How Predictable are Components of the Aggregate Market Portfolio?

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Abstract

We analyze return predictability for *components* of the aggregate market, including portfolios sorted on industry, size, and book-to-market. Considering a variety of economic variables and lagged industry returns as predictors, both in-sample and out-of-sample tests highlight substantial differences in return predictability across components. Among industry portfolios, construction, textiles, apparel, furniture, printing, automobiles, and manufacturing exhibit the most predictability, while portfolios of small-cap and high book-to-market firms also display considerable predictability. Three key findings provide economic explanations for component predictability: (i) component predictability is markedly more evident during recessions, linking predictability to business-cycle fluctuations; (ii) based on a novel out-of-sample decomposition, time-varying macroeconomic risk premiums captured by the conditional CAPM and conditional Fama-French 3-factor model largely account for component predictability; (iii) industry concentration and market capitalization significantly explain differences in return predictability across industries, consistent with the information-flow frictions emphasized by Hong, Torous, and Valkanov (2007). We further show that predictability can be exploited to improve portfolio performance for component-rotation investment strategies.

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

Keywords: Return predictability; Industries; Size; Book-to-market; Business cycle; Rational asset pricing; Information-flow frictions; Component-rotation portfolio

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Abstract

We analyze return predictability for *components* of the aggregate market, including portfolios sorted on industry, size, and book-to-market. Considering a variety of economic variables and lagged industry returns as predictors, both in-sample and out-of-sample tests highlight substantial differences in return predictability across components. Among industry portfolios, construction, textiles, apparel, furniture, printing, automobiles, and manufacturing exhibit the most predictability, while portfolios of small-cap and high book-to-market firms also display considerable predictability. Three key findings provide economic explanations for component predictability: (i) component predictability is markedly more evident during recessions, linking predictability to business-cycle fluctuations; (ii) based on a novel out-of-sample decomposition, time-varying macroeconomic risk premiums captured by the conditional CAPM and conditional Fama-French 3-factor model largely account for component predictability; (iii) industry concentration and market capitalization significantly explain differences in return predictability across industries, consistent with the information-flow frictions emphasized by Hong, Torous, and Valkanov (2007). We further show that predictability can be exploited to improve portfolio performance for component-rotation investment strategies.

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How Predictable are Components of the Aggregate Market Portfolio?

Stock return predictability is crucial to many fundamental issues in finance, including portfolio allocation, the cost of capital, and market efficiency (Cochrane (2008)). It is thus not surprising that a voluminous literature exists on the predictability of stock returns, with numerous economic variables proposed as predictors.[1] Many studies report in-sample evidence of return predictability, and despite some thorny econometric issues, the emerging consensus from in-sample studies is that stock returns contain a significant predictable component (Campbell (2000)). Out-of-sample evidence of return predictability, however, has proved more elusive, as exemplified by the recent study of Welch and Goyal (2008), who find that many popular predictors are unable to deliver consistent out-of-sample gains with respect to U.S. equity premium prediction relative to a simple forecast based on the historical average; also see Bossaerts and Hillion (1999) and Goyal and Welch (2003). Spiegel (2008) provides an overview of several recent major studies, including Campbell and Thompson (2008), who find greater out-of-sample predictability after imposing theoretically motivated restrictions. Furthermore, Rapach, Strauss, and Zhou (2009) demonstrate that a forecast combination approach generates consistent and significant out-of-sample gains, and they link out-of-sample predictability to the real economy.

In contrast to the extant literature on return predictability, which focuses almost exclusively on the *aggregate* market portfolio, the present paper parses the market and examines return predictability for *component* portfolios delineated by industry, market capitalization, and book-to-market value. Investigating return predictability for component portfolios is relevant for a number of reasons. First, analyzing the predictability of component portfolio returns has potentially important implications for asset-pricing tests of the cross section of returns, as shown by Ferson and Harvey (1999), among others, as well as measuring the cost of capital, along the lines of Fama and French (1997). Second, component return predictability can have significant asset-allocation implications, suggesting that investors should stand ready to alter their portfolio weights over time

[1]Predictors from the literature include the dividend-price ratio (Dow (1920), Fama and French (1988, 1989)), 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)). See Campbell (2000) and Welch and Goyal (2008) for surveys of the vast literature on return predictability.

in line with changes in expected returns across components. Third, and in a related vein, analyzing component return predictability helps to establish the proper benchmarks for the many mutual funds that specialize in particular market segments. Fourth, an investigation of component return predictability improves our understanding of the sources of return predictability by illuminating the roles played by aggregate business conditions and equity-market frictions. Indeed, exploring how business-cycle fluctuations and equity-market frictions relate to component return predictability is a central part of the present paper.

There are relatively few papers that analyze return predictability for component portfolios. A leading example is Ferson and Harvey (1999), who estimate predictive regression models for 25 portfolios sorted on size and book-to-market using a relatively small number of economic variables as predictors.[2] Cooper, Gulen, and Vassalou (2002) investigate the profitability of trading rules based on 10 economic variables for 10 size and 10 book-to-market portfolios, and Avramov (2002) provides a Bayesian analysis of the predictability of 6 portfolios sorted on size and book-to-market using 14 economic variables as predictors.

Relative to these studies, we do the following. First, we analyze predictability for a large number of component portfolios—33 industry, 10 size, and 10 book-to-market portfolios—and potential predictors—14 economic variables from Welch and Goyal (2008) and 33 lagged industry returns from Hong, Torous, and Valkanov (2007, HTV). Note that HTV investigate the ability of lagged returns on industry portfolios to predict aggregate market returns (also see Elaswarapu and Tiwari (1996)); in contrast, we analyze the ability of lagged industry returns, as well as the 14 popular economic variables from Welch and Goyal (2008), to predict industry portfolio returns themselves.[3] Second, we employ both in-sample and out-of-sample tests of component predictability, and our out-of-sample tests focus on the ability of a *forecast combination* method to outperform historical average benchmark forecasts. As recently shown by Rapach, Strauss, and Zhou (2009) in the context of aggregate market predictability, the forecast combination approach incorporates information from many potential predictors in a tractable way to generate forecasts that are consistently superior to forecasts based on individual predictors.[4] As we demonstrate below, this is also

[2] Along the same line, Ferson and Korajczyk (1995) and Kirby (1998) estimate in-sample predictive regression models for 10 size-sorted portfolios using a similar set of economic variables as predictors. Ferson and Korajczyk (1995) also estimate in-sample predictive regression models for 12 industry portfolios.

[3] Menzly and Ozbas (2006) analyze cross-autocorrelation in industry portfolio returns, and Moskowitz and Grinblatt (1999) and Hou (2007) investigate serial correlation in intraindustry returns. In a related vein, Cohen and Frazzini (2008) consider cross-autocorrelation in returns among firms with important customer-supplier links. A few studies investigate predictability for a large number of individual firms and the implications for portfolio allocation; see, for example, Avramov and Chordia (2006), who conduct a Bayesian analysis.

[4] While forecast combination has received considerable recent attention in the macroeconomic forecasting literature

the case for forecasting component returns. Third, as already mentioned, we extensively explore economic explanations for differences in return predictability across component portfolios relating to macroeconomic risk and the information-flow frictions recently emphasized by HTV.

Parsing aggregate market return predictability into industry, size, and book-to-market portfolio return predictability uncovers a number of interesting and distinct empirical facts. In-sample results reveal that economic variables, such as inflation, long-term government bond returns, and net equity issuance, significantly predict one-month-ahead returns for most portfolios sorted by industry, size, or book-to-market; other economic variables, such as the dividend yield, term spread, and Treasury bill rate, significantly predict some industries but not others. Using lagged industry returns as predictors yields even greater differences in predictability across components. For example, predictive regression models for construction, textiles, furniture, print, and manufacturing have economically sizable average R^2 statistics above 2% using 15 pre-selected lagged industry returns as predictors, while these same predictors have very little explanatory power in predictive regression models for petroleum, utilities, paper, and chemicals, where the average R^2 statistics are approximately zero. For predictive regression models of size portfolios based on lagged industry returns, the average R^2 statistics range from an economically small value of 0.23% to a substantial 5.08%; moreover, the average R^2 statistics decrease monotonically from small- to large-cap firms. Return predictability is also typically stronger for high as opposed to low book-to-market portfolios using lagged industry returns as regressors, with an average R^2 of 1.62% for the highest book-to-market portfolio.[5]

Our out-of-sample test results using forecast combination reveal extensive predictability in real time for a number of component portfolios. For a 1966–2004 forecast evaluation period, we find significant out-of-sample return predictability for 23 (16) of 33 industry portfolios using the 14 economic variables (lagged industry returns) as predictors. Furthermore, the degree of out-of-sample predictability is substantially greater for certain industries, especially with lagged industry returns as predictors, according to the Campbell and Thompson (2008) out-of-sample R^2 statistic and rel-

(see, e.g., Stock and Watson (1999, 2003, 2004)), applications in the finance literature are relatively rare. In addition to Rapach, Strauss, and Zhou (2009), Aiolfi and Favero (2005), Timmermann (2008), and Huang and Lee (2009) apply different types of combining methods to forecast aggregate market returns. Also see Mamaysky, Spiegel, and Zhang (2007), who find that combining predictions from an ordinary least squares model and the Kalman filter model of Mamaysky, Spiegel, and Zhang (2008) significantly increases the number of mutual funds with predictable out-of-sample alphas.

[5] In agreement with our results for size and book-to-market portfolio returns, Avramov (2002) finds that returns for a portfolio of small value stocks are the most predictable among 6 portfolios he considers using Bayesian methods. Similarly, our results for size portfolios agree with in-sample predictive regression results in Ferson and Koraczyk (1995) and Kirby (1998), who find greater predictability for small stocks.

ative Sharpe ratio. The economic variables significantly predict out-of-sample returns for all of the size portfolios, although the degree of predictability is somewhat limited. Lagged industry returns significantly forecast returns for the seven smallest size portfolios, the degree of predictability increases substantially as size decreases, and the predictability of the smallest size portfolio is very strong. Similarly, the economic variables significantly predict returns on an out-of-sample basis for all of the book-to-market portfolios, but again the degree of predictability is limited, while lagged industry returns significantly forecast returns for the two highest book-to-market portfolios. Overall, our in-sample and out-of-sample predictive regression results demonstrate that the degree of predictability can vary significantly across component portfolios. These variations in return predictability across components are opaque in studies focusing only on the aggregate market portfolio. In addition, lagged industry returns generate greater cross-sectional differences in predictability.

We explore economic explanations for component predictability using three approaches. First, with both economic variables and lagged industry returns serving as predictors, we show that out-of-sample component return predictability is typically magnified during U.S. recessions. Since recessions are periods of rapidly changing macroeconomic fundamentals and heightened risk aversion, predictability thus appears related to time-varying risk premiums associated with business-cycle fluctuations (Fama and French (1989), Campbell and Cochrane (1999), Cochrane (1999, 2007)). Second, we develop a method of forming combination forecasts of component returns based on a conditional asset-pricing model. This allows us to decompose out-of-sample component predictability into exposure to time-varying macroeconomic risk premiums and alpha predictability. Considering conditional asset-pricing models based on the CAPM and Fama-French 3-factor model, our results suggest that exposure to time-varying macroeconomic risk premiums accounts for most of the out-of-sample predictability in component portfolios, with greater exposure typically associated with enhanced predictability. Third, in the spirit of HTV, we examine the importance of information-flow frictions in explaining differences in return predictability across industry portfolios. We find that both industry concentration and industry capitalization are negatively and significantly related to the degree of return predictability across industries. HTV posit that information about macroeconomic fundamentals is less readily known in some industries and thus diffuses more slowly across the broader equity market, and our findings support HTV's emphasis on information-flow frictions. Overall, our results identify the components of the aggregate market that are subject to the greatest time-varying macroeconomic risk exposure and information-flow frictions, and they suggest that these factors are important in understanding return predictability.

Finally, we examine whether component predictability improves portfolio performance with a *component-rotation* investment strategy.[6] We consider a monthly "maximum" portfolio that is entirely allocated to the component with the highest expected return, where the component expected return is based on either the combination or constant expected return forecast. If the economic variables or lagged industry returns offer useful information for forecasting component returns, portfolio allocations based on the combination forecasts should outperform allocations based on constant expected return forecasts. We show that this is typically the case. Sharpe ratios and cumulative returns are substantially higher for portfolios that select the component to invest in using combination forecasts compared to constant expected return forecasts. Not surprisingly, identifying the component using the constant expected return forecasts results in a very limited degree of rotation among individual components. In contrast, there is considerably more rotation among components based on combination forecasts.

The remainder of the paper is organized as follows. Section I provides statistical evidence on the predictability of component portfolio returns based on in-sample tests. Section II analyzes component portfolio return predictability using out-of-sample tests. Section III considers economic reasons for component portfolio predictability. Section IV analyzes component-rotation investment strategies. Section V concludes.

I. In-Sample Predictability Tests

This section outlines the predictive regression model framework, describes the data, and reports in-sample test results of predictability for component portfolios.

A. Econometric Methodology

Following much of the literature, we analyze stock return predictability in the context of a bivariate predictive regression model:

$$r_{i,t} = a_i + b_{i,j} x_{j,t-1} + e_{i,t}, \tag{1}$$

where $r_{i,t}$ is the return on portfolio i in excess of the risk-free interest rate, $x_{j,t}$ is a potential predictor variable, and $e_{i,t}$ is a zero-mean disturbance term. Nearly all studies in the vast literature

[6]This is closely related to popular industry- and sector-rotation strategies used in practice, which are an important reason for the growth of large-sector ETFs.

on return predictability focus on aggregate stock market predictability, in which $r_{i,t}$ is the excess return on the aggregate market portfolio. In contrast, we are interested in return predictability when $r_{i,t}$ is a *component* of the aggregate market portfolio. More specifically, we analyze return predictability for 33 industry, 10 size, and 10 book-to-market portfolios. (The data are described in detail below.)

The predictive ability of $x_{j,t}$ with respect to $r_{i,t}$ is typically analyzed by inspecting the t-statistic corresponding to $\hat{b}_{i,j}$, the ordinary least squares (OLS) estimate of $b_{i,j}$ in (1). Under the null hypothesis of no predictability, $b_{i,j} = 0$; the constant expected excess return model prevails ($r_{i,t} = a_i + \varepsilon_{i,t}$). Under the alternative hypothesis, $b_{i,j}$ is different from zero, and $x_{j,t}$ contains information useful for predicting $r_{i,t}$; a time-varying expected excess return model applies. There is a well-known small-sample bias associated with estimating (1) arising from the fact that $x_{j,t}$ is not an exogenous regressor (Stambaugh (1986, 1999)). This potentially complicates inference using conventional asymptotics. We thus base our inference on a bootstrap procedure similar to the procedures used by, for example, Nelson and Kim (1993), Mark (1995), Kothari and Shanken (1997), Kilian (1999), and Rapach and Wohar (2006).[7] Studies of predictability sometimes consider long-horizon regressions, but this raises additional econometric issues due to overlapping return observations; see, for example, Richardson and Stock (1989), Valkanov (2003), and Boudoukh, Richardson, and Whitelaw (2008). To avoid these issues, and for brevity, we focus on single-period (monthly) returns in our applications. We also use one-sided tests of statistical significance, since this provides more powerful tests, and theory typically suggests the expected sign of $b_{i,j}$ (Inoue and Kilian (2004)).

B. Data

We analyze return predictability for three different sets of component portfolio returns. The first set is composed of monthly returns on value-weighted industry portfolios, which are available from the data library at Kenneth French's web site.[8] Following HTV, we use monthly returns on 33 industry portfolios available from 1945:12–2004:12: AGRIC (Agriculture, Forestry, and Fish-

[7] The bootstrap is designed to avoid finite-sample size distortions. There are estimation procedures based on alternative asymptotic frameworks that provide potentially more powerful tests of return predictability while controlling for size distortions; see, for example, Campbell and Yogo (2006). Nevertheless, basing inference on OLS estimation of (1) and the bootstrap procedure provides extensive evidence of predictability for a number of component portfolio returns, so low power does not seem to be a serious problem for our applications. Bayesian methods have also been developed for predictive regression models like (1) (see, e.g., Stambaugh (1999)) and for predictive systems (Pástor and Stambaugh (2008)). While beyond the scope of the present paper, it would be interesting in future research to examine predictability for the component portfolios we consider using Bayesian methods.

[8] The library is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

ing), MINES (Mining), OIL (Oil and Gas Extraction), STONE (Nonmetalic 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).[9]

The second set of component portfolio returns is composed of monthly returns for 10 portfolios sorted on market capitalization. The market capitalization-sorted portfolio return data are also available from French's data library, and the size portfolios in ascending order are denoted by S1,...,S10. The third set of component portfolio returns contains monthly returns for 10 portfolios sorted on book-to-market value, again from French's data library, and the decile portfolios in ascending order are given by BM1,...,BM10. Since Fama and French (1992, 1993), these size and book-to-market portfolios have been the subject of much research that investigates the contemporaneous cross section of returns, while we analyze the predictability of these portfolios in the time-series dimension.

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

- Dividend-payout ratio (log), D/E: difference between the log of dividends and log of earnings on the S&P 500 index.
- Stock variance, SVAR: sum of squared daily returns on the S&P 500 index.
- Default return spread, DFR: difference between long-term corporate bond and long-term government bond returns.

[9]These are the industry mnemonics used in the data library from the Fama and French 38 industry portfolios. 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, following HTV.

- Long-term yield, LTY: long-term government bond yield.
- Long-term return, LTR: return on long-term government bonds.
- Inflation, INFL: calculated from the CPI (all urban consumers); following Welch and Goyal (2008), since inflation rate data are released in the following month, we use $x_{i,t-2}$ in (1) for inflation.
- Term spread, TMS: difference between the long-term yield and Treasury bill rate.
- Treasury bill rate, TBL: interest rate on a 3-month Treasury bill (secondary market).
- Default yield spread, DFY: difference between BAA- and AAA-rated corporate bond yields.
- 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.
- Book-to-market ratio, B/M: ratio of book value to market value for the Dow Jones Industrial Average.
- Net equity expansion, NTIS: ratio of twelve-month moving sums of net issues by NYSE-listed stocks to total end-of-year market capitalization of NYSE stocks.

These variables include many of the predictors of aggregate market portfolio returns from the literature. The valuation ratios (D/P, D/Y, E/P, and B/M) and interest rate variables (LTY, TMS, TBL, and DFY) are especially prominent in the literature on aggregate market return predictability. The data are monthly and described in more detail in Welch and Goyal (2008).[10]

The second set of predictors is composed of lagged industry returns (the same industry returns described above). Our inclusion of lagged industry returns as potential predictors is motivated by HTV, who provide evidence that lagged industry returns have statistically and economically significant predictive ability with respect to aggregate market returns. HTV develop a theoretical model

[10]The data are available at http://www.bus.emory.edu/AGoyal/Research.html.

with information-diffusion frictions that provides an explanation for the ability of lagged industry returns to predict aggregate market returns. Interestingly, their theoretical model implies aggregate market predictability as a result of cross-serial correlation in individual industry returns, so our focus on the ability of lagged industry returns to predict industry returns themselves represents a direct test of HTV's theoretical model.

Table I reports summary statistics for excess returns for the industry, size, and book-to-market portfolios, as well as the 14 economic variables from Welch and Goyal (2008), for 1945:12–2004:12. As a benchmark return series, the table includes summary statistics for the return on the aggregate CRSP value-weighted market portfolio. Panel B shows that average monthly industry returns range from 0.44% (PHONE) to 0.94% (SMOKE), while the standard deviations range from 3.86% (UTILS) to 7.21% (WOOD). As is well known, Panels C and D show that returns are generally higher and more volatile for small-cap or higher book-to-market firms.

[Insert Table I about here]

C. Industry Portfolio Excess Returns

Table II reports estimation results for (1) when $r_{i,t}$ is the excess return for an industry portfolio and $x_{j,t}$ is one of the 14 economic variables from Welch and Goyal (2008). After accounting for the lagged predictor in (1), our estimation sample is 1946:01–2004:12. The entries in the table report the t-statistic corresponding to $b_{i,j}$ in (1) (top number) and R^2 statistic (bottom number) for each industry/predictor combination. Average R^2 statistics across predictors (industries) are shown in the last column (rows) of Table II. The number of industries for which a given predictor is significant in (1) at the 5% level is also shown. For reference, the MKT row reports results for the aggregate market portfolio. While predictive regression models typically have relatively small R^2 statistics, Campbell and Thompson (2008) show that an R^2 greater than approximately 0.5% for monthly returns can signal economically meaningful predictability gains; also see Kandel and Stambaugh (1996) and Xu (2004).

[Insert Table II about here]

Six predictors—LTR, INFL, TMS, TBL, D/Y, and NTIS—enter significantly in (1) for the excess return on the aggregate market portfolio. As shown in the penultimate row of Table II, these are also the predictors that most frequently predict excess returns across industries. Among the 33 industry returns considered, LTR, INFL, TMS, TBL, D/Y, and NTIS are significant predictors of excess returns for 28, 25, 19, 18, 15, and 24 industry portfolios, respectively. From this perspective, there is—not surprisingly—a link between aggregate market predictability and predictability across industries. Nevertheless, there are important differences in predictability across industry portfolios. For example, LTR has relatively high R^2 statistics of 3.00%, 1.62%, and 1.73% for CHAIR, PRINT, and GLASS, respectively, but very small (and statistically insignificant) statistics of 0.14%, 0.02%, 0.10%, and 0.14% for AGRIC, OIL, PTRLM, and INSTR, respectively. Looking at the last column of Table II, industry returns appear most predictable on average for TXTLS, APPRL, CHAIR, PAPER, GLASS, and CARS, where the average R^2 across predictors is greater than or equal to 0.50%. Predictability is weaker on average in industries such as AGRIC, STONE, and METAL, where the average R^2 across predictors is less than 0.25%.

Table III reports predictive estimation results for industry returns using lagged industry returns as predictors. To conserve space and facilitate comparison with HTV, we report estimation results for the 15 lagged industry returns that are significant predictors of aggregate market returns over 1946:01–2004:12. Our group of 15 lagged predictors is similar to the group of significant aggregate market predictors identified by HTV using monthly data for 1946–2002. What stands out in Table III is the marked differences in return predictability across many of the industries. For example, the last column of Table III shows that CNSTR, TXTLS, CHAIR, PRINT, and MANUF have average R^2 statistics well above 2%, which clearly represent economically meaningful predictability gains. In contrast, industries such as OIL, CHEMS, PTRLM, and UTILS have average R^2 statistics below 0.15%.

[Insert Table III about here]

D. Size Portfolio Returns

We next examine return predictability for 10 portfolios sorted on market capitalization, and the results are reported in Tables IV and V. Relative to the industry portfolios analyzed in the previous subsection, there appears to be more uniformity in the degree of return predictability across size portfolios when the 14 economic variables serve as predictors in Table IV. The six economic variables that are significant predictors of aggregate market returns are also significant predictors of returns for 8–10 of the size portfolios, and the R^2 statistics are relatively stable across the size portfolios. The most notable differences in predictability across portfolios occur when INFL serves as the predictor. In this case, the R^2 statistics are 2.16% and 1.60% for S1 and S2, respectively, clearly higher than the R^2 statistics for S3–S10.

[Insert Table IV about here]

Much more marked differences in predictability across size portfolios are evident in Table V when lagged industry returns serve as predictors. Each of the 15 lagged industry returns is a significant predictor of excess returns for the S1 portfolio, and the predictors have a very high average R^2 of 5.08% for S1. In contrast, only two of the lagged industry returns are significant predictors of excess returns for S10 (PRINT and TV, with R^2 statistics of 0.50% and 0.46%, respectively), and the average R^2 across predictors is a relatively paltry 0.23% for S10. The last column of Table V shows that the average R^2 decreases monotonically as market capitalization increases. Overall, Table V indicates that return predictability based on lagged industry returns is much stronger for small-cap portfolios.

[Insert Table V about here]

E. Book-to-Market Portfolio Returns

Table VI reports results for predictive regression models of book-to-market portfolios with the 14 economic variables serving as predictors. The results are broadly similar to those in Table IV for the size portfolios in that pronounced differences in predictability across component portfolios are not clearly evident. For example, the average R^2 statistics in the last column of Table VI are similar across the book-to-market portfolios.

