Can We Count on Accounting Fundamentals for Industry Portfolio Allocation?

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The accounting literature provides considerable evidence that equity markets do not always process public information correctly, completely, and quickly; the resulting lapses leave open opportunities to forecast excess returns and, consequently, to even possibly capture alpha on an ongoing basis. According to Abarbanell and Bushee [1998], "evidence that the market underreacts to accounting information has been apparent in the literature since Ball and Brown [1968] and consistently supported in the literature." For instance, Bernard and Thomas [1989] document the presence of a "delayed price response." Consistent with these findings, studies by Sloan [1996] and Hirshleifer, Hou, and Teoh [2009] find that accruals and cash flows can predict stock returns one year ahead.[1] Thus, the accounting literature documents that firm-level accounting data can both explain and lead firm-level returns.

In contrast, much of the finance literature on stock return predictability focuses on forecasting excess market returns with select macroeconomic or aggregate financial variables such as the lagged dividend-to-price ratio (e.g., Fama and French [1989] and Chen [2009]).[2] Our article instead examines the ability of industry-level and aggregate accounting variables to predict industry excess stock returns. It then explores whether we can count on these industry return forecasts to select long–short industry portfolios in real time that consistently outperform a buy-and-hold strategy in terms of average return, terminal payout, and Sharpe ratio.

The focus on industry-level data offers several advantages compared to prior work on aggregate predictability. First, a considerable amount of wealth is actively managed by portfolio managers in industry/sector portfolios; therefore, it is important to identify potential strategies that evaluate the economic relevance of predictability via portfolio allocation strategies. Vardharaj and Fabozzi [2007] demonstrate that "allocation policy explains one-third to nearly three-quarters of among-fund variation in returns, nearly 90 percent of across-time variation." Yet, the academic literature has neglected the salience of industry portfolio allocation.[3]

Second, forecasting the relevance of industry accounting variables on future industry returns is important, because this predictive relationship may differ relative to the more studied equity premium relationship between the market return and aggregate accounting variables. For example, Sloan [1996], Kothari, Lewellen, and Warner [2006], and Hirshleifer, Hou, and Teoh [2009] find that firm-level accounting variables have different effects on firm-level returns than those found by tests evaluating these relationships using aggregate data. We focus on industries because they are a convenient way of aggregating individual firms for time-series analyses. Fama and French provide consistent industry data over several decades; whereas, time-series analysis at the firm-level is complicated by frequent firm entries and exits that limit time-series data and lead to survival bias, the presence of very large numbers of firms for short periods of time, and potential problems with the tremendous variability associated with firm-level data.

Third, evaluating the link between 43 industry accounting variables and 43 value-weighted (VW) industry excess returns implies multiple (albeit correlated) tests of the predictive relationship and portfolio allocation to assess robustness.[4] Predictability differences between individual industry and industry portfolio returns are further likely to vary along the business cycle and across decades; thus, evaluating predictability and portfolio allocation among numerous industries across time presents more robust evidence than testing only one time series, such as the market return.

A number of prominent finance papers posit that return predictability can occur when information is not instantaneously transmitted, particularly for stocks with low analyst coverage or low market capitalization (e.g., Lo and MacKinlay [1990], Brennan, Jegadeesh, and Swaminathan [1993], and Hong and Stein [1999]). Hong, Lim, and Stein [2000], in particular, provide strong evidence that gradual diffusion of information occurs for small stocks—those not extensively covered by analysts—and when firms with low analyst coverage have "bad news" to report. Hou [2007] supports the gradual diffusion model, finding that big firms lead smaller firms within the same industries and returns sluggishly adjust to negative information.

Hong, Torous, and Valkanov [2007] explain how industry returns lead aggregate returns by up to two months and motivate their results with a gradual information model. They conclude that "findings suggest that stock markets react with a delay to information in industry excess returns regarding fundamentals and that information diffuses only gradually across markets." Cohen and Frazzini [2008] further demonstrate that returns do not promptly incorporate news concerning economically related firms, which generates return predictability across assets; they attribute predictability to investor inattention.[5] These findings suggest that gradual diffusion of information can be effective in motivating industry return predictability.

