainty equivalent return (in annualized percent) for an investor with a power utility function and risk aversion coefficient of three. Buy and hold is the CRSP aggregate market portfolio (MKT). The historical average forecasting model employs historical average forecasts of industry portfolio excess returns. The unrestricted model generates forecasts using a recursively estimated predictive regression model based on the first two principal components of 14 economic variables and 33 lagged industry returns. The CAPM-restricted (Fama-French-restricted) model generates forecasts using principal component MKT (MKT, SMB, and HML) forecasts—generated from a recursively estimated predictive regression model based on the first two principal components of the 14 economic variables and 33 lagged industry returns—and recursively estimated betas for each industry. θₚ is the Lo (2008) active ratio (in percent); t-statistics are given in parentheses.

<table>
<thead>
<tr>
<th>Forecasting model</th>
<th>Mean (%)</th>
<th>Std. dev. (%)</th>
<th>Sharpe ratio</th>
<th>CER (ann. %)</th>
<th>θₚ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy-and-hold portfolio (MKT)</td>
<td>0.34</td>
<td>4.55</td>
<td>0.08</td>
<td>5.89</td>
<td></td>
</tr>
<tr>
<td>Historical average</td>
<td>0.43</td>
<td>5.58</td>
<td>0.08</td>
<td>5.12</td>
<td>−20.69</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[−87.05]</td>
</tr>
<tr>
<td>Unrestricted</td>
<td>0.83</td>
<td>5.87</td>
<td>0.14</td>
<td>9.26</td>
<td>23.99</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[106.30]</td>
</tr>
<tr>
<td>CAPM restricted</td>
<td>0.55</td>
<td>6.58</td>
<td>0.08</td>
<td>4.30</td>
<td>14.58</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[50.01]</td>
</tr>
<tr>
<td>Fama-French restricted</td>
<td>0.89</td>
<td>6.01</td>
<td>0.15</td>
<td>9.93</td>
<td>38.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[148.11]</td>
</tr>
</tbody>
</table>
Fig. 1. Principal component and historical average forecasts of industry portfolio excess returns, 1966:01–2008:12. Black (gray) lines delineate principal component (historical average) forecasts of industry portfolio excess returns. The principal component forecast is generated from a predictive regression model based on the first two principal components of 14 economic variables and 33 lagged industry returns.
Fig. 2. Sorted $R^2_{i,OS}$ statistics (in percent) for principal component forecasts of industry portfolio excess returns, 1966:01–2008:12. The figure displays the $R^2_{i,OS}$ statistics reported in Table 2 for principal component forecasts in ascending order. Italics indicate $R^2_{i,OS}$ statistics that are significant at the 10% level in Table 2.
Cross-sectional regression results:
Slope coefficient = 3.46 (t-statistic = 8.01)
R-square = 59%

Fig. 3. $R^2_{i,OS}$ statistics (in percent) and standard deviations of principal component forecasts of industry portfolio excess returns, 1966:01–2008:12. The figure displays a scatterplot of $R^2_{i,OS}$ statistics and principal component forecast standard deviations. The figure also reports results for a cross-sectional regression model with $R^2_{i,OS}$ as the left-hand-side variable and standard deviation as the right-hand-side variable. (An intercept is included in the cross-sectional regression.) The solid line delineates the fitted cross-sectional regression line.
Cross-sectional regression results:
Slope coefficient = 2.99 (t-statistic = 4.80)
R-square = 26%

\[ R^2, \beta_{i,OS} \] statistics (in percent) and average betas for CAPM-restricted principal component forecasts of industry portfolio excess returns, 1966:01–2008:12.

The figure displays a scatterplot of \( R^2, \beta_{i,OS} \) statistics and average estimated betas for CAPM-restricted principal component forecasts. The figure also reports results for a cross-sectional regression model with \( R^2, \beta_{i,OS} \) as the left-hand-side variable and average beta as the right-hand-side variable. (An intercept is included in the cross-sectional regression.) The solid line delineates the fitted cross-sectional regression line.