[Insert Table VI about here]

When lagged industry returns serve as predictors in Table VII, there are stark differences in return predictability across book-to-market portfolios. This is similar to Table V for size portfolios, which also uses lagged industry returns as predictors. More specifically, the two highest book-to-market portfolios, BM9 and BM10, have the two highest average R^2 statistics, 1.11% and 1.62%, respectively, while the next highest average R^2 statistic is 0.87% (for BM3). In addition, each of the 15 lagged industry returns is a significant predictor of excess returns for BM9 and BM10. Table VII points to greater predictability for high book-to-market portfolios using lagged industry returns as predictors.

[Insert Table VII about here]

II. Out-of-Sample Predictability Tests

As indicated in the introduction, out-of-sample return predictability has been more difficult to establish, especially on a consistent basis over time. To examine the robustness of the in-sample results, we next consider out-of-sample tests of return predictability for component portfolios. This section describes the construction of the out-of-sample forecasts, forecast evaluation methods, and out-of-same test results for component portfolios.

A. Econometric Methodology

Following Campbell and Thompson (2008) and Welch and Goyal (2008), we generate out-of-sample forecasts of excess returns using an expanding estimation window. More specifically, we first divide the total sample of T observations for $r_{i,t}$ and $x_{j,t}$ into an in-sample portion composed of the first n_1 observations and an out-of-sample portion composed of the last n_2 observations. The initial out-of-sample forecast of the excess return on a component portfolio based on the predictor $x_{j,t}$ is given by

$$\hat{r}_{i,n_1+1} = \hat{a}_{i,n_1} + \hat{b}_{i,j,n_1} x_{j,n_1}, \tag{2}$$

where $\hat{a}_{i,n_1}$ and $\hat{b}_{i,j,n_1}$ are the OLS estimates of a_i and $b_{i,j}$, respectively, in (1) generated by regressing $\{r_{i,t}\}_{t=2}^{n_1}$ on a constant and $\{x_{j,t}\}_{t=1}^{n_1-1}$. The next out-of-sample forecast is given by

$$\hat{r}_{i,n_1+2} = \hat{a}_{i,n_1+1} + \hat{b}_{i,j,n_1+1} x_{j,n_1+1}, \tag{3}$$

where $\hat{a}_{i,n_1+1}$ and $\hat{b}_{i,j,n_1+1}$ are generated by regressing $\{r_{i,t}\}_{t=2}^{n_1+1}$ on a constant and $\{x_{j,t}\}_{t=1}^{n_1}$. Proceeding in this manner through the end of the out-of-sample period, we generate a series of n_2 out-of-sample excess return forecasts based on $x_{j,t}$ ($\{\hat{r}_{i,t+1}\}_{t=n_1}^{T-1}$). We emphasize that this out-of-sample forecasting exercise mimics the situation of a forecaster in real time. As in our in-sample tests in Section I above, a constant expected excess return model is the relevant benchmark model under the null hypothesis of no predictability. Following Campbell and Thompson (2008) and Welch and Goyal (2008), we simulate real-time forecasts based on the constant expected excess return model using the historical average, $\bar{r}_{i,t+1} = \sum_{j=1}^{t} r_{i,j}$.

We use the Campbell and Thompson (2008) out-of-sample R^2 statistic, R^2_{OS}, to compare the $\hat{r}_{i,t+1}$ and $\bar{r}_{i,t+1}$ forecasts. The R^2_{OS} statistic is akin to the familiar in-sample R^2 and is given by

$$R^2_{OS} = 1 - \frac{\sum_{k=1}^{n_2} (r_{i,n_1+k} - \hat{r}_{i,n_1+k})^2}{\sum_{k=1}^{n_2} (r_{i,n_1+k} - \bar{r}_{i,n_1+k})^2}. \tag{4}$$

The R^2_{OS} statistic measures the reduction in mean square prediction error (MSPE) for the predictive regression model forecast compared to the historical average forecast. Thus, when $R^2_{OS} > 0$, the $\hat{r}_{i,t}$ forecast outperforms the $\bar{r}_{i,t}$ forecast according to the MSPE metric. We also test whether the predictive regression model forecast has a significantly lower MSPE than the historical average benchmark forecast, which is tantamount to testing the null hypothesis that $R^2_{OS} \leq 0$ against the alternative hypothesis that $R^2_{OS} > 0$. The most popular test procedure is the Diebold and Mariano (1995) and West (1996) statistic, which has an asymptotic standard normal distribution when comparing forecasts from non-nested models. Clark and McCracken (2001) and McCracken (2007), however, show that this statistic has a non-standard distribution when comparing forecasts from *nested* models, as is clearly the case when comparing the predictive regression model forecast to the historical average forecast.

Clark and West (2007) develop an adjusted version of the Diebold and Mariano (1995) and West (1996) statistic that can be used in conjunction with the standard normal distribution to generate asymptotically valid inferences when comparing forecasts from nested linear models. The Clark and West (2007) *MSPE-adjusted* statistic is conveniently calculated by first defining

$$f_{i,t+1} = (r_{i,t+1} - \bar{r}_{i,t+1})^2 - [(r_{i,t+1} - \hat{r}_{i,t+1})^2 - (\bar{r}_{i,t+1} - \hat{r}_{i,t+1})^2], \tag{5}$$

then regressing $\{f_{i,s+1}\}_{s=n_1}^{T-1}$ on a constant, and finally calculating the t-statistic corresponding to the constant. A p-value for a one-sided (upper-tail) test is then computed using the standard normal distribution. In Monte Carlo simulations, Clark and West (2007) demonstrate that the *MSPE-adjusted* statistic performs reasonably well in terms of size and power when comparing forecasts from nested linear models for a variety of sample sizes.

We also compute the Sharpe ratio for the portfolio selected by a mean-variance investor who allocates her portfolio monthly between a component portfolio and risk-free bills using the predictive regression model forecast of the excess return on the component portfolio. This exercise requires the investor to forecast the variance of stock returns, and following Campbell and Thompson (2008), we assume that the investor estimates the variance using a five-year rolling window of monthly returns. We then compute the Sharpe ratio for the portfolio selected by a mean-variance investor in a similar setting who instead uses the historical average forecast of the excess return on the component portfolio.[11] The relative Sharpe ratio is the Sharpe ratio for the portfolio of the investor who uses the predictive regression model forecast divided by the Sharpe ratio for the port-

[11]Following Campbell and Thompson (2008), we restrict the portfolio weight attached to the component portfolio to lie between 0 and 1.5 (inclusive).

folio of the investor who uses the historical average forecast. If the relative Sharpe ratio is greater than unity, then the Sharpe ratio is higher for the portfolio formed on the basis of the predictive regression model forecast of industry returns.

When estimating forecasting models, we use the first 20 years of data as an in-sample period and compute excess return forecasts via an expanding estimation window, as described above. This leaves us with an out-of-sample forecast evaluation period of 1966:01–2004:12. This period covers six NBER-dated recessions, the long economic expansion of the 1990s, and the bear market of the early 2000s.

In addition to individual predictive regression model forecasts, we compute *combination forecasts* of component portfolio returns. We do this for two reasons. First, combination forecasts provide a convenient means for summarizing the collective predictive ability of a large number of individual predictors. Second, Rapach, Strauss, and Zhou (2009) recently find that combination forecasts substantially improve forecasts of aggregate market excess returns. More specifically, they show that combinations of forecasts generated by individual predictive regression models based on the economic variables from Welch and Goyal (2008) provide statistically and economically significant out-of-sample gains relative to the historical average forecast, despite the inconsistent and often poor out-of-sample performance of individual model forecasts. These gains likely stem from the ability of forecast combination to improve forecasting performance in the presence of substantial model uncertainty and instability.[12] An alternative approach to incorporating information from a large number of potential predictors is to include all of the potential predictors in a single multiple regression model, what Welch and Goyal (2008) call the "kitchen sink" model. Welch and Goyal (2008) and Rapach, Strauss, and Zhou (2009), however, show that the kitchen sink model performs very poorly in out-of-sample forecasting.[13]

We employ a simple forecast combining method: the mean of the individual predictive regression model forecasts. Rapach, Strauss, and Zhou (2009) find that the mean combination forecast performs well with respect to forecasting aggregate market excess returns. The mean combination forecast has also proved useful in macroeconomic contexts; see, for example, Stock and Watson (2003) with respect to forecasting output growth and inflation.

[12]See, for example, Hendry and Clements (2004) and Timmermann (2006).

[13]Rapach, Strauss, and Zhou (2009) analyze the restrictions implied by forecast combination relative to the unrestricted kitchen sink model. They argue that these restrictions improve forecasting performance in environments with a highly complex and constantly evolving data-generating process; also see the comparison of combination and kitchen sink model forecasts in Huang and Lee (2009). Another approach for incorporating information from a very large number of economic variables is factor analysis. Ludvigson and Ng (2007) apply this approach using 350 macroeconomic and financial variables in analyzing aggregate market return predictability.

B. Industry Portfolio Excess Returns

Table VIII reports out-of-sample results for excess returns on industry portfolios using the 14 economic variables from Welch and Goyal (2008) as predictors. As in our in-sample exercises in Section I above, we include results for excess returns on the aggregate market portfolio as a benchmark. The entries in Table VIII give the R^2_{OS} statistic (in percent, top number) and relative Sharpe ratio (bottom number). Among the 14 economic variables, only LTR produces a significant R^2_{OS} (0.28%) for the excess return on the aggregate market portfolio, while the relative Sharpe ratio is greater than unity for LTY, LTR, TMS, TBL, D/Y, and NTIS. The combination forecast in the last column of Table VIII yields a statistically significant and economically sizable R^2_{OS} of 1.09% for the aggregate market return, and the relative Sharpe ratio is 1.27.

Turning to the industry portfolios, we see some marked differences in predictability across industries. Focusing on the combination forecast results in the last column, TXTLS, APPRL, CHAIR, RUBBER, GLASS, and CARS have R^2_{OS} statistics greater than 0.90%, and all are statistically significant. The relative Sharpe ratios are also well above unity for these industries. There are some individual predictors, especially LTR, that produce relatively high R^2_{OS} statistics for these industries; for example, LTR has an R^2_{OS} of 2.75% for CHAIR and 1.57% for GLASS. Nevertheless, the combination forecasts typically improve out-of-sample forecasting performance relative to the individual predictive regression models for the most predictable industries.

[Insert Table VIII about here]

While some industries evince significant return predictability, others, such as AGRIC, MINES, OIL, STONE, SMOKE, and PHONE, generally display substantially less return predictability. For these industries, the combination forecast R^2_{OS} statistics range from only 0.11%–0.22%, and the R^2_{OS} statistics for the individual predictive regression models are almost always negative for these industries. The relative Sharpe ratios are greater than unity for these industries, but they are still typically well below those for the TXTLS, APPRL, CHAIR, RUBBER, GLASS, and CAR industries identified above with relatively high R^2_{OS} statistics.[14]

[14] To get a better sense of the consistency of the out-of-sample predictability of the industry portfolio returns, following Welch and Goyal (2008), we also generated time-series plots for each industry of the difference between the cumulative square forecast error for the historical average forecast and the cumulative square forecast error for the combination forecast for 1966:01–2004:12. These plots provide a useful visual perspective on the consistency of the out-of-sample predictability of industry returns, and they indicate that the 1966:01–2004:12 out-of-sample results hold relatively consistently for a variety of out-of-sample periods. The complete results are not reported for brevity and are available upon request from the authors.

Table IX reports out-of-sample results for excess returns on industry portfolios when lagged industry returns serve as predictors. Again to conserve space and facilitate comparison with HTV, we report results using a set of 15 lagged industry returns as predictors. These are the 15 lagged industry returns that have the highest R^2 statistics over the 1946:01–1965:12 in-sample period with respect to predicting aggregate market returns. Note that the selection of these 15 industries does not entail "look-ahead" bias, as the industries are selected using data from the in-sample period only.

[Insert Table IX about here]

Similar to the in-sample results, we see even more marked differences in return predictability across industries when we use lagged industry returns as predictors in Table IX relative to using the 14 economic variables as predictors (as in Table VIII). As a benchmark, the R^2_{OS} statistic (relative Sharpe ratio) for the aggregate market return is 0.21% (1.15) over the 1966:01–2004:12 out-of-sample period for the combination forecast. Again focusing on the combination forecast results in the last column of Table IX, there are seven industries for which R^2_{OS} is greater than 1.50% (CNSTR, TXTLS, APPRL, CHAIR, PRINT, CARS, and MANUF), and R^2_{OS} is greater than 2% for five of these industries (CNSTR, TXTLS, CHAIR, PRINT, and MANUF). These out-of-sample forecasting gains are all statistically significant and clearly economically significant as well. The relative Sharpe ratios are also large for these industries, and they indicate increases in the Sharpe ratio ranging from 34%–80% relative to the historical average forecast that ignores information on lagged industry returns. On the other hand, there are a number of industries that exhibit substantially less out-of-sample predictability, including OIL, FOOD, SMOKE, PAPER, CHEMS, PTRLM, METAL, PHONE, UTILS, and MONEY. These industries all have R^2_{OS} statistics that are less than 0.10%. These industries also have relative Sharpe ratios that are typically less than or only slightly above unity. Overall, the out-of-sample results for industry portfolio returns reported in this section match up reasonably well with the in-sample results in Section I above.

C. Size Portfolio Returns

Table X reports out-of-sample results for size portfolio excess returns using the 14 economic variables as predictors. Among the individual economic variables, relatively few have positive R^2_{OS} statistics. LTR, INFL, and TMS perform the best overall, with a number of positive and significant R^2_{OS} statistics. While the individual economic variables generally have limited predictive ability for the size portfolio returns, the R^2_{OS} statistics in the last column of Table X show that the combination forecasts offer out-of-sample gains relative to the historical average forecasts for all of the size portfolios. These statistics are all positive and significant, although pronounced differences in predictability across size portfolios are not evident: The R^2_{OS} statistics for the combination forecasts in Table X all lie within the relatively narrow range of 0.81%–1.08%. The relative Sharpe ratios also point to out-of-sample gains for the combination forecasts relative to the historical average forecasts and limited differences in predictability across size portfolios.

[Insert Table X about here]

Table XI reports out-of-sample results for size portfolios using 15 lagged industry returns as predictors, where these predictors are again the 15 lagged industry returns with the highest R^2 statistics over the 1946:01–1965:12 in-sample period with respect to predicting aggregate market returns. In contrast to Table X, there are marked differences in the degree of predictability across size portfolios in Table XI. Focusing on the results for the combination forecasts in the last column of the table, we see that the extent of predictability is strongest for S1, where the R^2_{OS} is an economically substantial 5.85%, while the R^2_{OS} falls to -0.24% for S10. In fact, the R^2_{OS} statistics decrease monotonically as size increases. The R^2_{OS} statistics are positive for S1–S9 and significant for S1–S7. Among the individual predictors, the R^2_{OS} statistics are all significant for TXTLS, CHAIR, PAPER, CHEMS, GLASS, MACHIN, INSTR, TV, MONEY, and SRVC for S1–S6, and there is again a monotonic decrease in predictive ability for these lagged industry returns as size increases. Table XI further demonstrates sizable increases in the Sharpe ratio for the smallest size portfolios, and the gains once again monotonically decrease as size increases. The out-of-sample results presented in this section for size portfolios reinforce the in-sample results in Section I above.

[Insert Table XI about here]

D. Book-to-Market Portfolio Returns

Out-of-sample results for book-to-market portfolio excess returns using 14 economic variables as predictors are reported in Table XII. Similar to the results in Table X for the size portfolios, there is only limited evidence of predictive ability for the 14 economic variables individually (LTR displays the greatest overall predictive ability), while the combination forecasts yield significant out-of-sample gains across all of the book-to-market portfolios in the last column of Table XII.

Again similar to Table X, we do not see considerable differences in the degree of predictability across the book-to-market portfolios.

[Insert Table XII about here]

Table XIII presents out-of-sample results for book-to-market portfolios using the same lagged industry returns from Tables IX and XI as predictors. As in Table XII, there is relatively limited evidence overall of predictive ability for the individual industry lagged returns, although a number of individual lagged returns demonstrate significant predictive ability for BM9 and BM10. The results for the combination forecasts in the last column of Table XIII also indicate that the degree of predictability is strongest for the high book-to-market portfolios, and the R^2_{OS} statistics for the combination forecasts are positive and significant for BM9 and BM10. The finding of greater predictability for high book-to-market portfolios emerges on an out-of-sample basis in this section and on an in-sample basis in Section I above.

[Insert Table XIII about here]

III. Economic Explanations for Component Predictability

We next explore economic explanations for component predictability, focusing on out-of-sample combination forecasts. This section presents results for three approaches based on business-cycle fluctuations, rational/alpha predictability decompositions, and industry characteristics.

A. Out-of-Sample Predictability Across NBER-Dated Business-Cycle Phases

Fama and French (1989), Campbell and Cochrane (1999), and Cochrane (1999, 2007) argue that return predictability emanates from time-varying macroeconomic risk premiums corresponding to business-cycle fluctuations and changes in risk aversion. To investigate the correspondence between component predictability and business-cycle fluctuations, Table XIV (XV) reports R^2_{OS} statistics for the combination forecasts based on 14 economic variables (lagged industry returns) computed separately over NBER-dated recessions and expansions. Recessions (expansions) comprise 65 (403) of the observations for the forecast evaluation period.

Tables XIV and XV show that predictability is often considerably amplified during periods of recession. With respect to the combination forecasts of industry returns based on the 14 economic variables in Table XIV, Panel B, the average R^2_{OS} statistic across industries is 1.64% during recessions and only 0.38% during expansions, and the industries with the highest R^2_{OS} statistics over the entire forecast evaluation period also tend to have the highest R^2_{OS} statistics during recessions.[15] A similar pattern emerges for combination forecasts of industry returns based on lagged industry returns in Table XV, Panel B, where the average R^2_{OS} across industries is 2.38% (0.21%) during recessions (expansions), and the industries with the highest R^2_{OS} statistics over the full forecast evaluation period also generally have the highest values during recessions.

[Insert Table XIV about here]

[Insert Table XV about here]

Similar differences in R^2_{OS} statistics across recessions and expansions are evident for the size and book-to-market portfolios in Tables XIV and XV, respectively, with especially notable differences for the size portfolios using lagged industry returns as predictors in Table XV, Panel C. Insofar as recessions delineate periods of rapidly changing macroeconomic fundamentals and elevated risk aversion, the markedly stronger predictability in some component portfolios during recessions in Tables XIV and XV indicates that the combination forecasts are picking up economically meaningful changes in macroeconomic fundamentals and that particular industries are especially sensitive to these changes.

B. Decomposing Out-of-Sample Predictability

Studies such as Stambaugh (1983), Campbell (1987), Connor and Korajczyk (1989), Ferson and Harvey (1991, 1999), Ferson and Korajczyk (1995), Kirby (1998), and Avramov (2004) analyze the implications of rational asset pricing for return predictability. This provides a framework for determining the extent to which component predictability results from exposure to time-varying systematic/macroeconomic risk premiums as opposed to alpha predictability, where the latter can be interpreted as corresponding to asset mispricing. We investigate this issue using a novel out-of-sample approach based on combination forecasts of aggregate market and component portfolio returns.[16]

Following Avramov (2004), among others, consider the following model for component i's

[15] In line with our findings, Cooper, Gulen, and Vassalou (2002) find that the profitability of trading rules based on 10 economic variables for size and book-to-market portfolios is especially evident during U.S. recessions. Henkel, Martin, and Nadari (2008) and Perez-Quiros and Timmermann (2000) provide evidence of enhanced predictability during U.S. recessions for aggregate market and firm-level returns, respectively.

[16] We are grateful to Rossen Valkanov for discussion that led to the inclusion of this subsection.

excess return:

$$r_{i,t} = \alpha_i(x_{t-1}) + \beta_i' f_t + \varepsilon_{i,t}, \tag{6}$$

where x_{t-1} is an M-vector of lagged state variables or predictors, f_t is a K-vector of portfolio-based factors capturing systematic risk, and β_i is a K-vector comprised of component i's beta. Assume that

$$f_t = \lambda(x_{t-1}) + u_t, \tag{7}$$

where u_t is a zero-mean vector of disturbance terms. Equation (7) allows the factors to vary with the lagged state variables, leading to time-varying risk premiums. A conditional version of a rational asset-pricing model implies[17]

$$E(r_{i,t}|x_{t-1}) = \beta_i' E(f_t|x_{t-1}) = \beta_i' \lambda(x_{t-1}). \tag{8}$$

When $K = 1$, we can consider (8) as the conditional CAPM, so that f_t is a scalar representing the excess return on the aggregate market portfolio, and $\lambda(x_{t-1})$ is the expected market equity premium. Under rational asset pricing in the form of the conditional CAPM, any predictability in $r_{i,t}$ emanates solely from the predictability of aggregate market returns in conjunction with the sensitivity of $r_{i,t}$ to the market portfolio, as given by $\beta_i \lambda(x_{t-1})$, implying $\alpha_i(x_{t-1}) = 0\ \forall\ t$. Predictability in $r_{i,t}$ beyond what is produced by $\beta_i \lambda(x_{t-1})$ represents alpha predictability, as it implies $\alpha_i(x_{t-1}) \neq 0\ \forall\ t$. Insofar as (7) adequately captures systematic risk, $\alpha_i(x_{t-1}) \neq 0\ \forall\ t$ corresponds to mispricing in component i.

We calculate *rational pricing-restricted* combination forecasts of $r_{i,t}$ based on (8) to decompose the R^2_{OS} statistics (in Section II) into their rational and alpha predictability portions. To begin, consider forming a combination forecast of $r_{i,t}$ based on (8) under the conditional CAPM. From Section II, we already have a time-t combination forecast of the aggregate market return that incorporates time-$(t-1)$ information from 14 economic variables or lagged industry returns; denote this forecast as $\hat{f}_t^C$, which can be viewed as a real-time estimate of $\lambda(t-1)$. It is straightforward to compute an estimate of β_i for time t by regressing the component i excess return on the aggregate market excess return using data from the beginning of the sample through $t-1$; denote this estimate by $\hat{\beta}_{i,t}$.[18] The rational pricing-restricted combination forecast of $r_{i,t}$ based on (8) is then

[17] This specification assumes that β_i is time-invariant, following Stambaugh (1983), Campbell (1987), Connor and Korajczyk (1989), Kirby (1998), and Avramov (2004). Ferson and Harvey (1991), Evans (1994), and Ferson and Korajczyk (1995) present empirical evidence that time variation in risk premiums (λ) is substantially greater than that in β_i; also see Ghysels (1998). Note that our recursive out-of-sample estimation procedure for β_i, described below, allows for some time variation in β_i.

[18] Note that there is no "look-ahead" bias in doing this, as we only use data available at the time of forecast formation in estimating β_i.

given by

$$\hat{r}^R_{i,t} = \hat{\beta}_{i,t}\hat{f}^C_t. \tag{9}$$

In other words, one obtains this combination forecast with the use of an asset-pricing model, in this case, the conditional CAPM.

Denote the combination forecast of $r_{i,t}$ from Section II by $\hat{r}^C_{i,t}$. In contrast to $\hat{r}^R_{i,t}$, $\hat{r}^C_{i,t}$ does not impose the asset-pricing restriction given by (8). It thus constitutes an unrestricted combination forecast based on 14 economic variables or lagged industry returns that permits both rational and alpha predictability.