A preview of our results reveals several compelling findings. Combination forecasts of industry-level and aggregate accruals, book-to-market, earnings, investments, and gross profits ratios are significant in forecasting 26 one-quarter-ahead industry excess returns. Sharpe ratios are higher than the benchmark in 34 industries and more than 10% greater than the benchmark in most industries. Further, utility gains relative to the benchmark are substantial, averaging 5% across industries. Both the higher Sharpe ratios and utility gains demonstrate that the increased predictability generated by combination forecasts is not at the expense of correspondingly higher risk.

In this article, we focus on the implication of out-of-sample industry predictability on portfolio allocation. We show that forecasts of industry returns that combine information from accounting variables in real time lead to sizable portfolio gains relative to a passive buy-and-hold strategy. An industry-rotation strategy that selects the top decile of industries with the highest expected returns and shorts the bottom decile of industries with the lowest expected returns using a 130/30 weighting strategy outperforms the buy-and-hold benchmark by nearly five times. Long–short strategies outperfom the benchmark 67% of the time and, importantly, their accuracy is consistent over three decades. We also utilize a more leveraged 200/100 strategy that fully shorts industries with the lowest expected returns and reinvests the proceeds into industries with the highest expected returns. Results highlight terminal dollar payoffs nine times the benchmark. Further, a Fama and French three-factor model demonstrates significant alpha; for example, a 130/30 (200/100) portfolio allocation strategy generates an alpha of 10.5% (19.4%).

MOTIVATION, DATA AND METHODOLOGY

Motivation

In our study, we combine quarterly industry-level and economy-wide data from 1976.1 to 2013.4 for accruals, book-to-market, earnings, and investment and gross profits information to forecast stock returns—because economic fundamentals should not only be linked to stock returns, but also successfully predict these returns if information diffuses gradually. An important paper by Dechow [1994] demonstrates the relevance of accruals in providing an improved summary measure of firm performance. Barth et al. [1999] argue that accrual accounting is at the heart of earnings management, and that accruals provide explanatory power in the equity market beyond that of the book-to-market ratio alone. The importance of earnings goes back to the seminal paper by Ball and Brown [1968], and is cited in a large number of works including Bernard and Thomas [1989] and Nichols and Wahlen [2004].

Fama and French [1995, 2015] show that the book-to-market ratio is an important factor in explaining the cross section of stock returns. Recent work by Novy-Marx [2013] documents that gross profits (revenue minus cost of goods sold) is an important variable in explaining the cross section of returns, whereas Aharoni, Grundy, and Zeng [2013] find that investment explains returns. In their most recent paper, Fama and French [2015] introduce a five-factor model with investment and gross profits augmenting their three-factor model, demonstrating that these variables help explain the cross section of stock returns.

Our article, in contrast, stresses the importance of evaluating predictability and portfolio performance over time and adopts the perspective of a real-world investor based on an out-of-sample (OOS) framework, because in-sample methodology may mask instability between financial variables (Goyal and Welch [2008]). The accounting literature provides further evidence that the relationship between accounting variables and stock returns may have deteriorated over time while also exhibiting temporal instability (e.g., Amir and Lev [1996] and Collins, Maydew, and Weiss [1997]). Hence, it is important to evaluate predictability and allocation over a long sample period and adopt a methodology that is relatively robust to such potential breaks.

Hendry and Clements [2004] and Timmermann [2006] demonstrate that while structural instabilities are prevalent in individual predictive models, combination forecast methods palliate these instabilities and improve the overall performance of out-of-sample prediction. Rapach, Strauss, and Zhou [2010] show that combination forecast methods mitigate temporal instability of individual predictive regression models and provide stable, consistent forecasts for the S&P 500 relative to the random walk. Out-of-sample testing of combination forecasts is particularly relevant if the data-generating process evolves over time and utilizes a large number of potential explanatory variables, because in-sample analysis tends to overfit, leading to spurious results and misspecification.

Data

We utilize Compustat firm-level data to compile quarterly industry-level accounting variables—including accruals, book-to-market ratios, earnings, and investment and gross profits—based on the Fama–French 49 industry classifications from Kenneth French's data library. All sampled firms must have at least $10 million market capitalization, and possess the necessary information to construct the five accounting variables given below; additionally, each industry must include at least six firms. This requirement generates industry-level data using firms that possess medium-large market capitalizations while excluding small micro-cap firms that may have different liquidity and risk characteristics.