Then we are ready to decompose the R^2_{OS} statistic by computing two subsidiary R^2_{OS} statistics. The first is a modified version of (4) that measures the reduction in MSPE for the rational pricing-restricted combination forecast relative to the historical average forecast,

$$R^2_{OS,R} = 1 - \frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}^R_{i,n_1+k})^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \bar{r}_{i,n_1+k})^2}. \tag{10}$$

The $R^2_{OS,R}$ statistic gauges the extent of rational out-of-sample predictability in component i as implied by the conditional CAPM. The next statistic measures the decrease in MSFE for the unrestricted combination forecast compared to the rational pricing-restricted combination forecast,

$$R^2_{OS,\alpha} = 1 - \frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}^C_{i,n_1+k})^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}^R_{i,n_1+k})^2}. \tag{11}$$

This statistic quantifies the degree of out-of-sample predictability beyond rational predictability, thereby providing a measure of out-of-sample alpha predictability. Observe from (4), (10), and (11) that

$$R^2_{OS,\alpha} = 1 - \left[\frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}^C_{i,n_1+k})^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \bar{r}_{i,n_1+k})^2}\right]\left[\frac{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \bar{r}_{i,n_1+k})^2}{\sum_{k=1}^{n_2}(r_{i,n_1+k} - \hat{r}^R_{i,n_1+k})^2}\right] = 1 - \left(\frac{1-R^2_{OS}}{1-R^2_{OS,R}}\right). \tag{12}$$

Solving for R^2_{OS} in (12), we have

$$R^2_{OS} = R^2_{OS,R} + R^2_{OS,\alpha} - R^2_{OS,R}R^2_{OS,\alpha}. \tag{13}$$

For "small" $R^2_{OS,R}$ and $R^2_{OS,\alpha}$, the cross-product term is approximately zero, so that

$$R^2_{OS} \approx R^2_{OS,R} + R^2_{OS,\alpha}. \tag{14}$$

Our approach thus (approximately) dichotomizes R^2_{OS}, a measure of total out-of-sample predictability, into $R^2_{OS,R}$ and $R^2_{OS,\alpha}$, the sum of predictability due to exposure to time-varying risk premiums and alpha variation, respectively.

Table XVI (XVII) reports $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics for combination forecasts that use 14 economic variables (lagged industry returns) as predictors. Panel A of Table XVI indicates that 30 of the 33 industries have positive and significant $R^2_{OS,R}$ statistics, meaning that rational pricing as captured by the conditional CAPM explains a significant portion of the out-of-sample predictability for almost all industries. Furthermore, $R^2_{OS,\alpha}$ is only significant for two industries (SMOKE and CARS), and the magnitude of the $R^2_{OS,\alpha}$ statistics is typically substantially less than that of the corresponding $R^2_{OS,R}$ statistics. Taken together, these results suggest that the out-of-sample predictability in industry returns based on economic variables is almost entirely attributable to rational out-of-sample predictability based on the conditional CAPM as opposed to alpha predictability. The results for the size and book-to-market value portfolios in Panels B and C, respectively, of Table XVI are similar to those in Panel A. Again, little of the out-of-sample predictability in size and book-to-market returns appears attributable to alpha predictability.

[Insert Table XVI about here]

There is, however, more out-of-sample evidence of alpha predictability in industry returns when lagged industry returns serve as predictors in Table XVII, Panel A. Eight of the 33 industries exhibit significant alpha predictability as measured by the $R^2_{OS,\alpha}$ statistic. As in Table XVI, there is still substantial evidence of rational predictability for most of the industries, with 19 industries displaying a significant $R^2_{OS,R}$ statistic. Panel B (C) of Table XVII also reveals significant alpha predictability for the S1–S4 size (BM10 value) portfolios. The S1–S7 size and BM10 value portfolios exhibit significant rational predictability. Relative to the results in Table XVI based on economic variables as predictors, the results in Table XVII based on lagged industry returns as predictors indicate that rational (alpha) predictability is responsible for a lesser (greater) degree of the total out-of-sample predictability in component returns.

[Insert Table XVII about here]

Rational asset pricing built on the conditional CAPM suggests that the out-of-sample gains in predictability for the rational pricing-restricted forecast relative to the historical average forecast should be more pronounced for components with greater exposure to the market portfolio. We investigate the relationship between the extent of rational predictability and a component's beta in Figure 1. Each panel in Figure 1 presents a scatterplot relating a component's $R^2_{OS,R}$ statistic to the average $\hat{\beta}_{i,t}$ over the out-of-sample period. Economic variables (lagged industry returns) serve as the predictors when generating $\hat{f}_t^C$ on the left-hand-side (right-hand-side) panels of the figure. Each panel includes a fitted regression line and estimation results for a cross-section regression model with $R^2_{OS,R}$ (average $\hat{\beta}_{i,t}$) as the regressand (regressor).[19]

[Insert Figure 1 about here]

Panels A and B of Figure 1 show a clear positive correlation between the industry $R^2_{OS,R}$ statistics and average β_i estimates. Furthermore, the estimated slope coefficients reveal a significant relationship in each panel, and the R^2 statistics for the cross-section regressions are a reasonably sizable 23% and 25% in Panels A and B, respectively. Panel C indicates a significantly positive relationship between $R^2_{OS,R}$ and the average β_i estimates for size portfolios when economic variables serve as predictors, while Panel D shows a strong positive relationship based on lagged industry returns as predictors, with a t-statistic of 7.33 and a very substantial R^2 of 82% for the cross-section regression model. In contrast to the results in Figure 1, Panels A–D, there is no evidence of a significantly positive relationship between $R^2_{OS,R}$ and the average β_i estimates for book-to-market value portfolios in Panels E and F.

To check the robustness of the results in Tables XVII and XVIII, we consider a conditional multi-factor model. We use the popular Fama and French (1992, 1993, 1995) 3-factor model, so that $\beta_i = (\beta_{i,MKT}, \beta_{i,SMB}, \beta_{i,HML})'$ and $f_t = (MKT_t, SMB_t, HML_t)'$ in (6), where MKT_t is the time-t excess return on the aggregate market portfolio and SMB_t (HML_t) is the return on the well-known "big minus small" ("high minus low") portfolio. Fama and French argue that SMB_t and HML_t capture important systematic risk factors, and their 3-factor model prices size and book-to-market portfolios substantially better than the CAPM. There is also empirical evidence that SMB_t and HML_t are related to macroeconomic fundamentals and risk; see, for example, Liew and Vassalou (2000).

By proceeding in a manner analogous to generating the conditional CAPM forecast, we compute a rational pricing-restricted combination forecast based on the conditional Fama-French 3-factor model. The rational pricing-restricted combination forecast now takes the form

$$\hat{r}_{i,t}^R = \hat{\beta}_{i,t}' \hat{f}_t^C, \tag{15}$$

where $\hat{\beta}_{i,t} = (\hat{\beta}_{i,MKT,t}, \hat{\beta}_{i,SMB,t}, \hat{\beta}_{i,HML,t})'$ and $\hat{f}_t^C = (\widehat{MKT}_t^C, \widehat{SMB}_t^C, \widehat{HML}_t^C)'$. $\widehat{MKT}_t^C$ is the same time-t combination forecast of the excess return on the aggregate market portfolio based on time-

[19] An intercept term is included in the cross-section regression model. The t-statistics reported in Figure 1 are based on White (1980) heteroskedasticity-consistent standard errors.

$(t-1)$ information (either 14 economic variables or lagged industry returns) that we used previously. $\widehat{SMB}_t^C$ and $\widehat{HML}_t^C$ are combination forecasts of SMB_t and HML_t, respectively, based on time-$(t-1)$ information, which are straightforward to compute. $\hat{\beta}_{i,MKT,t}$, $\hat{\beta}_{i,SMB,t}$, $\hat{\beta}_{i,HML,t}$ are time-t estimates of the betas for component i, which are calculated by regressing the component i excess return on the 3 Fama-French factors using data from the start of the sample through $t-1$. Armed with $\hat{r}_{i,t}^R$ generated using (15), we can again decompose R_{OS}^2 into $R_{OS,R}^2$ and $R_{OS,\alpha}^2$, where rational predictability now corresponds to the conditional 3-factor model.

When $\widehat{MKT}_t^C$, $\widehat{SMB}_t^C$, and $\widehat{HML}_t^C$ are based on the 14 economic variables, the $R_{OS,R}^2$ and $R_{OS,\alpha}^2$ statistics are similar to those in Table XVI for the conditional CAPM. When using the 14 economic variables as predictors, most of the out-of-sample predictability in component returns thus appears rational, whether we rely on the conditional CAPM or 3-factor model. Because of the similarities, we do not report the complete results.[20]

When we use lagged industry returns as predictors, however, there are some significant differences in the extent of rational predictability detected by the conditional CAPM and 3-factor model. Table XVIII reports $R_{OS,R}^2$ and $R_{OS,\alpha}^2$ statistics for the conditional 3-factor model with lagged industry returns serving as predictors. The bottom part of each panel in the table also reports estimation results for a cross-section regression model that relates $R_{OS,R}^2$ to the set of average estimated betas. Comparing the results in Panel A of Tables XVII and XVIII, it is interesting to observe that five of the industries with significant $R_{OS,\alpha}^2$ statistics based on the conditional CAPM (CNSTR, APPRL, CHAIR, PRINT, and MANUF) no longer have significant $R_{OS,\alpha}^2$ statistics based on the conditional 3-factor model. The conditional 3-factor model thus eliminates the alpha predictability evident in these industries left over by the conditional CAPM. SMOKE, TXTLS, and CARS continue to have significant $R_{OS,\alpha}^2$ statistics in Table XVIII, Panel A, although $R_{OS,\alpha}^2$ is reduced by over half for TXTLS. Overall, the conditional 3-factor model appears to eliminate much of the alpha predictability unaccounted for by the conditional CAPM. The cross-section regression results in Table XVIII, Panel A indicate that the SMB_t factor plays an important role in reducing alpha predictability: industries with greater exposure to SMB_t have significantly higher $R_{OS,R}^2$ statistics.

[Insert Table XVIII about here]

With respect to the size portfolios results reported in Panel B, we continue to see interesting contrasts between Tables XVII and XVIII. Based on the conditional CAPM, S1–S4 all have

[20]They are available upon request from the authors.

statistically and economically significant $R^2_{OS,\alpha}$ statistics. The $R^2_{OS,\alpha}$ statistics for S1–S4 fall substantially for the conditional 3-factor model, and S2–S4 are no longer significant. While $R^2_{OS,\alpha}$ remains significant for S1 in Table XVIII, Panel B, it falls by more than 75% from Table XVII, Panel B. Similar results are obtained for the book-to-market portfolios: $R^2_{OS,\alpha}$ is only significant for BM10 in Table XVII, Panel C, but it is no longer significant in Table XVIII, Panel C. The conditional 3-factor model thus accounts for the alpha predictability in BM10 left over by the conditional CAPM. The cross-section regression results in Panels B and C of Table XVIII again point to the importance of the SMB_t factor in increasing the degree of rational predictability in component returns.

While beyond the scope of the present paper, we could consider additional conditional asset-pricing models, including, for example, models with additional potential macroeconomic risk factors from Chen, Roll, and Ross (1986).[21] Nevertheless, it is interesting that conditional asset-pricing models based on a small number of well-known factors can account for most of the out-of-sample predictability in a variety of component portfolio returns.

C. Out-of-Sample Predictability and Industry Characteristics

To gain additional insight into economic explanations for differences in component predictability, we examine the relationships between the R^2_{OS} statistics for the combination forecasts in the last column of Table IX and two industry characteristics, industry concentration share and industry market capitalization share. This is motivated by the information-flow frictions recently emphasized by HTV. If information-flow frictions are pertinent, we expect stronger predictability in industries with greater concentration, since the equity market is better able to acquire information for the relatively small number of large firms in these industries. In contrast, information should be more costly to obtain—and information-flow frictions more relevant—for industries characterized by a comparatively large number of small firms; we thus expect a greater degree of predictability for these industries. In a similar vein, we posit a lesser (greater) degree of predictability for industries that make up a larger (smaller) share of the overall equity market.

Panel A (B) of Figure 2 presents a scatterplot relating the R^2_{OS} statistics for the combination forecasts based on lagged industry returns in Table IX to industry concentration (industry market capitalization). Industry concentration is measured as the sum of the earnings share (in percent) accruing to the eight largest firms in the industry, while industry market capitalization is measured

[21]Ferson and Harvey (1991) and Ferson and Korajczyk (1995) consider these factors in conditional asset-pricing models. We leave the analysis of additional conditional asset-pricing models to future research.

as the industry market capitalization share of the entire equity market on average over our sample period.[22]

[Insert Figure 2 about here]

Panel A of Figure 2 shows a negative correlation between industry concentration and out-of-sample predictability across industries. In addition, a cross-section OLS regression of the R^2_{OS} statistics on industry concentration yields a negative and significant slope coefficient (t-statistic equals -3.08) and an R^2 statistic of 12%. These results are in line with our conjecture that less concentrated industries are typically more predictable due to information-flow frictions. Panel B of Figure 2 shows a negative correlation between industry market capitalization and out-of-sample predictability, and the cross-section regression confirms a significant relationship (t-statistic equals -5.15) with relatively high explanatory power (R^2 of 31%). Furthermore, when we estimate a multivariate cross-section regression model with industry concentration and market capitalization appearing jointly as regressors, both of these variables are significant determinants of the R^2_{OS} statistics (t-statistics of -3.26 and -5.44, respectively), and the R^2 for this cross-section regression is a sizable 43%.[23] Taken together, the results in Figure 2 and the cross-section regression results in Table XVIII, Panel A, in which the coefficient on $\bar{\bar{\beta}}_{i,SMB,t}$ is significantly positive, signal the relevance of market structure and size for the predictability of industry returns.

IV. Component-Rotation Investment Strategy

As a final empirical exercise, we further analyze the economic significance of time-varying versus constant expected returns for component portfolios in the context of a component-rotation investment strategy. To implement the strategy, we construct "maximum" portfolios based on combination or historical average forecasts of component returns. The maximum portfolio is entirely allocated to the component with the highest forecasted return for the next month. The component with the highest predicted return is identified using either the combination or historical average forecasts of component returns. Intuitively, if combination forecasts provide useful information

[22] The industry concentration data are for 1997 and from the Census Bureau. Industry market capitalization data are from the data library at Kenneth French's web site.

[23] We also estimated cross-section regressions for the R^2_{OS} statistics for the combination forecasts based on the 14 economic variables in the last column of Table VIII. While the slope coefficients corresponding to industry concentration and market capitalization shares are negative, they are not significant at conventional levels. This is in line with HTV's focus on lagged industry returns instead of more common economic variables when analyzing information-flow frictions.

beyond that contained in historical average forecasts, portfolio performance should improve when we identify the portfolio to invest in during the next month using the combination instead of historical average forecasts.

Summary statistics for the maximum portfolios are reported in Table XIX. Results are reported for each set of component portfolios (industry, size, and book-to-market) and combination forecasts based on either the 14 economic variables or lagged industry returns. With the exception of book-to-market components based on economic variables, the average monthly return is higher and standard deviation lower when we identify the component with the highest predicted return using the combination instead of historical average forecasts. Of course, a higher average return and lower standard deviation translates into a higher Sharpe ratio. Indeed, the last column of Table XIX shows that the increase in the Sharpe ratio is often sizable. For example, for size components based on lagged industry returns, the Sharpe ratio is 98% higher when we select the size component using the combination instead of historical average forecasts.

[Insert Table XIX about here]

Figure 3 shows the cumulative gross return for the different maximum portfolios. Equivalently, it shows the value of investing $1 in a given maximum portfolio starting in 1966:01, where all of the proceeds are reinvested each month. As a reference, the figure also shows the cumulative gross return for the aggregate market portfolio, the classic buy-and-hold market strategy. Figure 3 shows sizable increases in wealth accumulation for maximum portfolios based on combination forecasts relative to historical average forecasts, especially when lagged industry returns serve as predictors of component returns. As indicated by the Sharpe ratios in Table XIX, these increases in wealth accumulation typically do not come at the expense of greater portfolio risk.

[Insert Figure 3 about here]

To glean greater insight into the nature of asset allocation for the maximum portfolios based on lagged industry returns, Figure 4 shows the particular component that the maximum portfolio invests in each month. The panels on the right-hand-side of Figure 4 indicate—not surprisingly—that there is relatively little rotation among components based on the historical average forecasts. For the industry components, the maximum portfolio almost always invests in industry 24 (INSTR) through the late 1970s, industry 3 (OIL) through the mid 1980s, and industry 28 (TV) thereafter (Panel B). The maximum portfolio for the size components is almost always allocated to S1 through the late 1980s, S3 through the 2002, and S1 again thereafter (Panel D). The maximum portfolio for the book-to-market components always invests in S8 through the mid 1980s and almost always in S10 thereafter (Panel F). In contrast, the panels on the left-hand-side of Figure 4 recommend considerably more rotation among the component portfolios throughout the 1966:01–2004:12 period. This is true for industry, size, and book-to-market components. The results in Table XIX and Figure 4 demonstrate that the more frequent rotation typically pays off in terms of improved maximum portfolio performance.

[Insert Figure 4 about here]

V. Conclusion

We conduct an extensive analysis of return predictability for a variety of component portfolios using a large number of potential predictors from the literature on aggregate market return predictability. Focusing on three sets of component portfolios sorted on industry, size, and book-to-market, in-sample and out-of-sample tests both point to important differences in predictability across component portfolios. More specifically, we find that returns are more predictable for (i) particular industries, including construction, textiles, apparel, furniture, printing, automobiles, and manufacturing; (ii) small-cap in contrast to large-cap stocks; and (iii) high as opposed to low book-to-value stocks. Employing a forecast combination approach, the predictability we find is robust to the use of individual predictors and particular sample periods. Overall, differences in return predictability across component portfolios are more evident using lagged industry returns rather than a set of 14 popular economic variables as predictors.

We also explore economic explanations for the differences in return predictability across component portfolios. Out-of-sample predictability is especially evident during U.S. recessions, indicating an important role for time-varying risk premiums corresponding to business-cycle fluctuations. We also develop an innovative decomposition based on combination forecasts that apportions out-of-sample component predictability into exposure to time-varying macroeconomic risk premiums and alpha predictability. Our results suggest that exposure to time-varying risk premiums largely accounts for the out-of-sample predictability in component portfolios. Furthermore, differences in return predictability across industry portfolios are significantly related to industry concentration and capitalization, and the direction of the relationships are consistent with information-flow frictions in the equity market (Hong, Torous, and Valkanov (2007)). Overall, our results point to the importance of business-cycle fluctuations and information-flow frictions in understanding return predictability more generally.

Finally, we demonstrate that component predictability has important asset-allocation implications for a component-rotation investment strategy. Portfolios that use the combination forecasts to identify the component with the highest predicted return for the next month exhibit superior performance compared to portfolios that use historical average forecasts. Combination forecasts recommend more frequent rotation among components compared to historical average forecasts, and such a rotation strategy based on component predictability often leads to sizable investment gains.

Our results could be extended in a number of directions. First, we focus on a large number of predictors from the literature on aggregate market return predictability. It would be interesting to also consider portfolio-specific predictors such as a component's own dividend-price ratio. Second, given that particular components appear to be substantially more predictable than others, it would be worthwhile to investigate whether we can exploit component predictability to improve aggregate market predictability. A forecast of the aggregate market return can naturally be formed as a weighted average of the individual component forecasts. Of course, since the optimal forecasting weights for the individual components are not known, they must be estimated, and this presents forecasting challenges. Third, our out-of-sample asset-allocation exercise allocates all of the portfolio to a single component. Instead, we could hold all N of the individual components in the portfolio and "tilt" the portfolio toward the components with the highest expected returns. Selecting the optimal weights for this type of strategy entails forecasting the covariance matrix of returns, which presents its own set of challenges. We leave these interesting and important extensions to future research.

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Table I
Summary statistics

The table reports sample means and standard deviations (in percentage points) for excess returns on various portfolios and economic variables for 1945:12–2004:12. Sharpe ratios are also reported for the excess returns. All excess returns are computed relative to the risk-free rate. Panel A reports summary statistics for the CRSP aggregate value-weighted market portfolio (MKT). Panel B reports summary statistics for 33 valued-weighted industry portfolios. Panel C (D) reports summary statistics for 10 portfolios sorted on market capitalization (book-to-market value); S1,...,S10 (BM1,...,BM10) delineate deciles in ascending order for portfolios formed on market capitalization (book-to-market value). Panel E reports summary statistics for 14 economic variables.

Variable	Mean	Std. dev.	Sharpe ratio	Variable	Mean	Std. dev.	Sharpe ratio	Variable	Mean	Std. dev.	Sharpe ratio
				Panel A: Aggregate market portfolio excess returns							
MKT	0.61	4.25	0.14								
				Panel B: Industry portfolio excess returns							
AGRIC	0.50	7.13	0.07	PAPER	0.74	5.32	0.14	CARS	0.68	5.43	0.13
MINES	0.54	6.38	0.08	PRINT	0.66	5.28	0.13	INSTR	0.76	5.34	0.14
OIL	0.75	6.64	0.11	CHEMS	0.68	4.56	0.15	MANUF	0.65	6.31	0.10
STONE	0.73	6.74	0.11	PTRLM	0.82	4.93	0.17	TRANS	0.57	5.69	0.10
CNSTR	0.65	6.99	0.09	RUBBER	0.69	5.98	0.12	PHONE	0.44	4.69	0.09
FOOD	0.69	4.21	0.16	LETHR	0.82	6.27	0.13	TV	0.91	6.67	0.14
SMOKE	0.94	5.83	0.16	GLASS	0.60	5.84	0.10	UTILS	0.53	3.86	0.14
TXTLS	0.56	5.93	0.09	METAL	0.52	6.19	0.08	WHLSL	0.71	5.42	0.13
APPRL	0.45	6.52	0.07	MTLPR	0.65	4.87	0.13	RTAIL	0.68	5.09	0.13
WOOD	0.67	7.21	0.09	MACHIN	0.67	5.79	0.12	MONEY	0.72	4.81	0.15
CHAIR	0.55	5.50	0.10	ELCTR	0.72	6.22	0.12	SRVC	0.72	6.45	0.11
				Panel C: Size portfolio excess returns							
S1	0.84	6.12	0.14	S6	0.72	5.01	0.14				
S2	0.79	5.95	0.13	S7	0.75	4.90	0.15				
S3	0.82	5.67	0.14	S8	0.71	4.76	0.15				
S4	0.78	5.45	0.14	S9	0.66	4.39	0.15				
S5	0.78	5.23	0.15	S10	0.56	4.12	0.14				
				Panel D: Book-to-market portfolio excess returns							
BM1	0.52	4.98	0.10	BM6	0.74	4.26	0.17				
BM2	0.58	4.55	0.13	BM7	0.73	4.28	0.17				
BM3	0.61	4.51	0.14	BM8	0.88	4.38	0.20				
BM4	0.61	4.44	0.14	BM9	0.88	4.64	0.19				
BM5	0.72	4.17	0.17	BM10	0.96	5.47	0.17				
				Panel E: Economic variables							
D/E	-0.70	0.18		INFL	0.003	0.004		D/Y	−3.39	0.42	
SVAR	0.002	0.003		TMS	0.02	0.01		E/P	−2.69	0.42	
DFR	0.000	0.01		TBL	0.05	0.03		B/M	0.58	0.25	
LTY	0.06	0.03		DFY	0.01	0.004		NTIS	0.02	0.02	
LTR	0.01	0.03		D/P	−3.39	0.42					

Table II
In-sample predictive regression results for industry portfolio excess returns with 14 economic variables as predictors

The entries in the table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j} x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted industry portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. The MKT row reports results for the excess return on the CRSP aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1946:01–2004:12; "*" indicates significance at the 5% level. "Sig.(5%)" indicates the number of industries for which the t-statistic is significant at the 5% level for the predictor given in the column heading. "Avg. R^2" is the row or column average of the R^2 statistics; the row average excludes MKT.