Once industry data have been constructed, we only consider industries with consistent data availability beginning in 1976. A relatively long time period is required to sufficiently analyze OOS predictability, evaluate the performance of OOS portfolio strategies, and assess consistency over time. As a result, we excluded six industries because they lacked the necessary data.[6] The construction of accounting variables, based on Hirshleifer, Hou, and Teoh [2009], Novy-Marx [2013], and Aharoni, Grundy, and Zeng [2013] is as follows:

1. *Accruals (ACC)*: Change in Noncash Current Assets minus Change in Current Liabilities, excluding Changes in Short-Term Debt and Taxes Payable, plus Depreciation and Amortization Expense; scaled by Total Assets.
2. *Book-to-Market (BM)*: Book Value of Shareholder Equity plus Deferred Taxes minus Preferred Stock; scaled by Market Value of Equity.
3. *Earnings (EARN)*: Net Income; scaled by Total Assets.
4. *Gross Profits (GP)*: Revenues minus Cost of Goods Sold; scaled by Total Assets.
5. *Investment (INV)*: Change in Gross Property, Plant and Equipment, plus Change in Inventory; scaled by lagged Total Assets.

To construct excess return data, we use monthly VW industry returns from Kenneth French's website, and then subtract the prevailing risk-free rate; thus, all returns presented are excess returns. Because our analyses focus on the ability of OOS forecast methods to simulate a real-time situation that portfolio managers may face, the timing of data availability is an especially relevant concern. Based on SEC requirements, firms must make quarterly accounting statements (i.e., 10-Q filings) available within 45 days of the end of each fiscal quarter. To accommodate for this delay affecting the real-time availability of data, we construct quarterly returns using a one-quarter additional lead throughout the sample. For example, we use data up to and including the third quarter of 1989 to forecast returns at the beginning of the OOS period in the first quarter of 1990.

Methodology

Goyal and Welch [2008] find substantial evidence that OOS market return predictability has dramatically deteriorated since the mid-1970s, resulting in inconsistent and ambiguous inferences over the past several decades. However, Rapach, Strauss, and Zhou [2010] demonstrate that combination forecast methods utilizing Goyal and Welch's variables lead to economically significant OOS results that are consistent over time and substantially outperform the benchmark return. Combination methods are appropriate when 1) it is difficult to determine which variables are most relevant a priori and 2) the specified model is potentially subject to inherent instability from ongoing, unobservable shocks. Since these conditions should characterize industry returns as well, we consider OOS combination forecast methods.

We begin by positing the following bivariate predictive regression model, a standard framework for analyzing return predictability:

$$r_{i,t+1} = a_i^j + b_i^j x_t^j + e_{i,t+1}^j \tag{1}$$

where $r_{i,t+1}$ is the time t+1 return for industry i in excess of the risk-free rate, x_t^j is a potential predictive variable, and $e_{i,t+1}^j$ is a disturbance term with a mean of zero. We focus on OOS return predictability because it is critically important for investors making decisions using real-time information. We divide the total sample—consisting of T observations for $r_{i,t+1}$ and x_t^j—into an in-sample period consisting of the first n_1 observations (note that this is a fixed rolling window, where $n_1 = 55$), and an OOS period consisting of the last n_2 observations (in our case, $n_2 = 96$). We use a rolling window to allow coefficient estimates to slowly evolve over time.[7]

The initial OOS forecast of the return for industry i based on predictor x_t^j is represented as

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

where $\hat{a}_{i,n_1}^j$ and $\hat{b}_{i,n_1}^j$ are the ordinary least squares (OLS) estimates of a_i^j and b_i^j, respectively, generated by regressing $\{r_{i,t}\}_{t=2}^{n_1}$ on a constant and $\{x_t^j\}_{t=1}^{n_1}$. Continuing this process throughout the OOS period, we generate a series of n_2 OOS return forecasts based on $x_t^j : \{\hat{r}_{i,t+1}^j\}_{t=n_1}^{T-1}$, where n_1 is a fixed window. This forecasting exercise simulates the real-time information available to a forecaster throughout the OOS forecast period. In order to incorporate information from these individual predictive regression forecasts for a given industry i, we combine them based on the following:

$$\hat{r}_{i,t+1}^c = \alpha^i + \sum_{j=1}^{n} w_{j,t} \beta_{j,t}^i x_{j,t} + \varepsilon_{j,t+1}^i \tag{3}$$

where $\hat{r}_{i,t+1}^c$ denotes the combined forecast for the return in industry i, and $w_{j,t}$ represents the information weighting used within a combination forecast. We use Stock and Watson's [2004] discounted mean square forecast error (MSFE) procedure in which "the weights depend inversely on the historical performance of each individual forecast."[8]