Return	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	Avg. R^2
MKT	0.28	−1.05	0.33	−1.38	2.53*	−2.75*	2.23*	−2.32*	1.45	2.18	2.29*	2.08	1.02	−1.84*	
	0.01	0.15	0.02	0.27	0.89	1.06	0.70	0.76	0.30	0.67	0.73	0.61	0.15	0.47	0.48
AGRIC	−0.42	0.63	1.14	−0.58	0.98	−1.44	1.33	−1.14	1.00	1.22	1.38	1.42	0.51	−2.14*	
	0.03	0.06	0.18	0.05	0.14	0.29	0.25	0.19	0.14	0.21	0.27	0.28	0.04	0.64*	0.20
MINES	0.17	2.22*	0.78	−2.41*	2.22*	−1.12	0.84	−2.70*	0.92	0.43	0.56	0.36	0.08	−1.57	
	0.00	0.69	0.09	0.81	0.69	0.18	0.10	1.02	0.12	0.03	0.04	0.02	0.00	0.35	0.30
OIL	−0.67	−0.26	0.47	−2.50*	0.39	−1.39	0.42	−2.59*	−0.53	1.74	1.69*	2.05	1.09	0.32	
	0.06	0.01	0.03	0.88	0.02	0.27	0.02	0.94	0.04	0.43	0.40	0.59	0.17	0.01	0.28
STONE	−0.46	0.08	0.91	−1.26	2.38*	−0.77	−0.71	−0.90	0.83	1.36	1.60	1.58	1.00	−1.90*	
	0.03	0.00	0.12	0.23	0.79	0.08	0.07	0.12	0.10	0.26	0.36	0.35	0.14	0.51*	0.23
CNSTR	−0.82	−0.55	0.66	−1.83*	3.16*	−1.95*	1.53	−2.45*	1.41	0.98	1.30	1.35	0.56	−2.68*	
	0.09	0.04	0.06	0.47	1.39	0.54	0.33	0.84	0.28	0.14	0.24	0.26	0.05	1.00	0.41
FOOD	0.11	−0.92	1.01	0.82	2.55*	−2.43*	1.55*	0.11	2.95*	1.39	1.44	1.36	0.56	−3.68*	
	0.00	0.12	0.14	0.10	0.91	0.83	0.34	0.00	1.21	0.27	0.29	0.26	0.04	1.88	0.46
SMOKE	−1.41	−0.68	0.51	0.96	2.39*	−0.70	0.23	0.82	1.83*	0.03	0.03	0.64	−0.23	−3.72*	
	0.28	0.07	0.04	0.13	0.80	0.07	0.01	0.10	0.47	0.00	0.00	0.06	0.01	1.92	0.28
TXTLS	1.43	−0.37	1.25	−0.24	2.40*	−2.52*	2.56*	−1.36	3.20*	1.71	2.05*	1.09	1.42	−2.80*	
	0.29	0.02	0.22	0.01	0.81	0.89	0.92	0.26	1.42	0.41	0.59	0.17	0.29	1.10	0.53
APPRL	0.48	−1.21	0.87	−0.21	2.18*	−2.33*	2.07*	−1.12	3.50*	1.89	2.18*	1.70	1.71	−3.40*	
	0.03	0.21	0.11	0.01	0.67	0.76	0.60	0.18	1.71	0.51	0.67	0.41	0.41	1.61	0.56
WOOD	0.41	0.69	0.86	−1.56*	2.97*	−1.33	1.34	−2.11*	1.55	0.44	0.65	0.27	0.27	−1.94*	
	0.02	0.07	0.10	0.34*	1.23	0.25	0.26	0.62*	0.34	0.03	0.06	0.01	0.01	0.53	0.28
CHAIR	0.56	−0.88	−0.39	0.27	4.68*	−1.85*	1.92*	−0.58	3.17*	1.20	1.60	0.97	0.73	−3.12*	
	0.04	0.11	0.02	0.01	3.00	0.48	0.52	0.05	1.40	0.20	0.36	0.13	0.07	1.36	0.55
PAPER	0.91	−0.16	0.53	−1.88*	2.69*	−2.45*	1.43	−2.45*	1.09	2.30*	2.30*	1.92	1.18	−1.29	
	0.12	0.00	0.04	0.50*	1.01	0.84	0.29	0.84	0.17	0.74*	0.74	0.52	0.20	0.23	0.44
PRINT	0.17	−1.31	0.75	0.02	3.42*	−3.06*	2.12*	−0.91	2.87*	1.42	1.73	1.36	1.05	−2.27*	
	0.00	0.24	0.08	0.00	1.62	1.31	0.63	0.12	1.15	0.28	0.42	0.26	0.15	0.72	0.50
CHEMS	0.01	−0.91	0.27	−1.19	2.27*	−2.39*	1.02	−1.60*	0.76	1.87	1.86*	1.89	0.62	−2.42*	
	0.00	0.12	0.01	0.20	0.72	0.80	0.15	0.36	0.08	0.49	0.48	0.50	0.05	0.82	0.34
PTRLM	−0.53	−1.83*	−0.02	−1.55*	0.85	−1.93*	1.63*	−2.22*	−0.04	1.67	1.61	1.93	0.90	−1.27	
	0.04	0.47	0.00	0.34*	0.10	0.52	0.37	0.69	0.00	0.39	0.36	0.52	0.11	0.23	0.30

Table II — *Continued*

Return	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	Avg. R^2
RUBBER	1.26	0.15	0.61	−1.33	1.59*	−2.16*	2.32*	−2.32*	1.74*	2.62	2.66*	2.09	1.28	−2.08*	
	0.23	0.00	0.05	0.25	0.35	0.66	0.76	0.75	0.42	0.96	0.99	0.61	0.23	0.61	0.49
LETHR	−0.22	−0.45	0.84	−0.26	2.60*	−2.43*	2.04*	−1.15	4.39*	0.71	0.94	0.81	1.01	−2.59*	
	0.01	0.03	0.10	0.01	0.95	0.82	0.59	0.19	2.65	0.07	0.13	0.09	0.14	0.94	0.48
GLASS	0.66	0.11	−0.49	−0.56	3.53*	−1.71*	2.65*	−1.71*	2.64*	2.16	2.36*	1.89	1.28	−1.81*	
	0.06	0.00	0.03	0.04	1.73	0.41	0.98	0.41	0.98	0.65	0.78	0.50	0.23	0.46	0.52
METAL	−0.40	0.87	0.58	−2.24*	1.36	−1.26	0.88	−2.56*	0.51	1.20	1.29	1.39	0.42	−1.22	
	0.02	0.11	0.05	0.71*	0.26	0.23	0.11	0.92	0.04	0.20	0.23	0.27	0.03	0.21	0.24
MTLPR	0.57	−1.06	1.16	−0.96	2.74*	−2.60*	2.71*	−2.12*	1.80*	1.73	2.00*	1.50	0.73	−1.88*	
	0.05	0.16	0.19	0.13	1.05	0.95	1.02	0.63	0.46	0.42	0.56	0.32	0.08	0.50	0.47
MACHIN	0.45	−0.68	−0.48	−2.36*	1.76*	−2.71*	1.89*	−3.12*	0.67	1.11	1.28	0.93	0.15	−0.15	
	0.03	0.06	0.03	0.78	0.43	1.03	0.50	1.36	0.06	0.18	0.23	0.12	0.00	0.00	0.34
ELCTR	0.17	−1.07	−0.43	−0.93	1.77*	−2.24*	2.17*	−1.86*	1.49	1.46	1.53	1.40	0.51	−0.53	
	0.00	0.16	0.03	0.12	0.44	0.71	0.66	0.49	0.31	0.30	0.33	0.28	0.04	0.04	0.28
CARS	0.50	−1.78*	0.59	−1.45	2.82*	−2.94*	3.31*	−2.86*	1.95*	1.89	2.19*	1.68	1.11	−1.70*	
	0.04	0.45	0.05	0.29	1.11	1.21	1.52	1.14	0.54	0.50	0.68	0.40	0.18	0.41	0.61
INSTR	1.00	−1.36	0.79	−2.25*	0.99	−2.85*	1.11	−2.67*	0.14	1.07	1.12	0.64	−0.18	−1.12	
	0.14	0.26	0.09	0.71	0.14	1.13	0.17	1.00	0.00	0.16	0.18	0.06	0.00	0.18	0.30
MANUF	0.97	−0.38	0.90	−0.97	2.37*	−2.19*	1.88*	−1.76*	2.34*	1.56	1.92*	1.15	0.95	−1.96*	
	0.13	0.02	0.11	0.13	0.79	0.68	0.50	0.44	0.77	0.35	0.52	0.19	0.13	0.54	0.38
TRANS	−0.01	−0.75	1.00	−0.81	3.12*	−2.51*	1.98*	−1.66*	2.18*	1.55	1.71	1.57	0.95	−2.14*	
	0.00	0.08	0.14	0.09	1.36	0.88	0.55	0.39	0.67	0.34	0.41	0.35	0.13	0.64	0.43
PHONE	0.23	−1.70*	−0.76	0.48	2.13*	−1.57	1.10	−0.02	1.14	2.12	2.14*	2.04*	1.07	−0.81	
	0.01	0.41	0.08	0.03	0.64	0.35	0.17	0.00	0.18	0.63	0.64	0.59	0.16	0.09	0.28
TV	0.23	−0.25	0.91	0.01	1.70*	−1.98*	1.87*	−0.82	2.13*	2.05	2.23*	1.97	1.60	−1.90*	
	0.01	0.01	0.12	0.00	0.41	0.55	0.49	0.09	0.64	0.59	0.70	0.55	0.36	0.51	0.36
UTILS	−0.73	−0.08	−0.27	−0.57	2.90*	−2.43*	1.07	−1.02	1.20	1.85	1.83*	2.19*	1.24	−2.56*	
	0.08	0.00	0.01	0.05	1.17	0.83	0.16	0.15	0.20	0.48	0.47	0.67	0.22	0.92	0.39
WHLSL	0.03	−0.36	0.35	−0.81	3.24*	−2.11*	0.93	−1.19	2.06*	1.47	1.70	1.47	1.06	−2.41*	
	0.00	0.02	0.02	0.09	1.46	0.63	0.12	0.20	0.60	0.31	0.41	0.31	0.16	0.82	0.37
RTAIL	0.90	−1.04	0.74	−0.20	3.09*	−2.16*	1.64*	−0.92	3.23*	1.19	1.38	0.81	0.69	−2.63*	
	0.11	0.15	0.08	0.01	1.33	0.65	0.38	0.12	1.45	0.20	0.27	0.09	0.07	0.97	0.42
MONEY	−0.27	−0.84	0.38	−0.74	3.51*	−2.31*	1.85*	−1.54*	1.62*	1.75	1.86*	1.89	0.87	−1.97*	
	0.01	0.10	0.02	0.08	1.71	0.75	0.48	0.33	0.37	0.43	0.49	0.50	0.11	0.54	0.42
SRVC	0.05	−0.59	0.81	−0.20	1.56*	−2.53*	1.74*	−0.96	2.17*	1.70	1.85*	1.69	1.08	−2.30*	
	0.00	0.05	0.09	0.01	0.34	0.89	0.43	0.13	0.66	0.41	0.48	0.40	0.16	0.74	0.34
Sig.(5%)	0	4	0	9	28	25	19	18	18	1	15	2	0	24	
Avg. R^2	0.06	0.13	0.08	0.23	0.90	0.65	0.44	0.46	0.59	0.35	0.42	0.32	0.13	0.67	

Table III
In-sample predictive regression results for industry portfolio excess returns with 15 lagged industry returns as predictors

The entries in the table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted industry portfolio given in the row heading and $x_{j,t-1}$ is the lagged industry return given in the column heading. The MKT row reports results for the excess return on the CRSP aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1946:01–2004:12; "*" indicates significance at the 5% level. "Sig.(5%)" indicates the number of industries for which the t-statistic is significant at the 5% level for the predictor given in the column heading. "Avg. R^2" is the row or column average of the R^2 statistics; the row average excludes MKT. The 15 lagged industry returns included in the table are the 15 of 33 lagged industry returns that are significant in predicting the excess return on the CRSP aggregate value-weighted market portfolio.

Return	TXTLS	APPRL	PRINT	LETHR	GLASS	MACHIN	ELCTR	INSTR	MANUF	TRANS	TV	UTILS	RTAIL	MONEY	SRVC	Avg. R^2
MKT	2.50*	1.88*	2.71*	2.01*	1.67*	1.87*	1.68*	1.92*	1.74*	1.66*	2.62*	1.89*	2.31*	2.49*	2.40*	
	0.88	0.50	1.03	0.57	0.39	0.49	0.40	0.52	0.43	0.39	0.96	0.50	0.75	0.87	0.81	0.63
AGRIC	3.52*	2.54*	2.58*	2.52*	2.83*	3.30*	2.56*	2.64*	2.89*	2.82*	2.46*	1.25	2.04*	2.16*	2.93*	
	1.72	0.90	0.93	0.89	1.12	1.52	0.92	0.98	1.17	1.11	0.85	0.22	0.58	0.66	1.20	0.98
MINES	2.59*	2.28*	1.99*	2.56*	0.78	1.87*	1.33	1.30	1.01	1.87*	1.46	1.65*	1.76*	1.89*	1.32	
	0.94	0.73	0.55	0.92	0.09	0.49	0.25	0.24	0.14	0.49	0.30	0.38	0.44	0.50	0.25	0.45
OIL	0.92	0.75	0.17	1.21	0.66	0.50	0.91	0.66	0.40	0.55	−0.04	0.14	−0.17	0.75	0.02	
	0.12	0.08	0.00	0.21	0.06	0.04	0.12	0.06	0.02	0.04	0.00	0.00	0.00	0.08	0.00	0.06
STONE	2.72*	1.89*	2.29*	2.16*	1.78*	2.61*	2.23*	2.60*	1.99*	2.81*	2.67*	2.74*	1.53	3.56*	2.38*	
	1.03	0.50	0.74	0.66	0.45	0.96	0.70	0.95	0.56	1.11	1.00	1.05	0.33	1.76	0.80	0.84
CNSTR	4.66*	4.04*	4.84*	4.29*	3.11*	3.78*	3.89*	3.66*	3.92*	4.33*	3.95*	3.61*	4.02*	5.02*	3.93*	
	2.98	2.26	3.21	2.54	1.35	1.98	2.09	1.86	2.13	2.59	2.16	1.81	2.24	3.44	2.14	2.32
FOOD	1.93*	1.72*	2.00*	2.10*	0.77	0.87	0.20	1.16	2.23*	1.22	1.77*	1.56	2.33*	1.97*	1.67*	
	0.52	0.42	0.56	0.62	0.08	0.11	0.01	0.19	0.70	0.21	0.44	0.34	0.76	0.55	0.39	0.39
SMOKE	1.86*	0.90	1.24	1.99*	−0.54	0.13	−0.43	−0.19	0.86	1.32	−0.39	2.93*	0.74	1.80*	−0.31	
	0.49	0.11	0.22	0.56	0.04	0.00	0.03	0.00	0.10	0.24	0.02	1.20	0.08	0.46	0.01	0.24
TXTLS	5.43*	5.13*	4.64*	5.61*	3.78*	3.50*	3.04*	3.23*	4.51*	4.74*	3.54*	2.24*	5.43*	4.53*	4.11*	
	4.00	3.58	2.96	4.27	1.98	1.70	1.29	1.45	2.79	3.08	1.74	0.70	4.00	2.82	2.34	2.58
APPRL	4.31*	3.56*	4.10*	4.48*	2.49*	3.36*	2.65*	2.96*	3.48*	3.50*	3.18*	1.95*	4.08*	3.45*	3.99*	
	2.56	1.76	2.32	2.76	0.87	1.57	0.98	1.22	1.68	1.70	1.41	0.53	2.30	1.65	2.20	1.70
WOOD	2.53*	2.23*	2.57*	3.56*	1.35	1.64	1.95*	2.56*	2.74*	2.99*	2.74*	1.94*	3.07*	3.88*	3.11*	
	0.90	0.70	0.93	1.77	0.26	0.38	0.54	0.92	1.05	1.25	1.05	0.53	1.31	2.09	1.35	1.00
CHAIR	4.64*	4.40*	4.32*	5.42*	3.53*	3.90*	3.74*	3.96*	4.03*	4.85*	3.64*	3.66*	5.25*	4.94*	4.99*	
	2.95	2.66	2.57	3.98	1.73	2.10	1.94	2.17	2.24	3.22	1.83	1.86	3.75	3.34	3.40	2.65
PAPER	1.55	1.42	1.37	1.60	0.12	0.67	0.39	1.06	1.11	0.85	1.62	0.60	1.77*	1.02	1.39	
	0.34	0.28	0.27	0.36	0.00	0.06	0.02	0.16	0.17	0.10	0.37	0.05	0.44	0.15	0.27	0.20
PRINT	4.24*	3.83*	4.69*	3.84*	3.18*	3.85*	3.36*	4.18*	4.45*	3.82*	4.82*	2.94*	4.69*	4.38*	4.88*	
	2.48	2.03	3.02	2.04	1.41	2.06	1.58	2.42	2.72	2.02	3.18	1.21	3.02	2.64	3.26	2.34
CHEMS	0.70	1.23	1.34	1.04	0.31	0.30	−0.13	0.60	0.88	0.52	1.75*	1.25	1.38	0.90	0.93	
	0.07	0.21	0.25	0.15	0.01	0.01	0.00	0.05	0.11	0.04	0.43	0.22	0.27	0.11	0.12	0.14
PTRLM	0.85	0.51	−0.06	0.78	0.66	−0.26	0.41	0.15	−0.16	0.18	−0.25	−0.86	−0.05	0.25	0.11	
	0.10	0.04	0.00	0.09	0.06	0.01	0.02	0.00	0.00	0.00	0.01	0.10	0.00	0.01	0.00	0.03
RUBBER	2.27*	1.33	1.18	2.41*	1.05	1.88*	0.99	1.36	1.46	1.89*	1.75*	0.42	2.03*	1.36	1.74*	
	0.72	0.25	0.20	0.81	0.16	0.50	0.14	0.26	0.30	0.50	0.43	0.03	0.58	0.26	0.43	0.37
LETHR	4.21*	4.57*	3.84*	3.92*	1.74*	2.84*	1.71*	3.29*	3.88*	3.37*	2.66*	2.58*	4.44*	4.32*	3.55*	
	2.44	2.87	2.05	2.13	0.43	1.13	0.41	1.51	2.09	1.58	0.99	0.94	2.71	2.57	1.75	1.71
GLASS	3.09*	2.61*	3.23*	3.05*	2.49*	2.44*	2.43*	2.54*	2.10*	2.33*	2.79*	2.47*	2.82*	3.68*	2.66*	
	1.33	0.96	1.45	1.30	0.87	0.83	0.83	0.90	0.62	0.76	1.09	0.85	1.11	1.88	0.99	1.05
METAL	2.09*	1.26	1.64	1.47	0.74	1.80*	0.98	1.50	0.66	1.86*	1.77*	0.96	1.52	1.84*	1.42	
	0.62	0.22	0.38	0.31	0.08	0.46	0.14	0.32	0.06	0.48	0.44	0.13	0.32	0.48	0.28	0.31
MTLPR	3.96*	3.41*	3.91*	3.54*	2.47*	3.33*	2.66*	3.22*	3.10*	3.71*	3.44*	2.82*	3.94*	4.02*	3.47*	
	2.17	1.62	2.11	1.74	0.86	1.54	0.99	1.45	1.34	1.91	1.64	1.11	2.15	2.24	1.68	1.64

Table III — *Continued*

Return	TXTLS	APPRL	PRINT	LETHR	GLASS	MACHIN	ELCTR	INSTR	MANUF	TRANS	TV	UTILS	RTAIL	MONEY	SRVC	Avg. R^2
MACHIN	2.15*	1.45	3.63*	1.52	2.42*	2.51*	2.26*	2.50*	1.53	1.70*	2.58*	2.07*	2.11*	2.53*	2.65*	
	0.65	0.30	1.83	0.33	0.82	0.88	0.72	0.88	0.33	0.41	0.93	0.60	0.62	0.90	0.98	0.74
ELCTR	1.92*	1.04	1.95*	1.08	1.04	1.43	1.28	1.65*	0.98	1.05	2.69*	1.66*	1.77*	1.93*	1.51	
	0.52	0.15	0.54	0.16	0.15	0.29	0.23	0.38	0.14	0.16	1.01	0.39	0.44	0.52	0.32	0.36
CARS	4.30*	3.93*	4.12*	3.86*	3.58*	3.90*	3.41*	2.82*	2.96*	3.86*	3.99*	2.46*	4.46*	4.03*	4.27*	
	2.55	2.14	2.35	2.06	1.78	2.11	1.62	1.11	1.23	2.06	2.21	0.85	2.74	2.25	2.51	1.97
INSTR	1.98*	1.49	2.62*	1.39	1.73*	1.58	1.39	1.74*	1.91*	1.23	2.09*	1.19	1.76*	1.20	1.75*	
	0.55	0.31	0.96	0.27	0.42	0.35	0.27	0.42	0.51	0.21	0.61	0.20	0.44	0.20	0.43	0.41
MANUF	4.77*	4.47*	5.36*	4.70*	3.26*	3.72*	3.45*	3.77*	4.05*	4.58*	3.85*	3.29*	4.22*	5.16*	4.73	
	3.12	2.75	3.91	3.03	1.48	1.92	1.65	1.97	2.26	2.88	2.06	1.51	2.45	3.63	3.07	2.51
TRANS	3.18*	2.53*	3.21*	3.09*	2.42*	2.40*	2.32*	2.17*	2.32*	2.73*	2.77*	1.59	2.66*	3.17*	2.55*	
	1.41	0.90	1.44	1.33	0.82	0.81	0.75	0.66	0.76	1.05	1.07	0.35	0.99	1.40	0.91	0.98
PHONE	1.59	0.86	2.28*	1.30	0.31	0.52	0.44	0.16	0.09	0.37	1.85*	1.84*	0.97	1.42	1.10	
	0.36	0.10	0.73	0.24	0.01	0.04	0.03	0.00	0.00	0.02	0.48	0.48	0.13	0.28	0.17	0.21
TV	2.41*	1.87*	3.25*	1.85*	1.64	1.94*	2.22*	2.16*	2.63*	2.87*	3.38*	1.93*	2.89*	2.93*	3.34*	
	0.82	0.49	1.48	0.48	0.38	0.53	0.69	0.65	0.97	1.15	1.59	0.52	1.17	1.20	1.56	0.91
UTILS	0.02	−0.12	0.37	−0.03	−0.62	0.94	0.75	−0.04	−0.69	−0.02	0.83	1.43	0.28	0.75	0.35	
	0.00	0.00	0.02	0.00	0.05	0.12	0.08	0.00	0.07	0.00	0.10	0.29	0.01	0.08	0.02	0.06
WHLSL	4.18*	3.43*	3.60*	3.19*	3.06*	3.09*	2.68*	2.86*	3.08*	3.24*	2.64*	2.49*	3.25*	3.47*	3.76*	
	2.41	1.64	1.80	1.42	1.31	1.34	1.01	1.14	1.33	1.46	0.97	0.87	1.47	1.67	1.96	1.45
RTAIL	3.13*	2.60*	3.12*	3.33*	1.63	2.27*	1.97*	2.41*	3.03*	1.83*	2.52*	1.56	3.75*	2.90*	3.64*	
	1.36	0.95	1.36	1.55	0.37	0.72	0.54	0.81	1.28	0.47	0.89	0.34	1.95	1.18	1.84	1.04
MONEY	2.30*	2.11*	2.41*	2.51*	1.33	1.98*	1.72*	1.51	1.76*	1.83*	2.27*	2.42*	1.87*	2.64*	2.53*	
	0.74	0.62	0.82	0.88	0.25	0.55	0.42	0.32	0.44	0.47	0.73	0.82	0.49	0.98	0.90	0.63
SRVC	2.53*	2.23*	3.38*	2.16*	2.41*	2.46*	1.85*	2.22*	2.52*	2.16*	3.44*	1.98*	2.55*	3.04*	3.29*	
	0.89	0.70	1.59	0.66	0.81	0.85	0.48	0.69	0.89	0.65	1.65	0.55	0.91	1.29	1.50	0.94
Sig.(5%)	27	21	25	23	17	22	20	21	21	23	27	21	25	25	23	
Avg. R^2	1.33	1.01	1.32	1.23	0.62	0.85	0.65	0.79	0.92	1.01	1.02	0.64	1.22	1.31	1.18	

Table IV
In-sample predictive regression results for size portfolio excess returns with 14 economic variables as predictors

The entries in the table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j} x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the market capitalization-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization. The MKT row reports results for the excess return on the CRSP aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1946:01–2004:12; "*" indicates significance at the 5% level. "Sig.(5%)" indicates the number of market capitalization-sorted portfolios for which the t-statistic is significant at the 5% level for the predictor given in the column heading. "Avg. R^2" is the row or column average of the R^2 statistics; the row average excludes MKT.