Following Campbell and Thompson [2008], we impose "sensible" restrictions on the OOS forecasting procedure and assume that investors rule out a negative equity premium by setting the forecast to zero when it is negative. They determine that "these restrictions never worsen and almost always improve the OOS performance of our predictive regressions." To compare the $\hat{r}_{i,t+1}$ and $\bar{r}_{i,t+1}$ forecasts, we use their OOS R^2 statistic, R_{OS}^2, where $\bar{r}_{i,t+1} = \frac{1}{t}\sum_{k=1}^{t} r_{i,k}$ represents the relevant benchmark model under the null hypothesis of no predictability. The R_{OS}^2 statistic is akin to the familiar in-sample R^2 and is given by

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

The R_{OS}^2 statistic measures the reduction in the mean square prediction error (MSPE) for the predictive regression model forecast compared to the historical average forecast, $\bar{r}_{i,t}$. Thus, when $R_{OS}^2 > 0$, the $\hat{r}_{i,t}$ forecast outperforms the $\bar{r}_{i,t}$ forecast according to the MSPE metric. To test significance, we use the Clark and West [2007] statistic, which adjusts the Diebold and Mariano

[1995] ratio to a standardized normal. When estimating forecasting models, the first subperiod of data comprises the in-sample period and the return forecasts are estimated using an estimation window of 55 observations. The 24-year OOS period ranging from 1990.1–2013.4 encompasses different market environments including the bull market of the 1990's, the dot-com collapse in 2000, and the recent financial crisis and market rebound.

Realized utility gains are also calculated for a mean–variance investor on a real-time basis following Marquering and Verbeek [2004], Campbell and Thompson [2008], and Rapach, Strauss, and Zhou [2010]. The utility metric incorporates the risk borne by an investor over the OOS period, and represents the average utility for a mean–variance investor with a relative risk-aversion parameter value of three who allocates his or her portfolio monthly between stocks and risk-free treasuries with forecasts of the equity premium based on the historical average. We assume that the investor estimates variance using a 12-year rolling window of quarterly returns. The utility gain (or certainty-equivalent return) represents the portfolio management fee that an investor is willing to pay to have access to the additional information available in the combination forecast relative to the information in the historical average equity premium.

Results

Exhibit 1 presents in-sample evidence using the standard bivariate predictive regression models in columns 1–5 for our five industry-specific accounting variables and our five aggregate accounting variables for 43 value-weighted (VW) industries. Given our focus on the relevance of OOS combination forecasting methods, for conciseness, we present average and median-adjusted R^2 statistics across the 43 industries, as well as the number of industries for which these predictive models are statistically significant. R^2 statistics for all five industry-specific and aggregate variables average less than 3% across the 43 industries, and most industries are not significant. Thus, accounting variables using the standard bivariate predictive regression model do not significantly forecast industry stock returns.

The last column, column 6, uses a multivariate regression approach with all ten explanatory variables; the top panel reports in-sample results and shows the average adjusted R^2 increases to 6.0% with 25 industries significant at the 5% level. However, a "Kitchen-Sink" approach—a multivariate regression framework that uses all applicable explanatory variables—typically leads to overfitting within the in-sample period and results in poor overall fit for the OOS period (Clark [2004]). Consequently, Goyal and Welch [2008] recommend using OOS methodology to simulate a regression in real time and avoid overfitting and false inferences. Their kitchen-sink approach has a large negative OOS fit. Our results are similar; for example, the OOS results in column 6 (bottom panel) indicate that zero industries are significant and the average OOS R^2 (R^2_{OS}) are less than zero. Although a multivariate regression approach results in relatively high in-sample predictability, its failure out of sample points to an alternative approach of combining information from multiple variables—OOS combination forecast methods.

Exhibit 1

In-Sample Predictive Regression Results, 1976.1–2013.4

Ind-Level	ACC_i	BM_i	$EARN_i$	INV_i	GP_i	ALL_iR^2
AVG	−1.00%	1.03%	−3.31%	−0.30%	1.11%	6.04%
MED	−2.00%	−0.66%	−1.36%	−1.00%	−1.91%	9.59%
#1%	1	1	1	0	1	23
#5%	2	2	1	0	3	25
#10%	2	2	3	0	4	29
Agg-Level	**ACC**	**BM**	**EARN**	**INV**	**GP**	$ALL_iR^2_{os}$
AVG	−0.88%	−1.03%	2.59%	2.06%	−1.30%	−3.03%
MED	−1.12%	−0.25%	2.70%	1.80%	−2.51%	−3.59%
#1%	0	0	1	1	4	0
#5%	0	1	1	2	7	0
#10%	1	2	4	3	10	0

Notes: Columns 1–5 report in-sample R^2 statistics based on the bivariate predictive regression models, where Ind-Level (Agg-Level) use industry i (aggregate averages) of the accounting variables. ALL_iR^2 and $ALL_iR^2_{OS}$ report the in-sample and out-of-sample R^2 statistics for a multivariate regression using all five industry and all five aggregate variables, respectively. ACC_i, BM_i, and $EARN_i$ represent a 4-quarter moving average of accruals-to-total assets, book-to-market ratio, and earnings-to-total assets for industry i. INV_i and GP_i are investment-to-total assets and gross profits-to-total assets.

Exhibit 2 combines OOS bivariate forecasts from 1990.1–2013.4 for industry-level and aggregate accruals, book-to-market, earnings, investment, and gross profits. To avoid look-ahead bias, we additionally utilize principal components of book-to-market ratios for the 43 industries using an expanding window. Column 1 reveals average R^2_{OS} statistics of 2.8%, and 26 of the 43 industries are significant. Rapach, Strauss, and Zhou [2010] report that

Exhibit 2

OOS Combination Forecast Results, 1990.1–2013.4

IND	R^2_{os}	R^2_{os}/S^2	SBK	SCF	$\Delta\gamma$	IND	R^2_{os}	R^2_{os}/S^2	SBK	SCF	$\Delta\gamma$
Agric	2.41*	0.174	0.372	0.429	8.73	Guns	1.90	0.168	0.336	0.343	7.22
Food	2.95*	0.257	0.339	0.360	8.10	Mines	–0.59	–0.055	0.329	0.237	2.86
Soda	–0.86	–0.079	0.330	0.331	5.71	Coal	0.80	0.044	0.425	0.316	4.32
Beer	4.83**	0.330	0.383	0.369	8.85	Oil	1.56	0.129	0.348	0.354	7.47
Toys	2.84**	2.804	0.101	0.138	1.08	Util	1.28	0.161	0.282	0.290	5.37
Fun	4.31**	1.346	0.179	0.203	2.72	Telcm	5.26**	0.993	0.230	0.277	5.11
Books	7.24**	2.847	0.159	0.238	3.73	PerSv	4.47**	1.300	0.185	0.229	3.48
Hshld	5.81**	0.622	0.306	0.299	5.71	BusSv	3.16**	0.641	0.222	0.307	5.33
Hlth	2.63*	2.317	0.107	0.165	1.47	Hardw	4.58**	0.392	0.342	0.318	5.58
MedEq	1.45	0.185	0.280	0.275	4.95	Softw	5.48**	0.442	0.352	0.402	10.4
Drugs	2.10	0.149	0.375	0.389	9.36	Chips	6.03**	0.914	0.257	0.323	6.44
Chems	0.17	0.031	0.236	0.273	4.15	LabEq	0.34	0.051	0.260	0.367	5.50
Rubbr	2.04*	0.405	0.224	0.255	4.31	Paper	3.99**	1.054	0.194	0.256	4.11
BldMt	4.92**	0.999	0.222	0.290	5.19	Boxes	0.76	0.108	0.266	0.249	4.15
Cnstr	2.39**	0.379	0.251	0.310	4.00	Trans	1.59	0.268	0.243	0.356	5.05
Steel	1.31	0.146	0.299	0.257	2.99	Whlsl	4.29**	0.692	0.249	0.358	6.53
FabPr	2.28*	0.423	0.232	0.260	2.84	Rtail	1.56	0.136	0.339	0.381	8.68
Mach	–0.49	–0.086	0.239	0.208	2.60	Meals	1.17	0.111	0.326	0.347	6.86
ElcEq	2.41*	0.224	0.328	0.388	8.93	Banks	3.98**	1.041	0.196	0.248	4.11
Autos	2.47*	0.642	0.196	0.203	2.74	Insur	4.50**	0.954	0.217	0.274	5.01
Aero	1.51	0.215	0.265	0.340	6.450	RlEst	7.05**	2.623	0.164	0.422	3.25
Fin	3.31**	0.574	0.240	0.278	5.13	MKT	3.06*	0.375	0.285	0.390	7.53
AVG	2.82	0.399	0.266	0.300	5.27	1/N	2.58	0.333	0.278	0.352	6.13