Return	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	Avg. R^2
MKT	0.28	−1.05	0.33	−1.38	2.53*	−2.75*	2.23*	−2.32*	1.45	2.18	2.29*	2.08	1.02	−1.84*	
	0.01	0.15	0.02	0.27	0.89	1.06	0.70	0.76	0.30	0.67	0.73	0.61	0.15	0.47	0.48
S1	0.01	−0.62	1.11	−1.55	2.03*	−3.95*	2.53*	−2.62*	2.02*	0.48	1.02	0.48	0.36	−1.83*	
	0.00	0.05	0.17	0.34	0.58	2.16	0.90	0.96	0.57	0.03	0.15	0.03	0.02	0.47	0.46
S2	−0.52	−0.13	0.77	−1.05	2.26*	−3.39*	2.10*	−1.94*	2.17*	0.74	1.15	0.98	0.56	−2.18*	
	0.04	0.00	0.08	0.16	0.72	1.60	0.62	0.53	0.66	0.08	0.19	0.14	0.05	0.67	0.39
S3	−0.22	−0.19	0.86	−0.98	2.44*	−2.91*	2.02*	−1.84*	2.09*	1.37	1.72	1.48	0.91	−2.17*	
	0.01	0.01	0.10	0.13	0.83	1.18	0.57	0.47	0.61	0.27	0.42	0.31	0.12	0.66	0.41
S4	−0.07	−0.23	0.39	−0.86	2.67*	−2.70*	2.09*	−1.75*	2.34*	1.77	2.09*	1.81	1.27	−2.06*	
	0.00	0.01	0.02	0.10	1.00	1.02	0.61	0.43	0.77	0.44	0.61	0.46	0.23	0.60	0.45
S5	0.05	−0.08	0.31	−0.80	2.83*	−2.65*	2.17*	−1.74*	2.31*	1.75	2.03*	1.75	1.16	−2.16*	
	0.00	0.00	0.01	0.09	1.12	0.98	0.66	0.42	0.75	0.43	0.58	0.43	0.19	0.65	0.45
S6	0.42	−0.01	0.23	−0.99	2.94*	−2.83*	2.36*	−2.00*	2.21*	2.01	2.24*	1.84	1.21	−1.88*	
	0.02	0.00	0.01	0.14	1.20	1.12	0.78	0.56	0.69	0.57	0.71	0.48	0.21	0.50	0.50
S7	−0.18	−0.17	0.36	−0.96	2.91*	−2.92*	2.22*	−1.91*	2.22*	1.53	1.74*	1.62	0.84	−2.14*	
	0.00	0.00	0.02	0.13	1.18	1.19	0.69	0.51	0.69	0.33	0.43	0.37	0.10	0.64	0.45
S8	0.05	−0.23	0.41	−1.09	2.87*	−2.72*	1.91*	−1.89*	1.87*	1.66	1.77*	1.66	0.91	−1.95*	
	0.00	0.01	0.02	0.17	1.15	1.03	0.51	0.50	0.49	0.39	0.44	0.39	0.12	0.53	0.41
S9	−0.15	−0.60	0.67	−1.21	2.61*	−2.88*	2.11*	−2.10*	1.54	1.83	1.91*	1.92	0.79	−2.22*	
	0.00	0.05	0.06	0.21	0.95	1.16	0.62	0.62	0.33	0.47	0.51	0.52	0.09	0.69	0.45
S10	0.36	−1.65	0.18	−1.40	2.16*	−2.48*	2.09*	−2.28*	0.87	2.13	2.15*	2.00	0.72	−1.77*	
	0.02	0.38	0.00	0.28	0.66	0.86	0.61	0.73	0.11	0.64	0.65	0.56	0.07	0.44	0.43
Sig.(5%)	0	0	0	0	10	10	10	10	8	0	8	0	0	10	
Avg. R^2	0.01	0.05	0.05	0.17	0.94	1.23	0.66	0.58	0.57	0.36	0.47	0.37	0.12	0.59	

Table V
In-sample predictive regression results for size portfolio excess returns with 15 lagged industry returns as predictors

The entries in the table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the market capitalization-sorted portfolio given in the row heading and $x_{j,t-1}$ is the lagged industry return given in the column heading. S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization. The MKT row reports results for the excess return on the CRSP aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1946:01–2004:12; "*" indicates significance at the 5% level. "Sig.(5%)" indicates the number of market capitalization-sorted portfolios for which the t-statistic is significant at the 5% level for the predictor given in the column heading. "Avg. R^2" is the row or column average of the R^2 statistics; the row average excludes MKT. The 15 lagged industry returns included in the table are the 15 of 33 lagged industry returns that are significant in predicting the excess return on the CRSP aggregate value-weighted market portfolio.

Return	TXTLS	APPRL	PRINT	LETHR	GLASS	MACHIN	ELCTR	INSTR	MANUF	TRANS	TV	UTILS	RTAIL	MONEY	SRVC	Avg. R^2
MKT	2.50*	1.88*	2.71*	2.01*	1.67*	1.87*	1.68*	1.92*	1.74*	1.66*	2.62*	1.89*	2.31*	2.49*	2.40*	
	0.88	0.50	1.03	0.57	0.39	0.49	0.40	0.52	0.43	0.39	0.96	0.50	0.75	0.87	0.81	0.63
S1	7.14*	5.37*	6.94*	5.72*	6.06*	5.93*	5.98*	6.41*	5.44*	6.16*	6.72*	4.29*	5.52*	6.93*	7.07*	
	6.73	3.93	6.38	4.42	4.94	4.74	4.82	5.49	4.02	5.09	6.00	2.54	4.13	6.36	6.61	5.08
S2	5.46*	4.04*	5.24*	4.42*	4.47*	4.68*	4.49*	4.66*	4.04*	4.64*	5.19*	3.75*	4.56*	5.61*	5.29*	
	4.04	2.26	3.74	2.69	2.75	3.00	2.78	2.97	2.26	2.96	3.66	1.95	2.85	4.26	3.81	3.07
S3	4.71*	3.69*	4.92*	3.87*	3.80*	3.95*	3.62*	4.03*	3.70*	4.23*	4.63*	3.54*	4.11*	5.10*	4.58*	
	3.04	1.89	3.31	2.08	2.00	2.16	1.82	2.25	1.90	2.47	2.94	1.74	2.33	3.54	2.89	2.42
S4	4.71*	3.80*	4.75*	3.56*	3.52*	3.72*	3.29*	3.83*	3.61*	4.24*	4.29*	3.51*	4.03*	4.90*	4.24*	
	3.04	2.00	3.09	1.76	1.72	1.92	1.51	2.04	1.81	2.48	2.54	1.71	2.24	3.28	2.48	2.24
S5	3.95*	3.03*	3.95*	3.24*	2.88*	3.17*	2.73*	3.08*	2.97*	3.62*	3.68*	3.15*	3.65*	4.39*	3.59*	
	2.15	1.28	2.15	1.47	1.16	1.40	1.04	1.32	1.23	1.82	1.88	1.38	1.85	2.65	1.79	1.64
S6	3.72*	2.83*	3.91*	3.10*	2.77*	2.98*	2.68*	3.00*	2.71*	3.19*	3.28*	2.85*	3.29*	3.91*	3.30*	
	1.92	1.12	2.11	1.34	1.07	1.24	1.01	1.26	1.03	1.41	1.50	1.14	1.51	2.12	1.51	1.42
S7	3.53*	2.67*	3.37*	2.65*	2.39*	2.83*	2.52*	2.72*	2.66*	2.78*	3.19*	2.49*	2.96*	3.65*	3.32*	
	1.73	1.00	1.58	0.98	0.80	1.12	0.89	1.04	0.99	1.08	1.42	0.87	1.22	1.85	1.54	1.21
S8	2.47*	1.62	2.35*	1.88*	1.46	1.89*	1.57	1.75*	1.65*	1.75*	2.40*	2.37*	2.06*	2.66*	2.14*	
	0.85	0.37	0.77	0.50	0.30	0.50	0.35	0.43	0.38	0.43	0.81	0.79	0.60	0.99	0.64	0.58
S9	2.24*	1.54	2.22*	1.73*	1.36	1.67*	1.38	1.57	1.52	1.64	2.37*	1.81*	1.87*	2.37*	2.02*	
	0.70	0.33	0.70	0.42	0.26	0.39	0.27	0.35	0.33	0.38	0.79	0.46	0.49	0.79	0.58	0.48
S10	1.57	1.23	1.88*	1.27	0.82	0.98	0.85	1.10	0.92	0.65	1.81*	1.18	1.54	1.32	1.48	
	0.35	0.21	0.50	0.23	0.10	0.13	0.10	0.17	0.12	0.06	0.46	0.20	0.34	0.25	0.31	0.23
Sig.(5%)	9	7	10	9	7	9	7	8	8	8	10	9	9	9	9	
Avg. R^2	2.46	1.44	2.43	1.59	1.51	1.66	1.46	1.73	1.41	1.82	2.20	1.28	1.76	2.61	2.22	

Table VI
In-sample predictive regression results for book-to-market portfolio excess returns with 14 economic variables as predictors

The entries in the table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the book-to-market value-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value. The MKT row reports results for the excess return on the CRSP aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1946:01–2004:12; "*" indicates significance at the 5% level. "Sig.(5%)" indicates the number of value-sorted portfolios for which the t-statistic is significant at the 5% level for the predictor given in the column heading. "Avg. R^2" is the row or column average of the R^2 statistics; the row average excludes MKT.

Return	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	Avg. R^2
MKT	0.28	−1.05	0.33	−1.38	2.53*	−2.75*	2.23*	−2.32*	1.45	2.18	2.29*	2.08	1.02	−1.84*	
	0.01	0.15	0.02	0.27	0.89	1.06	0.70	0.76	0.30	0.67	0.73	0.61	0.15	0.47	0.48
BM1	0.60	−1.27	0.55	−1.84*	1.55*	−2.40*	1.90*	−2.62*	0.65	1.77	1.84*	1.52	0.35	−1.54	
	0.05	0.23	0.04	0.48	0.34	0.81	0.51	0.96	0.06	0.44	0.48	0.33	0.02	0.34	0.36
BM2	−0.23	−1.05	0.11	−0.90	2.37*	−2.26*	1.86*	−1.69*	1.82*	1.83	1.93*	1.95	0.91	−2.17*	
	0.01	0.15	0.00	0.11	0.79	0.72	0.49	0.40	0.47	0.47	0.53	0.53	0.12	0.66	0.39
BM3	−0.08	−0.85	0.51	−0.98	3.06*	−2.32*	2.34*	−1.98*	1.88*	1.62	1.77*	1.68	0.81	−2.31*	
	0.00	0.10	0.04	0.13	1.31	0.76	0.77	0.55	0.50	0.37	0.44	0.40	0.09	0.75	0.44
BM4	−0.67	−0.94	0.75	−0.65	2.91*	−2.42*	2.41*	−1.69*	2.11*	1.56	1.67	1.87	0.84	−2.39*	
	0.06	0.12	0.08	0.06	1.18	0.82	0.82	0.40	0.63	0.34	0.39	0.49	0.10	0.80	0.45
BM5	−0.17	−1.44	0.58	−1.92*	2.82*	−2.32*	2.09*	−2.78*	0.86	1.79	1.88*	1.89	0.75	−2.32*	
	0.00	0.29	0.05	0.52	1.11	0.75	0.61	1.08	0.11	0.45	0.50	0.50	0.08	0.75	0.49
BM6	−0.23	−0.60	0.38	−1.22	3.07*	−2.99*	1.95*	−2.04*	1.36	2.10	2.17*	2.22	1.19	−1.73	
	0.01	0.05	0.02	0.21	1.32	1.25	0.53	0.58	0.26	0.62	0.66	0.69	0.20	0.42	0.49
BM7	−0.42	−1.02	−0.34	−0.90	3.27*	−2.39*	1.76*	−1.65*	1.62*	1.32	1.38	1.52	0.59	−2.55*	
	0.02	0.15	0.02	0.12	1.49	0.80	0.44	0.38	0.37	0.25	0.27	0.32	0.05	0.91	0.40
BM8	−0.05	−0.49	0.07	−1.60*	2.35*	−2.51*	1.48	−2.20*	1.25	1.82	1.91*	1.86	1.32	−1.86*	
	0.00	0.03	0.00	0.36	0.78	0.88	0.31	0.68	0.22	0.47	0.52	0.49	0.25	0.49	0.39
BM9	−0.16	−1.29	0.32	−0.81	2.57*	−2.64*	1.66*	−1.52*	1.68*	2.04	2.25*	2.13	1.30	−1.93*	
	0.00	0.23	0.01	0.09	0.92	0.98	0.39	0.32	0.40	0.58	0.71	0.64	0.24	0.53	0.43
BM10	−0.50	−0.30	0.52	−0.54	2.61*	−2.95*	2.03*	−1.42	1.88*	1.46	1.71	1.70	1.07	−1.84*	
	0.04	0.01	0.04	0.04	0.95	1.22	0.58	0.28	0.50	0.30	0.41	0.41	0.16	0.48	0.39
Sig.(5%)	0	0	0	3	10	10	9	9	6	0	7	0	0	8	
Avg. R^2	0.02	0.14	0.03	0.21	1.02	0.90	0.54	0.57	0.35	0.43	0.49	0.48	0.13	0.61	

Table VII
In-sample predictive regression results for book-to-market portfolio excess returns with 15 lagged industry returns as predictors

The entries in the table report the t-statistic corresponding to $b_{i,j}$ (top number) and R^2 statistic in percent (bottom number) for the predictive regression model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the book-to-market value-sorted portfolio given in the row heading and $x_{j,t-1}$ is the lagged industry return given in the column heading. BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value. The MKT row reports results for the excess return on the CRSP aggregate value-weighted market portfolio. The t-statistic and R^2 statistic are based on OLS estimation for 1946:01–2004:12; "*" indicates significance at the 5% level. "Sig.(5%)" indicates the number of value-sorted portfolios for which the t-statistic is significant at the 5% level for the predictor given in the column heading. "Avg. R^2" is the row or column average of the R^2 statistics; the row average excludes MKT. The 15 lagged industry returns included in the table are the 15 of 33 lagged industry returns that are significant in predicting the excess return on the CRSP aggregate value-weighted market portfolio.

Return	TXTLS	APPRL	PRINT	LETHR	GLASS	MACHIN	ELCTR	INSTR	MANUF	TRANS	TV	UTILS	RTAIL	MONEY	SRVC	Avg. R^2
MKT	2.50*	1.88*	2.71*	2.01*	1.67*	1.87*	1.68*	1.92*	1.74*	1.66*	2.62*	1.89*	2.31*	2.49*	2.40*	
	0.88	0.50	1.03	0.57	0.39	0.49	0.40	0.52	0.43	0.39	0.96	0.50	0.75	0.87	0.81	0.63
BM1	1.91*	1.44	2.64*	1.55	1.37	1.52	1.33	1.94*	1.72*	1.15	2.25*	1.40	2.21*	1.79*	2.06*	
	0.51	0.29	0.97	0.34	0.26	0.33	0.25	0.53	0.42	0.19	0.71	0.28	0.69	0.45	0.59	0.45
BM2	1.99*	2.06*	2.74*	1.67*	1.46	1.68*	1.52	1.83*	1.92*	1.55	2.75*	1.73*	2.37*	2.40*	2.34*	
	0.56	0.60	1.05	0.39	0.30	0.40	0.33	0.47	0.52	0.34	1.06	0.42	0.79	0.81	0.77	0.59
BM3	2.86*	2.59*	2.94*	2.63*	1.78*	2.11*	1.96*	1.82*	2.07*	2.40*	3.00*	2.31*	2.91*	2.85*	2.70*	
	1.14	0.94	1.21	0.97	0.45	0.63	0.54	0.47	0.60	0.81	1.26	0.75	1.18	1.13	1.02	0.87
BM4	2.60*	2.32*	2.41*	2.49*	1.47	1.75*	1.35	1.52	1.80*	1.83*	2.17*	2.22*	2.07*	2.38*	2.17*	
	0.95	0.76	0.81	0.87	0.30	0.43	0.26	0.33	0.46	0.47	0.66	0.69	0.60	0.79	0.66	0.60
BM5	2.43*	2.07*	2.34*	2.46*	1.64	1.82*	1.52	1.32	1.86*	2.29*	1.85*	2.16*	2.09*	2.31*	1.95*	
	0.83	0.60	0.77	0.85	0.38	0.47	0.33	0.25	0.49	0.74	0.48	0.66	0.61	0.75	0.54	0.58
BM6	1.89*	1.40	1.65*	2.03*	1.12	1.76*	1.23	1.20	0.71	1.57	1.56	1.38	1.29	1.99*	1.75*	
	0.50	0.28	0.38	0.58	0.18	0.44	0.21	0.20	0.07	0.35	0.34	0.27	0.23	0.55	0.43	0.33
BM7	2.36*	1.52	1.71*	2.24*	1.20	1.61	1.01	1.53	0.98	1.55	1.67*	0.95	1.53	1.79*	1.66*	
	0.78	0.33	0.41	0.71	0.20	0.37	0.14	0.33	0.14	0.34	0.39	0.13	0.33	0.45	0.39	0.36
BM8	2.18*	1.84*	1.70*	2.39*	1.26	2.31*	1.61	1.72*	1.22	1.74*	2.31*	0.98	1.56	1.97*	2.07*	
	0.67	0.48	0.41	0.80	0.22	0.75	0.37	0.42	0.21	0.43	0.75	0.13	0.34	0.55	0.60	0.47
BM9	3.30*	2.72*	3.20*	2.79*	2.17*	3.12*	2.60*	2.39*	2.30*	2.87*	3.18*	1.75*	2.78*	3.22*	3.34*	
	1.52	1.04	1.43	1.09	0.66	1.36	0.94	0.80	0.74	1.15	1.41	0.43	1.08	1.45	1.56	1.11
BM10	4.38*	3.08*	3.90*	3.77*	2.87*	3.60*	3.49*	3.11*	2.79*	3.62*	3.89*	2.02*	3.08*	3.66*	3.34*	
	2.64	1.32	2.11	1.97	1.15	1.80	1.70	1.35	1.09	1.82	2.10	0.57	1.33	1.86	1.56	1.62
Sig.(5%)	10	7	10	9	3	8	3	6	7	6	9	6	7	10	10	
Avg. R^2	1.01	0.66	0.96	0.86	0.41	0.70	0.51	0.51	0.47	0.66	0.92	0.43	0.72	0.88	0.81	

Table VIII
Out-of-sample predictive regression results for industry portfolio excess returns with 14 economic variables as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 1966:01–2004:12 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted industry portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. The MKT row reports out-of-sample results for the excess return on the CRSP aggregate value-weighted market portfolio. The out-of-sample forecasts are formed recursively. The COMBINE column reports results for a combination forecast based on the 14 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent (top number) and relative Sharpe ratio (bottom number); "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	COMBINE
MKT	−0.56	−1.29	−0.49	−0.67	0.28*	0.13	−0.07	−0.10	−0.43	−0.01	0.03	−0.01	−1.02	−0.36	1.09*
	0.98	0.92	0.99	1.41	1.14	1.14	1.35	1.48	0.98	0.99	1.05	0.98	0.87	1.02	1.27
AGRIC	−0.36	−2.38	−0.37	−1.22	−0.57	−0.08	−0.31	−0.80	−0.60	−0.22	−0.13	−0.01	−0.53	0.43*	0.20
	0.82	0.92	0.96	1.05	0.81	0.82	0.78	1.05	0.85	1.14	1.16	1.04	0.96	0.79	1.21
MINES	−0.45	0.51	−0.25	0.18	0.08	−0.31	−0.79	0.44	−0.62	−0.42	−0.42	−0.38	−0.71	−0.44	0.12
	0.85	0.94	0.98	1.12	1.05	1.07	0.93	1.15	0.82	0.96	0.99	0.89	0.80	0.91	1.04
OIL	−0.41	−2.13	−0.32	−0.41	−0.61	−0.34	−1.08	−0.51	−0.53	−1.01	−1.01	−0.38	−1.48	−0.51	0.18
	0.92	0.91	0.95	1.36	1.09	1.02	1.10	1.44	0.92	1.02	1.07	0.98	0.81	0.92	1.18
STONE	−0.40	−0.94	−0.25	−0.80	−0.08	−0.12	−0.93	−1.04	−0.56	−0.29	−0.19	−0.09	−0.69	−0.40	0.11
	0.86	0.97	0.96	1.17	1.04	0.98	0.96	1.08	0.88	1.00	1.02	0.91	0.78	0.93	1.12
CNSTR	−0.58	−1.36	−0.40	−0.38	0.98*	−0.26	−0.31	0.22	−0.62	−0.42	−0.37	−0.36	−0.78	0.22*	0.70*
	0.79	0.85	0.92	1.18	1.06	0.86	0.83	1.10	0.84	1.16	1.19	1.01	0.88	1.00	1.27
FOOD	−0.58	−2.59	−0.32	−0.79	0.02*	−0.36	−0.26	−0.75	−0.16	−0.12	−0.11	−0.07	−0.89	1.38*	0.70*
	1.04	0.97	1.00	1.07	1.10	1.08	1.15	1.13	1.04	1.05	1.08	1.01	0.94	1.06	1.14
SMOKE	−0.05	−4.10	−0.32	−0.42	0.43	−0.37	−0.54	−0.35	−0.23	−0.56	−0.56	−0.32	−0.61	1.77*	0.03
	0.99	0.94	0.95	0.90	0.98	0.96	0.92	0.98	0.96	1.02	1.02	1.04	0.95	1.08	1.00
TXTLS	0.01	−0.54	−0.19	−0.82	0.42*	−0.22	0.20*	−0.32	1.15*	0.11	0.37	−0.15	−0.23	0.13*	1.09*
	1.19	0.89	0.95	1.00	1.20	0.90	1.44	1.28	1.22	1.41	1.54	1.20	1.24	1.15	1.53
APPRL	−0.42	−0.82	−0.41	−0.86	−0.05	−0.04	−0.58	−0.62	1.15*	0.31	0.51*	0.24	−0.13	1.34*	1.39*
	1.05	0.88	0.89	1.05	0.92	0.85	0.97	1.34	0.97	1.39	1.43	1.27	1.15	1.06	1.51
WOOD	−0.43	−0.42	−0.78	−0.51	0.95*	−0.17	−0.50	−0.08	−0.86	−0.35	−0.31	−0.33	−0.77	−0.14	0.36
	1.05	0.95	0.85	1.34	1.11	0.96	1.04	1.46	0.88	0.99	1.04	0.91	0.91	1.03	1.24
CHAIR	−0.46	−1.65	−0.47	−0.87	2.75*	0.10	−0.06	−0.70	0.80*	−0.17	−0.01	−0.19	−0.55	0.73*	0.97*
	0.97	0.89	0.75	0.92	1.14	0.91	0.92	0.96	0.90	1.25	1.33	1.19	0.99	0.95	1.24
PAPER	−0.42	−1.22	−0.42	−1.12	0.53*	0.17	−0.72	−0.66	−0.62	−0.88	−0.87	−0.92	−1.95	−0.22	0.77*
	1.02	0.95	1.01	1.35	1.27	1.11	1.18	1.33	0.98	1.01	1.01	1.01	0.91	0.99	1.26
PRINT	−0.50	−0.54	−0.44	−1.29	1.26*	0.08	0.15*	−0.93	0.60*	0.03	0.23	0.06	−0.51	−0.75	1.06*
	0.93	0.91	0.93	1.01	1.05	1.05	1.06	1.03	0.99	1.02	1.08	1.04	0.92	1.00	1.19
CHEMS	−0.68	−2.69	−0.51	−0.87	0.28*	−0.06	−0.93	−0.75	−0.61	−0.36	−0.34	−0.31	−1.65	0.16	0.63*
	0.98	0.92	1.01	1.42	1.09	1.11	1.18	1.36	0.93	0.93	0.93	0.98	0.94	1.04	1.14
PTRLM	−0.44	−3.57	−0.72	−1.29	−0.92	−0.07	−1.00	−1.11	−0.80	−0.61	−0.64	−0.27	−1.32	−0.19	0.45
	0.95	0.91	0.93	1.20	1.08	1.04	1.14	1.21	0.89	0.86	0.87	0.91	0.84	0.99	1.08

Table VIII — *Continued*

Return	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	COMBINE
RUBBER	−0.20	−2.06	−0.75	−0.90	−0.12	0.01	0.19*	−0.15	−0.12	−0.03	0.04*	−0.33	−0.90	−0.20	1.23*
	1.00	0.99	0.92	1.58	1.06	1.06	1.44	1.62	1.06	1.51	1.49	1.21	0.91	1.23	1.62
LETHR	−0.47	−2.01	−0.31	−0.70	0.45*	−0.01	0.02	−0.38	1.97*	−0.40	−0.38	−0.28	−0.62	0.56*	0.87*
	1.00	0.88	0.92	1.06	0.97	0.98	1.04	1.18	1.06	1.33	1.38	1.20	1.13	1.13	1.25
GLASS	−0.51	−0.26	−0.45	−0.89	1.57*	−0.10	0.49*	−0.41	0.44*	−0.22	−0.09	−0.17	−0.80	−0.17	1.02*
	0.95	0.97	0.94	1.38	1.21	1.06	1.35	1.46	1.05	1.17	1.27	1.04	0.78	0.99	1.52
METAL	−0.44	−0.16	−0.36	−0.34	−0.21	−0.16	−1.33	−0.42	−0.66	−0.70	−0.75	−0.48	−0.98	−0.54	0.31
	0.84	0.98	0.94	1.93	0.99	1.00	1.06	1.74	0.83	1.17	1.22	0.95	0.75	0.98	1.45
MTLPR	−0.40	−0.66	−0.14	−0.72	0.20	0.10	0.61*	0.01	−0.15	−0.07	0.03	−0.11	−0.71	−0.29	0.88*
	1.00	0.96	1.00	1.19	1.14	1.07	1.25	1.30	0.97	1.09	1.14	1.06	0.87	1.00	1.29
MACHIN	−0.49	−0.34	−0.34	0.33	0.05	0.41	0.05*	1.15*	−0.64	−0.44	−0.41	−0.38	−0.76	−0.90	0.58*
	0.98	1.01	0.96	1.64	1.21	1.27	1.32	1.68	0.95	0.84	0.92	0.85	0.82	1.02	1.26
ELCTR	−0.65	−0.27	−0.36	−0.52	−0.10	0.14	0.33*	0.07	−0.27	−0.56	−0.52	−0.49	−0.94	−0.65	0.54*
	0.88	0.98	0.97	1.42	1.07	1.12	1.17	1.44	0.91	1.02	1.07	0.91	0.75	0.95	1.27
CARS	−0.63	−0.17	−0.51	−0.49	0.59*	0.58	0.61*	0.45*	−0.06	−0.12	0.03	−0.28	−0.91	−0.48	1.83*
	0.89	1.06	0.95	1.56	1.26	1.12	1.55	1.64	1.02	1.21	1.30	1.01	0.84	1.14	1.65
INSTR	−0.46	−0.24	−0.48	−0.03	−0.84	0.48	−0.58	0.43*	−0.85	−0.16	−0.14	−0.31	−0.81	−1.07	0.36
	1.01	0.97	1.00	1.41	1.06	1.20	1.13	1.42	0.90	0.88	0.89	0.92	0.98	1.02	1.11
MANUF	−0.31	−0.32	−0.39	−0.84	0.47*	0.32	−0.03	−0.28	−0.22	0.10	0.29*	−0.09	−0.47	−0.05	0.86*
	1.06	0.88	0.96	1.00	1.12	1.04	1.10	1.10	1.07	1.39	1.48	1.23	1.09	1.07	1.35
TRANS	−0.43	−1.55	−0.34	−0.89	1.06*	−0.36	−0.24	−0.45	−0.04	−0.05	0.01	0.01	−0.62	−0.51	0.77*
	0.93	0.83	0.96	1.23	1.18	0.97	1.19	1.41	0.94	1.23	1.26	1.14	0.85	0.98	1.40
PHONE	−0.40	−0.35	−0.29	−0.50	0.23*	−0.01	−0.34	−0.45	−0.82	0.10	0.09	0.27	−0.34	−0.61	0.22
	0.95	0.95	0.96	1.10	1.17	1.03	1.06	1.16	0.97	0.93	0.94	0.98	0.89	0.94	1.07
TV	−0.45	−1.06	−0.59	−0.97	0.04	−0.14	−0.04	−0.61	−0.33	0.25	0.39*	0.27	−0.43	−0.51	0.85*
	0.96	0.94	0.94	0.96	1.03	1.01	1.11	1.04	0.96	1.22	1.26	1.12	1.00	1.03	1.17
UTILS	−0.41	−2.92	−0.52	−0.88	−0.42	−0.49	−0.58	−0.74	−1.31	−0.18	−0.22	0.25	−0.83	0.32	0.88*
	1.00	0.97	0.96	1.18	1.17	1.05	1.20	1.20	1.03	1.20	1.20	1.06	0.91	1.06	1.23
WHLSL	−0.51	−1.40	−0.53	−0.97	0.71*	−0.22	−0.56	−0.73	−0.21	0.00	0.08	0.01	−0.60	−0.02	0.61*
	0.94	0.95	0.93	0.98	1.03	1.09	0.89	1.00	0.94	1.06	1.10	1.04	0.95	1.01	1.12
RTAIL	−0.32	−0.71	−0.40	−0.83	0.68*	0.20	−0.42	−0.61	0.65*	−0.16	−0.09	−0.23	−0.72	0.17	0.81*
	1.02	0.94	0.95	1.11	1.09	1.04	1.10	1.29	0.96	1.03	1.08	1.00	0.89	1.07	1.22
MONEY	−0.58	−1.90	−0.44	−1.13	0.95*	−0.16	−0.53	−0.93	−1.12	−0.78	−0.81	−0.51	−1.60	−0.07	0.82*
	0.97	0.96	0.95	1.18	1.14	1.04	1.16	1.25	0.98	1.08	1.13	1.06	0.80	1.00	1.25
SRVC	−0.47	−0.67	−0.42	−0.92	−0.47	−0.14	−0.29	−0.65	−0.11	0.01	0.08	0.14	−0.48	−0.81	0.61*
	0.94	0.93	0.95	0.89	0.95	1.01	1.05	1.01	0.93	1.10	1.14	1.11	0.97	0.90	1.14

Table IX
Out-of-sample predictive regression results for industry portfolio excess returns with 15 lagged industry returns selected over 1946–1965 as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 1966:01–2004:12 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the value-weighted industry portfolio given in the row heading and $x_{j,t-1}$ is the lagged industry return given in the cell. The MKT row reports out-of-sample results for the excess return on the CRSP aggregate value-weighted portfolio. The out-of-sample forecasts are formed recursively. The 15 lagged industry returns are selected as the 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. The COMBINE column reports results for a combination forecast based on the 15 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent (top number) and relative Sharpe ratio (bottom number); "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	AGRIC	MINES	STONE	TXTLS	WOOD	CHAIR	PAPER	CHEMS	GLASS	MACHIN	INSTR	PHONE	TV	MONEY	SRVC	COMBINE
MKT	0.07 1.05	−0.59 0.98	−0.49 1.03	0.62* 1.31	−0.30 1.12	−0.44 1.00	−0.54 1.14	−0.30 1.13	−0.06 1.15	−0.19 1.14	−0.16 1.14	−0.69 0.99	0.75* 1.26	0.48 1.33	0.53 1.28	0.21 1.15
AGRIC	−0.27 1.00	−0.04 1.02	−0.36 0.76	1.21* 1.00	0.94* 1.00	0.57* 1.05	0.72* 1.03	0.15 0.99	1.12* 1.18	1.47* 1.14	1.02* 1.21	−0.15 0.77	0.76* 1.09	0.59* 1.09	1.06* 1.10	0.97* 1.18
MINES	0.01 1.10	−0.46 1.11	−0.47 1.01	0.58 1.44	0.92* 1.39	0.03 1.09	0.62 1.44	−0.06 1.22	−0.33 1.22	−0.03 1.41	−0.11 1.20	−0.54 0.96	0.02 1.16	0.19 1.36	−0.10 1.38	0.24 1.34
OIL	−0.16 0.99	−0.37 1.09	−0.52 0.94	−0.25 1.02	0.08 1.12	−1.66 0.78	−0.34 1.12	−0.32 0.99	−0.35 1.06	−0.46 1.00	−0.41 1.05	0.05 1.04	−0.30 0.96	−0.25 1.07	−0.38 1.00	−0.20 1.03
STONE	1.63* 1.29	0.33 1.08	−0.27 0.94	0.97* 1.24	0.34 1.13	0.75* 1.14	0.45 1.24	0.83* 1.27	0.07 1.09	0.64* 1.17	0.74* 1.22	0.13* 1.01	0.88* 1.18	1.79* 1.38	0.59 1.14	1.02* 1.27
CNSTR	0.98* 1.28	−0.13 0.96	−0.89 0.81	3.12* 1.48	2.05* 1.36	2.24* 1.38	1.45* 1.32	0.69* 1.21	1.06* 1.42	1.29* 1.23	1.67* 1.29	−0.62 0.81	2.14* 1.35	3.66* 1.48	2.31* 1.34	2.20* 1.40
FOOD	0.06 1.09	−0.27 1.04	0.14 1.11	0.09 1.20	−0.46 1.05	−0.32 1.04	−0.73 1.07	−0.55 1.07	−0.44 1.05	−0.81 1.08	−0.42 1.06	−0.83 1.03	−0.06 1.14	−0.05 1.20	0.01 1.17	−0.06 1.13
SMOKE	0.14 1.00	0.08 1.06	0.03 1.01	0.24 0.98	−0.36 0.94	−0.43 0.85	−0.21 0.99	−0.28 1.00	−0.30 0.96	−0.46 0.96	−0.38 0.93	−0.64 0.89	−0.24 0.98	0.21 1.01	−0.30 0.98	−0.08 0.99
TXTLS	1.27* 1.45	−0.36 0.97	−1.18 0.82	4.64* 2.29	3.43* 2.05	4.44* 2.06	1.71* 1.87	0.97* 1.56	2.09* 1.88	1.38* 1.56	1.49* 1.44	−0.17 1.03	1.66* 1.54	3.27* 1.85	2.68* 1.78	2.54* 1.80
APPRL	0.56* 1.22	−0.47 0.90	−0.50 0.83	2.90* 1.44	1.12* 1.20	1.82* 1.36	1.22* 1.25	0.93* 1.24	0.81* 1.27	1.48* 1.13	1.37* 1.23	−0.39 0.74	1.53* 1.11	1.79* 1.28	2.56* 1.29	1.73* 1.34
WOOD	0.03 1.06	−0.58 0.96	−1.04 0.85	0.68* 1.42	0.32 1.34	0.47 1.21	0.08 1.24	0.09 1.23	−0.46 1.23	−0.17 1.11	0.19 1.13	−0.70 0.99	0.76* 1.28	2.14* 1.58	0.95* 1.32	0.72* 1.32
CHAIR	1.08* 1.20	−0.58 0.90	−0.85 0.81	2.64* 1.42	1.77* 1.29	1.68* 1.36	1.10* 1.22	1.60* 1.27	1.41* 1.28	1.49* 1.08	1.78* 1.15	0.54* 1.04	1.67* 1.18	3.31* 1.47	3.04* 1.36	2.10* 1.34
PAPER	−0.05 1.03	−0.40 1.01	0.26 1.10	0.19 1.12	−0.20 1.04	−0.70 0.95	−0.76 1.07	−0.46 1.08	−0.42 1.01	−0.40 1.00	−0.41 1.13	−0.57 1.02	0.01 1.11	−0.17 1.12	−0.02 1.09	−0.10 1.08
PRINT	1.10* 1.19	−1.20 0.90	−1.29 0.92	1.93* 1.44	1.39* 1.32	1.47* 1.19	0.03* 1.15	0.71* 1.30	0.77* 1.24	0.79* 1.33	1.74* 1.27	−0.41 0.98	2.91* 1.47	2.11* 1.42	2.60* 1.46	2.15* 1.35
CHEMS	−0.18 0.99	−0.01 1.06	0.02 1.03	−0.30 1.04	−0.50 1.02	−1.07 0.96	−0.80 1.05	−0.63 1.08	−0.55 1.00	−0.58 1.01	−0.77 1.07	−0.54 0.97	−0.08 1.13	−0.27 1.05	−0.27 1.03	−0.24 1.05
PTRLM	−0.36 0.97	−0.63 0.94	−0.64 0.95	−0.25 0.98	−0.40 0.95	−1.57 0.87	−0.73 0.97	−0.54 0.94	−0.42 0.94	−0.52 0.93	−0.81 0.97	−0.30 1.01	−0.29 0.94	−0.53 0.98	−0.52 0.97	−0.41 0.95
RUBBER	−0.20 0.97	−0.35 0.95	−0.06 0.99	0.79* 1.29	0.27 1.11	−0.64 0.95	0.07 1.13	−0.28 0.98	−0.08 1.04	0.34 1.12	0.13 1.09	−0.65 0.87	0.13 1.24	0.10 1.07	0.32 1.17	0.16 1.06
LETHR	0.62* 1.16	−0.55 0.85	−0.50 0.90	2.34* 1.42	0.97* 1.23	1.82* 1.28	0.38 1.07	0.54 1.09	−0.05 1.03	0.53 1.07	1.13* 1.13	−0.71 0.77	0.82 1.04	2.23* 1.29	1.37* 1.21	1.19* 1.16
GLASS	−0.06 1.06	−0.51 0.97	−0.33 1.03	1.31* 1.40	0.86* 1.49	1.35* 1.38	1.19* 1.54	0.30 1.26	0.61 1.37	0.41 1.14	0.62* 1.29	−0.83 0.96	0.94* 1.27	1.98* 1.43	0.83* 1.30	0.97* 1.41

Table IX — *Continued*

Return	AGRIC	MINES	STONE	TXTLS	WOOD	CHAIR	PAPER	CHEMS	GLASS	MACHIN	INSTR	PHONE	TV	MONEY	SRVC	COMBINE
METAL	0.21	−0.52	−0.66	0.14	−0.10	−0.36	−0.51	−0.45	−0.65	−0.25	−0.38	−0.73	0.05	0.08	−0.08	0.01
	1.23	1.06	0.96	1.31	1.28	0.97	1.28	1.14	1.20	1.24	1.13	0.87	1.24	1.36	1.24	1.24
MTLPR	0.49	−1.00	−0.89	1.77*	0.94*	1.30*	0.39	−0.04	0.15	0.51*	0.69*	−0.18	1.27*	1.81*	1.33*	1.13*
	1.18	0.93	0.96	1.51	1.48	1.33	1.40	1.23	1.34	1.35	1.28	1.05	1.34	1.61	1.50	1.38
MACHIN	−0.21	−0.58	−0.71	0.25	−0.19	−0.03	−0.12	0.39	0.43	0.14	0.27	−0.93	0.69	0.53	0.72	0.46
	1.03	1.06	1.01	1.28	1.31	1.20	1.30	1.33	1.33	1.35	1.34	0.93	1.28	1.39	1.35	1.31
ELCTR	−0.04	−0.41	−0.08	0.24	−0.17	−0.56	−0.22	−0.09	−0.29	−0.14	−0.09	−0.63	0.70*	0.37	0.07	0.14
	1.07	0.98	0.99	1.16	1.15	0.98	1.10	1.06	0.99	1.07	1.08	0.92	1.18	1.16	1.04	1.11
CARS	1.11*	−0.51	−0.59	2.64*	1.54*	1.62*	0.70*	0.09	1.85*	2.14*	1.03*	0.15	2.09*	2.09*	2.79*	1.83*
	1.42	0.96	1.01	1.69	1.59	1.40	1.43	1.24	1.59	1.50	1.30	1.20	1.61	1.75	1.77	1.54
INSTR	−0.29	−0.52	−0.10	0.45	0.15	−0.30	−0.13	−0.44	0.06	0.02	0.20	−0.53	0.52	−0.44	0.09	0.12
	0.98	0.96	1.03	1.15	1.10	1.07	1.08	1.00	1.13	1.15	1.16	0.93	1.17	1.06	1.08	1.08
MANUF	0.58*	−0.17	−0.77	2.63*	1.68*	2.54*	1.70*	1.83*	1.41*	1.39*	2.02*	−0.74	2.11*	3.92*	2.74*	2.56*
	1.30	1.00	0.86	1.71	1.52	1.68	1.52	1.60	1.53	1.37	1.38	0.99	1.50	1.87	1.63	1.61
TRANS	0.15	−0.55	−1.19	1.34*	0.53*	0.05	−0.22	−0.42	0.44	0.14	0.04	−0.48	1.03	1.25*	0.80*	0.57
	1.09	0.94	0.87	1.42	1.38	1.13	1.17	1.06	1.32	1.22	1.15	0.90	1.31	1.45	1.27	1.28
PHONE	−0.18	−0.34	0.01	−0.11	−0.56	−0.36	−0.62	−0.44	−0.68	−0.89	−0.41	−0.94	0.20	−0.33	−0.36	−0.30
	0.97	0.99	1.05	1.01	0.95	0.91	0.97	0.96	0.92	0.93	0.95	0.91	1.01	1.04	0.98	0.98
TV	0.33	−0.48	−0.43	0.87*	0.55*	−0.28	0.34	0.65*	0.18	0.31	0.58*	−0.36	1.99*	1.36*	1.77*	0.95*
	1.09	0.93	0.95	1.17	1.15	1.02	1.11	1.11	1.11	1.09	1.12	0.97	1.24	1.23	1.22	1.16
UTILS	−0.30	0.90*	0.42	−0.49	−0.55	−0.49	−0.86	−0.26	−0.42	−0.63	−0.71	−0.33	−0.48	−0.67	−0.64	−0.10
	0.97	1.14	1.14	0.95	0.95	0.89	0.97	0.98	0.95	0.97	0.96	1.07	1.01	0.99	1.01	1.02
WHLSL	0.76*	−0.78	−1.09	1.75*	0.88*	0.85*	0.00	−0.21	0.80*	0.10	0.24	−1.17	0.84*	1.38*	1.39*	1.11*
	1.13	0.95	0.91	1.42	1.31	1.25	1.28	1.20	1.39	1.35	1.20	0.95	1.27	1.41	1.48	1.33
RTAIL	0.09	−0.29	−0.28	1.03*	−0.04	0.59	−0.06	0.53	0.02	0.28	0.62	−0.34	0.75*	0.83*	1.50*	0.69*
	1.07	0.99	1.01	1.27	1.14	1.08	1.07	1.19	1.07	1.06	1.08	0.99	1.18	1.28	1.34	1.18
MONEY	0.13	−0.69	−0.54	0.32	−0.44	−0.19	−0.73	−0.60	−0.36	−0.30	−0.28	−0.90	0.30	0.42	0.47	0.07
	1.04	0.98	1.01	1.24	1.07	1.03	1.14	1.07	1.07	1.09	1.03	0.98	1.15	1.28	1.21	1.12
SRVC	0.06	−0.62	−0.80	0.61*	−0.04	0.28	−0.18	0.12	0.13	0.02	0.29	−1.04	1.26*	0.77*	1.05*	0.61
	1.08	0.94	0.92	1.22	1.08	1.13	1.08	1.17	1.13	1.04	1.10	0.79	1.15	1.21	1.22	1.16

Table X
Out-of-sample predictive regression results for size portfolio excess returns with 14 economic variables as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 1966:01–2004:12 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the market capitalization-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization. The MKT row reports out-of-sample results for the excess return on the CRSP aggregate value-weighted market portfolio. The out-of-sample forecasts are formed recursively. The COMBINE column reports results for a combination forecast based on the 14 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent (top number) and relative Sharpe ratio (bottom number); "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	COMBINE
MKT	−0.56	−1.29	−0.49	−0.67	0.28*	0.13	−0.07	−0.10	−0.43	−0.01	0.03	−0.01	−1.02	−0.36	1.09*
	0.98	0.92	0.99	1.41	1.14	1.14	1.35	1.48	0.98	0.99	1.05	0.98	0.87	1.02	1.27
S1	−0.57	−0.27	−0.40	−0.54	−0.05	0.97*	0.37*	0.32	−0.30	−0.48	−0.41	−0.37	−0.65	−0.75	0.83*
	0.92	0.98	1.01	1.01	1.05	1.09	1.11	1.23	1.02	1.11	1.25	1.06	1.01	0.93	1.25
S2	−0.47	−0.70	−0.41	−0.71	0.16*	0.44	0.06*	−0.19	−0.14	−0.46	−0.38	−0.27	−0.66	−0.16	0.73*
	0.92	0.88	0.96	1.01	1.12	1.06	1.04	1.17	1.02	1.18	1.29	1.11	0.99	1.02	1.26
S3	−0.50	−0.78	−0.41	−0.77	0.29*	0.12	−0.03	−0.30	−0.24	−0.19	−0.06	−0.06	−0.58	−0.20	0.74*
	0.94	0.88	0.97	1.01	1.09	1.01	1.06	1.15	1.04	1.21	1.27	1.14	0.99	1.03	1.24
S4	−0.49	−0.73	−0.46	−0.80	0.50*	−0.02	0.09*	−0.32	0.08	0.00	0.16	0.10	−0.44	−0.31	0.91*
	0.94	0.89	0.94	1.04	1.11	1.00	1.10	1.17	1.07	1.25	1.33	1.16	0.98	1.04	1.28
S5	−0.51	−0.84	−0.46	−0.80	0.71*	−0.05	0.09*	−0.35	0.05	−0.08	0.03	−0.01	−0.58	−0.39	0.93*
	0.95	0.89	0.94	1.08	1.15	1.01	1.14	1.20	1.06	1.21	1.29	1.12	0.95	1.06	1.30
S6	−0.48	−1.23	−0.47	−0.79	0.69*	−0.04	0.15*	−0.24	−0.02	0.16	0.28	0.10	−0.51	−0.23	1.08*
	0.95	0.84	0.94	1.14	1.16	1.02	1.25	1.31	1.06	1.23	1.29	1.16	0.97	1.10	1.35
S7	−0.54	−1.27	−0.44	−0.82	0.63*	−0.08	0.08*	−0.30	−0.12	−0.24	−0.18	−0.12	−0.81	−0.16	0.96*
	0.94	0.85	0.94	1.19	1.10	1.05	1.22	1.33	1.00	1.11	1.17	1.08	0.86	1.08	1.30
S8	−0.53	−1.94	−0.42	−0.73	0.54*	−0.17	−0.19	−0.30	−0.27	−0.25	−0.23	−0.17	−0.82	−0.38	0.81*
	0.95	0.72	0.95	1.25	1.14	1.04	1.22	1.35	1.02	1.18	1.24	1.10	0.89	1.07	1.32
S9	−0.57	−2.07	−0.37	−0.70	0.34*	0.06	−0.01	−0.15	−0.49	−0.26	−0.24	−0.14	−1.05	−0.09	0.94*
	0.93	0.71	0.95	1.42	1.11	1.12	1.27	1.50	0.96	1.10	1.16	1.03	0.81	1.10	1.35
S10	−0.55	−1.05	−0.55	−0.68	−0.01	0.14	−0.28	−0.20	−0.62	−0.14	−0.15	−0.14	−1.30	−0.31	1.01*
	0.93	0.92	0.83	1.70	1.08	1.23	1.41	1.71	0.88	0.95	1.00	0.91	0.71	1.05	1.47

Table XI
Out-of-sample predictive regression results for size portfolio excess returns with 15 lagged industry returns selected over 1946–1965 as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 1966:01–2004:12 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the market capitalization-sorted portfolio given in the row heading and $x_{j,t-1}$ is the lagged industry return given in the cell. S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization. The MKT row reports out-of-sample results for the excess return on the CRSP aggregate value-weighted portfolio. The out-of-sample forecasts are formed recursively. The 15 lagged industry returns are selected as the 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. The COMBINE column reports results for a combination forecast based on the 15 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent (top number) and relative Sharpe ratio (bottom number); "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	AGRIC	MINES	STONE	TXTLS	WOOD	CHAIR	PAPER	CHEMS	GLASS	MACHIN	INSTR	PHONE	TV	MONEY	SRVC	COMBINE
MKT	0.07	−0.59	−0.49	0.62*	−0.30	−0.44	−0.54	−0.30	−0.06	−0.19	−0.16	−0.69	0.75*	0.48	0.53	0.21
	1.05	0.98	1.03	1.31	1.12	1.00	1.14	1.13	1.15	1.14	1.14	0.99	1.26	1.33	1.28	1.15
S1	2.10*	1.34*	−0.68	6.70*	3.37*	4.38*	4.07*	3.69*	4.84*	4.07*	5.36*	0.29*	6.43*	6.47*	7.10*	5.85*
	1.34	1.21	0.87	1.75	1.54	1.61	1.47	1.45	1.63	1.44	1.49	0.87	1.50	1.48	1.62	1.77
S2	0.96*	0.01	−0.77	3.95*	1.90*	2.33*	2.05*	2.40*	2.64*	2.41*	2.74*	−0.20	3.77*	4.37*	3.93*	3.13*
	1.29	1.11	0.82	1.68	1.51	1.54	1.47	1.45	1.58	1.40	1.42	0.83	1.41	1.54	1.57	1.65
S3	0.59*	−0.25	−1.10	2.72*	1.51*	1.54*	1.67*	1.70*	1.67*	1.35*	1.88*	−0.68	2.87*	3.46*	2.80*	2.34*
	1.20	1.08	0.82	1.54	1.49	1.41	1.45	1.36	1.54	1.39	1.37	0.81	1.38	1.46	1.50	1.53
S4	0.52*	−0.40	−1.02	2.78*	1.43*	1.41*	1.51*	1.59*	1.40*	1.18*	1.64*	−0.60	2.44*	3.30*	2.32*	2.10*
	1.20	1.03	0.85	1.58	1.49	1.41	1.42	1.34	1.48	1.35	1.33	0.82	1.33	1.50	1.43	1.49
S5	0.23	−0.66	−1.02	1.90*	1.03*	0.78*	0.91*	1.11*	0.78*	0.56*	0.83*	−0.63	1.64*	2.64*	1.58*	1.42*
	1.15	0.97	0.89	1.47	1.45	1.27	1.38	1.27	1.40	1.28	1.23	0.83	1.25	1.46	1.36	1.39
S6	0.24	−0.72	−0.98	1.54*	0.76*	0.52*	0.72*	0.64*	0.68*	0.37*	0.72*	−0.70	1.21*	2.00*	1.24*	1.16*
	1.15	0.95	0.92	1.52	1.42	1.23	1.40	1.27	1.44	1.32	1.26	0.84	1.23	1.44	1.37	1.39
S7	0.20	−0.65	−0.84	1.44*	0.45*	0.34	0.24	0.20	0.38	0.36	0.52	−0.74	1.20*	1.66*	1.23*	0.91*
	1.14	0.95	0.96	1.40	1.33	1.14	1.33	1.21	1.33	1.27	1.22	0.84	1.22	1.34	1.35	1.32
S8	−0.08	−0.50	−0.53	0.57*	−0.12	−0.29	−0.30	−0.16	−0.15	−0.22	−0.09	−0.81	0.48	0.68*	0.25	0.21
	1.06	0.90	1.01	1.26	1.18	0.98	1.20	1.09	1.17	1.11	1.08	0.83	1.14	1.22	1.18	1.16
S9	0.09	−0.45	−0.28	0.45	−0.14	−0.64	−0.45	−0.40	−0.15	−0.30	−0.22	−0.75	0.51	0.53	0.28	0.13
	1.11	0.92	1.07	1.22	1.12	0.86	1.15	1.08	1.14	1.13	1.10	0.91	1.20	1.21	1.21	1.16
S10	−0.12	−0.34	−0.17	−0.02	−0.59	−0.85	−0.91	−0.70	−0.48	−0.58	−0.64	−0.66	0.15	−0.33	−0.09	−0.24
	0.98	0.89	0.98	1.11	0.97	0.80	1.03	1.00	1.02	1.00	0.99	0.97	1.10	1.03	1.06	1.05

Table XII
Out-of-sample predictive regression results for book-to-market portfolio excess returns with 14 economic variables as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 1966:01–2004:12 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the book-to-market value-sorted portfolio given in the row heading and $x_{j,t-1}$ is the economic variable given in the column heading. BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value. The MKT row reports out-of-sample results for the excess return on the CRSP aggregate value-weighted market portfolio. The out-of-sample forecasts are formed recursively. The COMBINE column reports results for a combination forecast based on the 14 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent (top number) and relative Sharpe ratio (bottom number); "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	D/E	SVAR	DFR	LTY	LTR	INFL	TMS	TBL	DFY	D/P	D/Y	E/P	B/M	NTIS	COMBINE
MKT	−0.56	−1.29	−0.49	−0.67	0.28*	0.13	−0.07	−0.10	−0.43	−0.01	0.03	−0.01	−1.02	−0.36	1.09*
	0.98	0.92	0.99	1.41	1.14	1.14	1.35	1.48	0.98	0.99	1.05	0.98	0.87	1.02	1.27
BM1	−0.58	−0.89	−0.39	−0.39	−0.34	0.25	−0.19	0.27*	−0.69	−0.28	−0.24	−0.38	−1.23	−0.58	0.63*
	0.91	0.97	0.88	1.83	0.91	1.26	1.27	1.86	0.84	0.90	0.98	0.82	0.67	0.91	1.39
BM2	−0.63	−1.33	−0.62	−0.84	0.04*	−0.13	−0.20	−0.44	−0.13	−0.17	−0.13	−0.12	−1.02	0.02	0.83*
	0.87	0.80	0.82	1.55	1.03	1.11	1.23	1.54	0.95	1.27	1.34	1.11	0.81	1.09	1.44
BM3	−0.50	−1.81	−0.47	−0.83	0.72*	−0.13	−0.06	−0.40	−0.17	−0.25	−0.22	−0.14	−0.93	0.02	1.01*
	0.92	0.73	0.86	1.55	1.10	1.09	1.34	1.63	0.98	1.22	1.29	1.09	0.84	1.07	1.49
BM4	−0.34	−1.31	−0.39	−0.98	0.53*	−0.08	0.16*	−0.55	−0.20	−0.37	−0.35	−0.04	−0.96	0.33	1.05*
	0.94	0.80	0.88	1.45	1.12	1.06	1.30	1.52	0.88	1.23	1.28	1.13	0.80	1.13	1.50
BM5	−0.44	−0.65	−0.41	−0.30	0.63*	0.12	−0.18	0.36*	−0.88	−0.22	−0.21	−0.03	−0.84	−0.02	1.34*
	0.91	0.93	0.97	1.51	1.31	1.10	1.48	1.62	0.94	1.07	1.10	1.04	0.85	1.20	1.41
BM6	−0.60	−2.03	−0.48	−0.76	0.67*	−0.03	−0.23	−0.29	−0.60	−0.04	−0.04	0.08	−0.85	−0.39	1.01*
	0.92	0.80	0.93	1.21	1.10	1.07	1.17	1.26	0.94	0.98	1.01	1.03	0.84	1.07	1.23
BM7	−0.39	−3.95	−0.49	−0.99	1.23*	−0.01	−0.68	−0.80	−0.45	−0.46	−0.44	−0.18	−1.01	0.31*	0.84*
	0.99	0.48	0.86	1.23	1.06	1.02	1.14	1.26	0.91	0.90	0.93	0.97	0.81	1.01	1.19
BM8	−0.46	−1.38	−0.45	−0.65	0.25*	−0.27	−1.59	−0.64	−0.82	−0.14	−0.11	0.02	−0.91	−0.51	1.09*
	0.97	0.88	0.92	1.09	1.07	0.99	1.13	1.14	1.00	0.99	1.02	1.04	0.90	1.05	1.16
BM9	−0.50	−1.00	−0.53	−0.94	0.49*	−0.08	−0.97	−0.84	−0.74	0.14	0.23	0.23	−0.68	−0.31	1.03*
	0.96	0.90	0.94	1.01	1.06	0.96	1.07	1.05	1.01	1.13	1.17	1.15	1.00	1.03	1.16
BM10	−0.48	−1.30	−0.42	−0.90	0.75*	−0.35	−0.43	−0.65	−0.44	−0.18	−0.10	−0.07	−0.84	−0.73	0.83*
	0.95	0.88	0.96	1.03	1.06	0.96	1.01	1.06	0.97	1.14	1.23	1.17	0.96	1.02	1.16

Table XIII
Out-of-sample predictive regression results for book-to-market portfolio excess returns with 15 lagged industry returns selected over 1946–1965 as predictors

The table reports out-of-sample results for predictive regression model forecasts of excess returns pitted against benchmark historical average forecasts of excess returns for the 1966:01–2004:12 forecast evaluation period. The predictive regression model forecasts are based on the model, $r_{i,t} = a_i + b_{i,j}x_{j,t-1} + e_{i,t}$, where $r_{i,t}$ is the excess return for the book-to-market value-sorted portfolio given in the row heading and $x_{j,t-1}$ is the lagged industry return given in the column heading. BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value. The MKT row reports out-of-sample results for the excess return on the CRSP aggregate value-weighted portfolio. The out-of-sample forecasts are formed recursively. The 15 lagged industry returns are selected as the 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. The COMBINE column reports results for a combination forecast based on the 15 individual prediction regression model forecasts taken as a group. The entries in the table report the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}) in percent (top number) and relative Sharpe ratio (bottom number); "*" indicates that R^2_{OS} is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	AGRIC	MINES	STONE	TXTLS	WOOD	CHAIR	PAPER	CHEMS	GLASS	MACHIN	INSTR	PHONE	TV	MONEY	SRVC	COMBINE
MKT	0.07	−0.59	−0.49	0.62*	−0.30	−0.44	−0.54	−0.30	−0.06	−0.19	−0.16	−0.69	0.75*	0.48	0.53	0.21
	1.05	0.98	1.03	1.31	1.12	1.00	1.14	1.13	1.15	1.14	1.14	0.99	1.26	1.33	1.28	1.15
BM1	−0.23	−0.47	−0.33	0.19	−0.45	−0.45	−0.64	−0.25	−0.26	−0.28	−0.11	−0.69	0.39	0.03	0.28	0.05
	0.94	0.90	0.98	1.20	1.04	0.96	1.02	1.11	1.07	1.12	1.18	0.90	1.22	1.05	1.15	1.14
BM2	0.22	−0.48	−0.29	0.24	−0.21	−0.44	−0.50	−0.10	−0.07	−0.25	−0.10	−0.57	0.65*	0.39	0.53	0.18
	1.10	0.90	1.01	1.15	1.09	0.85	1.11	1.14	1.11	1.08	1.12	0.87	1.20	1.16	1.21	1.14
BM3	0.23	−0.79	−0.35	0.95*	0.06	−0.16	−0.33	−0.35	0.04	−0.05	−0.12	−0.56	1.03*	0.74*	0.76*	0.38
	1.09	0.82	0.96	1.31	1.11	0.92	1.15	1.08	1.22	1.15	1.09	0.95	1.26	1.27	1.28	1.19
BM4	0.23	−0.58	−0.52	0.73*	0.01	−0.16	−0.22	−0.34	0.00	−0.13	−0.23	−0.79	0.46*	0.41	0.32	0.21
	1.09	0.88	0.94	1.26	1.17	0.94	1.16	1.02	1.16	1.04	1.01	0.89	1.10	1.14	1.15	1.13
BM5	0.13	−0.56	−0.54	0.59	−0.11	−0.55	−0.39	−0.52	−0.09	−0.22	−0.33	−0.66	0.27	0.30	0.19	0.05
	1.09	0.89	0.99	1.27	1.11	0.85	1.14	0.99	1.19	1.05	1.01	0.94	1.05	1.20	1.13	1.09
BM6	−0.12	−0.61	−0.46	0.13	−0.54	−0.63	−0.57	−0.70	−0.41	−0.27	−0.47	−0.60	−0.02	0.07	−0.11	−0.13
	1.02	0.91	1.00	1.10	1.00	0.88	1.10	0.99	1.04	1.03	1.02	0.96	1.04	1.11	1.08	1.05
BM7	0.11	−0.35	−0.58	0.73*	−0.07	−0.99	−0.34	−0.44	−0.13	0.00	−0.14	−0.49	0.29	0.25	0.20	0.06
	1.04	0.90	0.98	1.20	1.06	0.84	1.07	1.01	1.03	1.04	1.04	0.97	1.06	1.11	1.08	1.06
BM8	−0.01	−0.38	−0.66	0.57*	−0.19	−0.85	−0.51	−0.73	−0.26	0.27	−0.21	−0.70	0.48	0.24	0.46	0.14
	1.04	0.94	0.99	1.16	1.04	0.92	1.07	1.00	1.04	1.07	1.02	0.93	1.06	1.10	1.10	1.06
BM9	0.36	−0.51	−1.34	1.25*	0.00	0.24	−0.12	−0.25	0.06	0.72*	0.17	−0.59	1.41*	1.17*	1.33*	0.78*
	1.09	0.95	0.93	1.25	1.12	1.08	1.10	1.05	1.14	1.16	1.04	0.91	1.16	1.21	1.26	1.16
BM10	0.87*	−0.52	−1.55	3.06*	1.07*	0.91*	0.26	−0.17	0.80*	1.31*	0.78*	−0.10	2.54*	1.96*	1.90*	1.47*
	1.12	0.95	0.86	1.43	1.20	1.14	1.14	1.08	1.21	1.21	1.14	0.94	1.29	1.31	1.29	1.27

Table XIV

R^2_{OS} statistics computed over NBER-dated recessions and expansions for industry, size, and book-to-market portfolio excess returns with 14 economic variables as predictors

The table reports R^2_{OS} statistics (in percent) for out-of-sample forecasts of industry (Panel B), size (Panel C), and book-to-market (Panel D) portfolio excess returns for 1966:01–2004:12 (S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization; BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value). Results are reported for combination forecasts using 14 economic variables as predictors (see Tables VIII, X, and XII). Panel A reports out-of-sample results for the excess return on the CRSP aggregate value-weighted portfolio. R^2_{OS} is the Campbell and Thompson (2008) out-of-sample R^2 statistic. The "Recession" columns report R^2_{OS} statistics computed over months designated by the NBER as recessions; the "Expansion" columns report R^2_{OS} statistics computed over non-recession (expansion) months. The "Average" rows give the averages across the portfolios in the individual panels.

Return	Recession	Expansion	Return	Recession	Expansion	Return	Recession	Expansion
Panel A: Aggregate market portfolio excess returns								
MKT	2.40	0.60						
Panel B: Industry portfolio excess returns								
AGRIC	0.40	0.15	PAPER	2.11	0.36	CARS	3.07	1.42
MINES	0.22	0.10	PRINT	3.00	0.34	INSTR	1.33	0.03
OIL	0.86	−0.07	CHEMS	1.84	0.25	MANUF	1.70	0.59
STONE	−1.36	0.37	PTRLM	0.76	0.35	TRANS	1.45	0.51
CNSTR	1.57	0.33	RUBBER	2.02	1.02	PHONE	0.93	0.12
FOOD	2.08	0.26	LETHR	2.78	0.26	TV	2.12	0.44
SMOKE	0.84	−0.09	GLASS	2.47	0.59	UTILS	1.66	0.62
TXTLS	1.82	0.89	METAL	0.88	0.18	WHLSL	1.68	0.24
APPRL	2.08	1.13	MTLPR	2.35	0.42	RTAIL	2.16	0.32
WOOD	0.92	0.17	MACHIN	1.97	0.12	MONEY	2.26	0.29
CHAIR	2.08	0.58	ELCTR	2.27	0.03	SRVC	1.68	0.26
Average	1.64	0.38						
Panel C: Size portfolio excess returns								
S1	1.71	0.57	S6	2.35	0.64			
S2	1.74	0.40	S7	2.28	0.47			
S3	1.66	0.43	S8	1.99	0.38			
S4	1.96	0.55	S9	2.07	0.52			
S5	2.01	0.53	S10	2.33	0.57			
Average	2.01	0.51						
Panel D: Book-to-market portfolio excess returns								
BM1	1.91	0.13	BM6	2.22	0.64			
BM2	2.46	0.30	BM7	1.86	0.46			
BM3	2.51	0.52	BM8	1.85	0.83			
BM4	2.42	0.61	BM9	1.81	0.81			
BM5	2.72	0.94	BM10	1.29	0.67			
Average	2.10	0.59						

Table XV
R^2_{OS} statistics computed over NBER-dated recessions and expansions for industry, size, and book-to-market portfolio excess returns with 15 lagged industry returns as predictors

The table reports R^2_{OS} statistics (in percent) for out-of-sample forecasts of industry (Panel B), size (Panel C), and book-to-market (Panel D) portfolio excess returns for 1966:01–2004:12 (S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization; BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value). Results are reported for combination forecasts using 15 lagged industry returns as predictors (see Tables IX, XI, and XIII). The 15 lagged industry returns are selected as the 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. Panel A reports out-of-sample results for the excess return on the CRSP aggregate value-weighted portfolio. R^2_{OS} is the Campbell and Thompson (2008) out-of-sample R^2 statistic. The "Recession" columns report R^2_{OS} statistics computed over months designated by the NBER as recessions; the "Expansion" columns report R^2_{OS} statistics computed over non-recession (expansion) months. The "Average" rows give the averages across the portfolios in the individual panels.

Return	Recession	Expansion	Return	Recession	Expansion	Return	Recession	Expansion
Panel A: Aggregate market portfolio excess returns								
MKT	1.74	−0.35						
Panel B: Industry portfolio excess returns								
AGRIC	2.31	0.66	PAPER	1.05	−0.46	CARS	3.44	1.29
MINES	1.75	−0.16	PRINT	8.23	−0.10	INSTR	1.65	−0.41
OIL	−0.38	−0.14	CHEMS	0.51	−0.48	MANUF	5.90	1.46
STONE	2.46	0.77	PTRLM	−0.63	−0.34	TRANS	1.47	0.22
CNSTR	4.98	1.02	RUBBER	1.11	−0.09	PHONE	−0.68	−0.25
FOOD	0.65	−0.29	LETHR	3.29	0.50	TV	4.10	−0.08
SMOKE	−0.44	−0.03	GLASS	3.64	0.19	UTILS	0.03	−0.15
TXTLS	3.33	2.32	METAL	1.41	−0.33	WHLSL	3.59	0.25
APPRL	4.18	0.84	MTLPR	3.93	0.25	RTAIL	2.16	0.15
WOOD	2.03	0.26	MACHIN	3.25	−0.45	MONEY	1.09	−0.30
CHAIR	4.06	1.40	ELCTR	1.99	−0.42	SRVC	3.01	−0.17
Average	2.38	0.21						
Panel C: Size portfolio excess returns								
S1	8.66	5.05	S6	3.29	0.39			
S2	5.57	2.40	S7	2.72	0.20			
S3	5.38	1.31	S8	1.56	−0.31			
S4	4.92	1.12	S9	1.18	−0.28			
S5	3.93	0.49	S10	0.69	−0.56			
Average	3.79	0.98						
Panel D: Book-to-market portfolio excess returns								
BM1	2.16	−0.80	BM6	0.45	−0.32			
BM2	1.46	−0.26	BM7	0.31	−0.05			
BM3	2.05	−0.19	BM8	0.84	−0.11			
BM4	1.86	−0.33	BM9	2.07	0.38			
BM5	0.55	−0.10	BM10	2.43	1.11			
Average	1.42	−0.07						

Table XVI
Conditional CAPM $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics for industry, size, and book-to-market portfolio excess returns with 14 economic variables as predictors

The table reports $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics (in percent) for out-of-sample forecasts of industry (Panel A), size (Panel B), and book-to-market (Panel C) portfolio excess returns for 1966:01–2004:12 (S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization; BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value). Results are reported for combination forecasts using 14 economic variables as predictors (see Tables VIII, X, and XII). $R^2_{OS,R}$ ($R^2_{OS,\alpha}$) measures the reduction in mean square prediction error for the rational pricing-restricted combination forecast based on the conditional CAPM relative to the historical average combination forecast (unrestricted combination forecast relative to the rational pricing-restricted combination forecast). "*" indicates that $R^2_{OS,R}$ or $R^2_{OS,\alpha}$ is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)
Panel A: Industry portfolio excess returns								
AGRIC	0.52*	−0.32	PAPER	1.25*	−0.49	CARS	1.47*	0.36*
MINES	0.48*	−0.35	PRINT	1.25*	−0.19	INSTR	1.41*	−1.06
OIL	0.66*	−0.48	CHEMS	0.78*	−0.15	MANUF	1.07*	−0.21
STONE	0.48*	−0.37	PTRLM	0.54*	−0.09	TRANS	0.85*	−0.08
CNSTR	0.90*	−0.20	RUBBER	1.15*	0.07	PHONE	0.24	−0.02
FOOD	0.39	0.32	LETHR	0.57*	0.31	TV	0.82*	0.03
SMOKE	−0.70	0.72*	GLASS	0.94*	0.08	UTILS	0.97*	−0.09
TXTLS	1.02*	0.07	METAL	0.43*	−0.11	WHLSL	0.93*	−0.32
APPRL	0.89*	0.50	MTLPR	0.93*	−0.06	RTAIL	0.80*	0.01
WOOD	0.89*	−0.53	MACHIN	1.01*	−0.44	MONEY	0.75*	0.07
CHAIR	0.90*	0.07	ELCTR	0.71*	−0.16	SRVC	0.66*	−0.05
Panel B: Size portfolio excess returns								
S1	1.04*	−0.21	S6	1.12*	−0.04			
S2	0.95*	−0.23	S7	1.00*	−0.04			
S3	0.98*	−0.24	S8	0.91*	−0.10			
S4	1.08*	−0.17	S9	0.97*	−0.03			
S5	1.00*	−0.07	S10	0.93*	0.08			
Panel C: Book-to-market portfolio excess returns								
BM1	0.73*	−0.10	BM6	2.22*	0.03			
BM2	0.84*	0.00	BM7	1.86*	0.14			
BM3	0.84*	0.17	BM8	1.85*	−0.18			
BM4	0.83*	0.22	BM9	1.81*	0.11			
BM5	1.53*	−0.19	BM10	1.29*	0.04			

Table XVII

Conditional CAPM $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics for industry, size, and book-to-market portfolio excess returns with 15 lagged industry returns selected over 1946–1965 as predictors

The table reports $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics (in percent) for out-of-sample forecasts of industry (Panel A), size (Panel B), and book-to-market (Panel C) portfolio excess returns for 1966:01–2004:12 (S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization; BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value). Results are reported for combination forecasts using 15 lagged industry returns as predictors (see Tables IX, XI, and XIII). The 15 lagged industry returns are selected as the 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. $R^2_{OS,R}$ ($R^2_{OS,\alpha}$) measures the reduction in mean square prediction error for the rational pricing-restricted combination forecast based on the conditional CAPM relative to the historical average combination forecast (unrestricted combination forecast relative to the rational pricing-restricted combination forecast). "*" indicates that $R^2_{OS,R}$ or $R^2_{OS,\alpha}$ is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic.

Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)
			Panel A: Industry portfolio excess returns					
AGRIC	0.66*	0.31	PAPER	0.16	−0.27	CARS	1.32*	0.51*
MINES	0.48	−0.24	PRINT	1.14*	1.02*	INSTR	1.28*	−1.17
OIL	0.18	−0.38	CHEMS	−0.41	0.17	MANUF	1.40*	1.17*
STONE	0.84*	0.19	PTRLM	−0.56	0.15	TRANS	0.36	0.21
CNSTR	1.17*	1.04*	RUBBER	0.25	−0.09	PHONE	−0.15	−0.15
FOOD	−0.34	0.28	LETHR	0.68*	0.51	TV	0.87*	0.08
SMOKE	−0.77	0.68*	GLASS	0.73*	0.24	UTILS	−0.45	0.35
TXTLS	1.18*	1.38*	METAL	−0.05	0.07	WHLSL	0.83*	0.28
APPRL	0.85*	0.89*	MTLPR	0.74*	0.39	RTAIL	0.64*	0.05
WOOD	0.69*	0.03	MACHIN	0.79*	−0.33	MONEY	0.10	−0.03
CHAIR	1.26*	0.84*	ELCTR	0.20	−0.06	SRVC	0.48*	0.14
			Panel B: Size portfolio excess returns					
S1	2.35*	3.58*	S6	0.85*	0.31			
S2	1.66*	1.50*	S7	0.66*	0.24			
S3	1.41*	0.94*	S8	0.23	−0.03			
S4	1.32*	0.79*	S9	0.12	0.02			
S5	1.01*	0.41	S10	−0.34	0.10			
			Panel C: Book-to-market portfolio excess returns					
BM1	0.08	−0.03	BM6	−0.12	−0.01			
BM2	0.07	0.11	BM7	−0.13	0.19			
BM3	0.26	0.12	BM8	0.42	−0.28			
BM4	0.07	0.13	BM9	0.69	0.10			
BM5	0.64	−0.59	BM10	0.89*	0.58*			

Table XVIII
Conditional 3-factor model $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics for industry, size, and book-to-market portfolio excess returns with 15 lagged industry returns selected over 1946–1965 as predictors

The table reports $R^2_{OS,R}$ and $R^2_{OS,\alpha}$ statistics (in percent) for out-of-sample forecasts of industry (Panel A), size (Panel B), and book-to-market (Panel C) portfolio excess returns for 1966:01–2004:12 (S1,...,S10 delineate deciles in ascending order for portfolios formed on market capitalization; BM1,...,BM10 delineate deciles in ascending order for portfolios formed on book-to-market value). Results are reported for combination forecasts using 15 lagged industry returns as predictors (see Tables IX, XI, and XIII). The 15 lagged industry returns are selected as the 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. $R^2_{OS,R}$ ($R^2_{OS,\alpha}$) measures the reduction in mean square prediction error for the rational pricing-restricted combination forecast based on the conditional 3-factor model relative to the historical average combination forecast (unrestricted combination forecast relative to the rational pricing-restricted combination forecast). "*" indicates that $R^2_{OS,R}$ or $R^2_{OS,\alpha}$ is significant at the 5% level according to the p-value corresponding to the Clark and West (2007) *MSPE-adjusted* statistic. Each panel also reports estimation results for a cross-section regression model with $R^2_{OS,R}$ (average estimated beta for each factor, $\bar{\hat{\beta}}_{i,j,t}$ for $j = MKT, SMB, HML$) as the regressand (regressor). An intercept term is included in the cross-section regression model; t-statistics are given in parentheses.

Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)
Panel A: Industry portfolio excess returns								
AGRIC	1.41*	−0.45	PAPER	0.22	−0.33	CARS	1.34*	0.50*
MINES	0.49	−0.25	PRINT	1.89*	0.26	INSTR	1.46*	−1.36
OIL	0.05	−0.26	CHEMS	−0.27	0.03	MANUF	2.62*	−0.07
STONE	1.22*	−0.20	PTRLM	−0.20	−0.21	TRANS	0.11	0.46
CNSTR	2.14*	0.05	RUBBER	0.16	0.00	PHONE	0.12	−0.42
FOOD	−0.34	0.28	LETHR	1.40*	−0.22	TV	1.10*	−0.15
SMOKE	−0.77	0.69*	GLASS	1.00*	−0.03	UTILS	−0.19	0.09
TXTLS	1.89*	0.66*	METAL	−0.73	0.74*	WHLSL	1.07*	0.04
APPRL	1.65*	0.09	MTLPR	1.03*	0.10	RTAIL	0.78*	−0.09
WOOD	0.71*	0.01	MACHIN	0.91*	−0.45	MONEY	0.15	−0.08
CHAIR	2.18*	−0.08	ELCTR	0.28	−0.14	SRVC	0.52	0.10

$$R^2_{OS,R} = \underset{(0.09)}{0.06}\bar{\hat{\beta}}_{i,MKT,t} + \underset{(5.83)}{1.70}\bar{\hat{\beta}}_{i,SMB,t} - \underset{(-1.44)}{0.69}\bar{\hat{\beta}}_{i,HML,t} + \underset{(0.32)}{0.22}, \quad R^2 = 55\%$$

Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)
Panel B: Size portfolio excess returns					
S1	5.05*	0.85*	S6	1.08*	0.09
S2	3.07*	0.06	S7	0.84*	0.07
S3	2.30*	0.04	S8	0.17	0.04
S4	2.12*	−0.02	S9	0.11	0.03
S5	1.46*	−0.04	S10	−0.19	−0.05

$$R^2_{OS,R} = -\underset{(-4.83)}{17.15}\bar{\hat{\beta}}_{i,MKT,t} + \underset{(4.99)}{2.34}\bar{\hat{\beta}}_{i,SMB,t} + \underset{(1.32)}{2.32}\bar{\hat{\beta}}_{i,HML,t} + \underset{(4.70)}{17.20}, \quad R^2 = 97\%$$

Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)	Return	$R^2_{OS,R}$ (%)	$R^2_{OS,\alpha}$ (%)
Panel C: Book-to-market portfolio excess returns					
BM1	0.32	−0.27	BM6	−0.09	−0.04
BM2	0.08	0.11	BM7	−0.09	0.15
BM3	0.22	0.16	BM8	0.28	−0.13
BM4	0.11	0.09	BM9	0.74*	0.04
BM5	0.61	−0.57	BM10	1.25*	0.22

$$R^2_{OS,R} = -\underset{(-0.08)}{0.19}\bar{\hat{\beta}}_{i,MKT,t} + \underset{(4.25)}{2.67}\bar{\hat{\beta}}_{i,SMB,t} - \underset{(-1.77)}{0.40}\bar{\hat{\beta}}_{i,HML,t} + \underset{(0.18)}{0.43}, \quad R^2 = 61\%$$

Table XIX
Summary statistics for maximum industry, size, and book-to-market portfolios

The table reports sample means and standard deviations (in percentage points), as well as Sharpe ratios, for excess returns on each maximum portfolio. The maximum portfolio is formed by allocating all of the portfolio each month for 1966:01–2004:12 to the individual component with the highest predicted return based on combination or historical average forecasts of industry, size, or book-to-market portfolios. The combination forecasts are based on 14 economic variables or the 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. The relative Sharpe ratio is the Sharpe ratio for the combination forecast divided by the Sharpe ratio for the historical average forecast.

	Combination forecasts			Historical average forecasts			
Porfolio	Mean	Std. dev.	Sharpe ratio	Mean	Std. dev.	Sharpe ratio	Relative Sharpe ratio
Max. industry return, 14 economic variables as preds.	0.83	6.67	0.13	0.60	6.72	0.09	1.41
Max. industry return, lagged industry returns as preds.	0.79	6.53	0.12	0.60	6.72	0.09	1.36
Max. size return, 14 economic variables as preds.	0.77	6.25	0.12	0.71	6.50	0.11	1.12
Max. size return, lagged industry returns as preds.	1.28	5.93	0.22	0.71	6.50	0.11	1.98
Max. book-to-market return, 14 economic variables as preds.	0.80	5.01	0.16	0.80	4.85	0.16	0.97
Max. book-to-market return, lagged industry returns as preds.	1.04	4.82	0.22	0.80	4.85	0.16	1.32

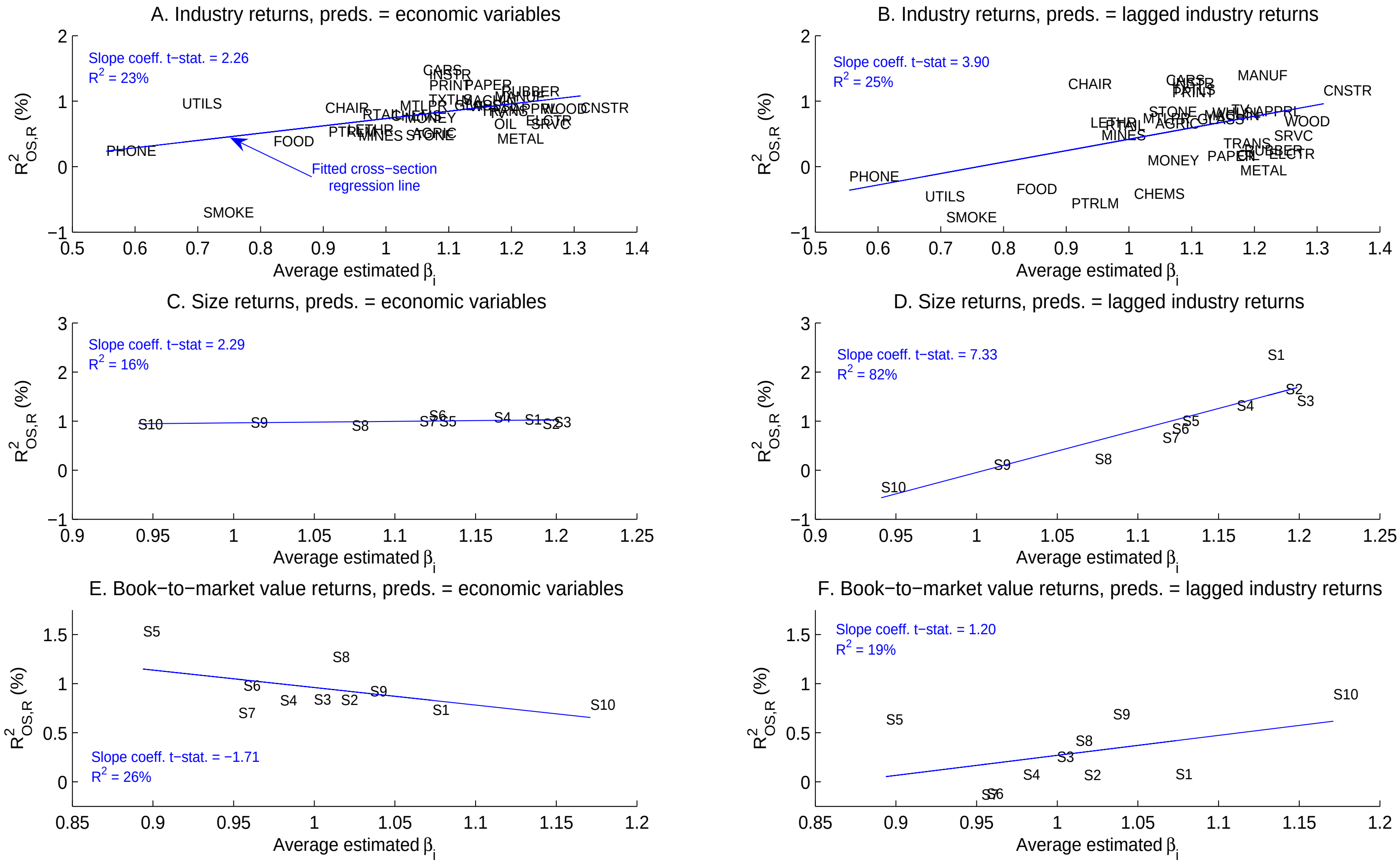

Figure 1. Relationship between $R^2_{OS,R}$ statistics and average estimated betas. Each panel contains a scatterplot relating the $R^2_{OS,R}$ statistics in Tables XVI and XVII to the average estimated β_i used to generate rational pricing-restricted combination forecasts over 1966:01–2004:12. Each panel includes a fitted regression line and regression results for a cross-section regression model with $R^2_{OS,R}$ as the regressand and average estimated β_i as the regressor (an intercept term is included in the cross-section regression model).

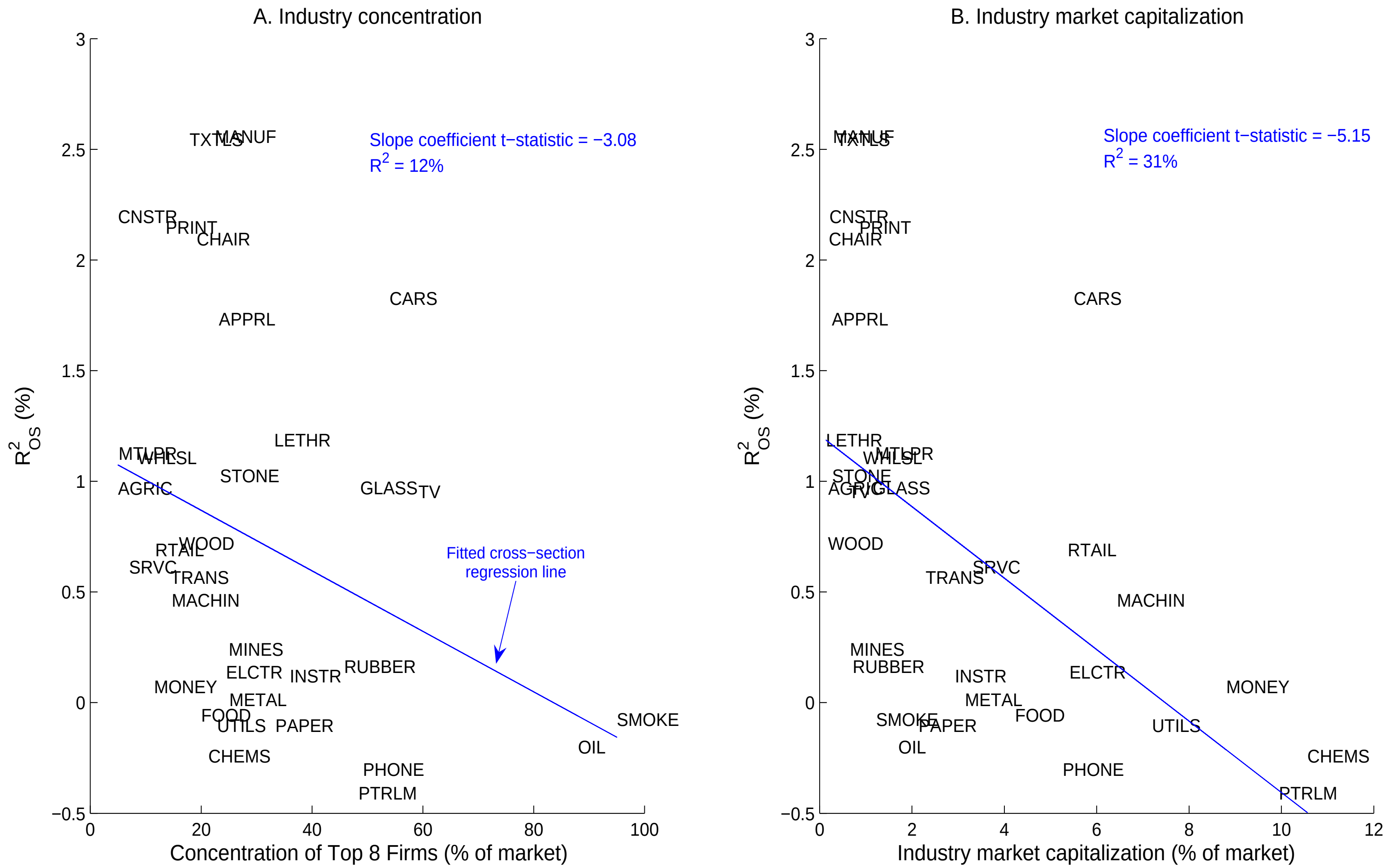

Figure 2. Relationship between industry concentration or market capitalization and R^2_{OS} statistics for industry portfolio excess returns. Each panel contains a scatterplot relating the R^2_{OS} statistics in Table IX to industry concentration (average market share of the eight largest firms) and market capitalization in Panels A and B, respectively. Each panel includes a fitted regression line and regression results for a cross-section regression model with R^2_{OS} as the regressand and industry concentration or market capitalization as the regressor (an intercept term is included in the cross-section regression model).

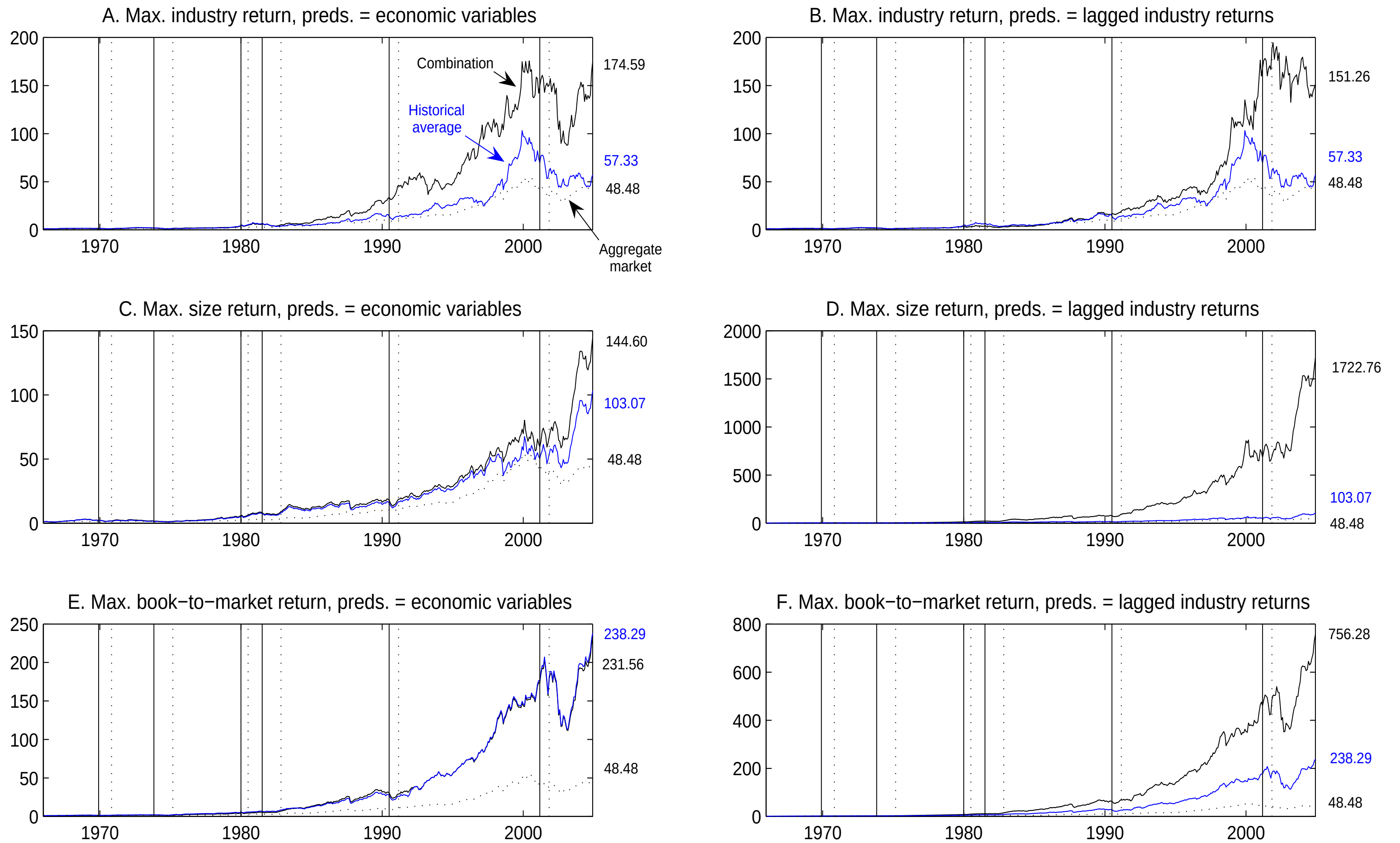

Figure 3. Cumulative gross return on maximum industry, size, and book-to-market portfolios. Each panel portray the cumulative gross return to each maximum portfolio. The maximum portfolio is formed by allocating all of the portfolio each month for 1966:01–2004:12 to the individual component with the highest predicted return based on combination (black line) or historical average (blue or gray line) forecasts of industry, size, or book-to-market portfolios. The combination forecasts are based on 14 economic variables or the 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. The cumulative gross return the CRSP aggregate value-weighted market portfolio is given by the dashed line. Solid (dashed) vertical lines indicates NBER-dated business cycle peaks (troughs).

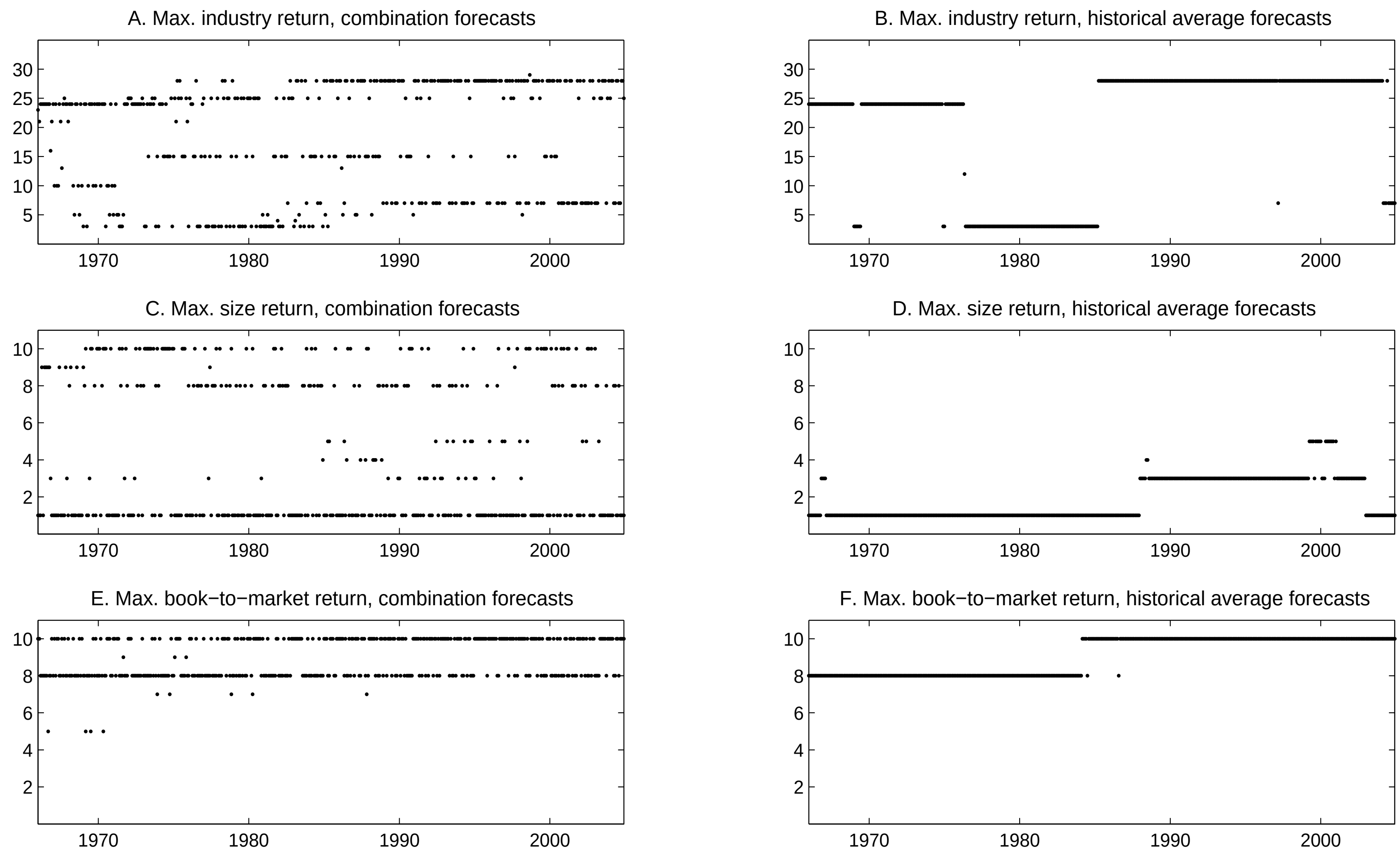

Figure 4. Selected components for maximum industry, size, and book-to-market portfolios. Each panel portrays the component selected for each maximum portfolio. The maximum portfolio is formed by allocating all of the portfolio each month for 1966:01–2004:12 to the individual component with the highest predicted return based on combination forecasts of industry, size, or book-to-market portfolios. The combination forecasts are based on 15 of 33 lagged industry returns with the highest R^2 for predictive regression models of aggregate market returns estimated over the 1946:01–1965:12 in-sample period. The numbers on the vertical axes in Panels A and B correspond to the industry number using the ordering of the industries as given in Table I, Panel B. The numbers on vertical axes in Panels C–F correspond to the ordered size or book-to-market portfolios.