Notes: Exhibit 2 reports out-of-sample R^2 $\left(R^2_{OS}\right)$ and the Campbell–Thompson metric, $\left(R^2_{OS}/S^2\right)$, as well as quarterly Sharpe ratios for the benchmark (SBK) and combination forecast (SCF). The $\Delta\gamma$ represents utility gain, or the annualized portfolio management fee that an investor with a risk-aversion coefficient of three (i.e., γ=3) would be willing to pay for the corresponding forecasting model. 1/N represents an equal-weighted portfolio of the 43 VW industries. MKT is the excess market return from French's data library.

*Note: ** and * indicate significance at the 1% and 5% levels, respectively.*

"small positive R^2_{OS}, such as 0.5% for monthly data and 1.0% for quarterly data, can signal an economically meaningful degree in terms of increased portfolio returns for an investor." In comparison, their work finds an R^2_{OS} statistic of 1.2%; hence, our average predictability finding of 2.8% indicates that combining information from accounting variables contributes to sizable industry predictability.

According to Campbell and Thompson [2008], relatively small positive R^2_{OS} values lead to an economically meaningful degree of return predictability: "even very small R^2 statistics are relevant for investors because they can generate large improvements in portfolio performance." In addition, they maintain that

> the right way to judge the magnitude of R^2 is to compare it with the squared Sharpe ratio S^2. If R^2_{OS} is large relative to S^2, then an investor can use the information in the predictive regression to obtain a large proportional increase in portfolio return. [2008]

Campbell and Thompson report a monthly S^2 of 1.2%, along with a corresponding monthly R^2_{OS} of 0.43%, suggesting that a mean–variance investor increases portfolio returns by a factor of 36% (i.e., 0.43/1.2). In keeping with this analysis, column 2 indicates that a similar investor can boost his or her portfolio returns by an average of 40%, and 17 industries yield gains exceeding 50%.

Columns 3 and 4 report Sharpe ratios for both the autoregressive benchmark (*SBK*) and combination forecasts (*SCF*). On average, *SCF* equals 0.30, which is 13% higher than the benchmark's 0.266; further, *SCF* exceeds *SBK* in 34 of 43 industries, and is considerably higher (i.e., more than 10% greater) in 26 industries. Combination forecasts also achieve impressive annual utility gains that average 5%; additionally, $\Delta\gamma > 4\%$ in 33 industries, which represents material economical gains, because this statistic is associated with annual management fees. In comparison, both Campbell and Thompson [2008] and Rapach, Strauss, and Zhou [2010] report utility gains of approximately 1%. Hence, combination forecasts of accounting variables generate relatively large utility gains—and further signal that the increases in predictability are not solely driven by increases in risk.

The bottom row of Exhibit 2 reports results for the market portfolio (the Fama–French value-weighted quarterly returns for the market, R_m-R_f) and a simple 1/N portfolio, in which the portfolio is an equal-weighted average of the 43 industry excess returns. In this case, combination forecasts combine only the aggregate accounting variables, and the market benchmark is the standard random walk. The R^2_{OS} for the market exceeds 3% and is significant; the portfolio exceeds 2.6%. Both statistics imply that combining accounting information leads to meaningful aggregate predictability. The Campbell–Thompson metric demonstrates that mean–variance investors can boost their return by more than a third for both portfolios. Further, Sharpe ratios for the market and industry portfolios are 37% and 26% greater, respectively, than their benchmarks. The market and industry portfolios possess utility gains of 7.5% and 6.1% and denote consequential material economic gains. Thus, combination forecasts of accounting variables predict both the market and a 1/N portfolio of value-weighted industries.

Exhibit 3 highlights alternative predictability results using a dozen macroeconomic and financial variables from Goyal and Welch [2008]. Rapach, Strauss, and Zhou [2010] demonstrate that combining these variables produces significant forecasts of aggregate excess monthly returns.[9] Can these variables also forecast industry returns? Do macroeconomic variables outperform accounting variables in forecasting industry returns?

Results using the 12 Goyal and Welch variables indicate that combining information leads to average R^2_{OS} of 1.4%, and only seven industries are significant. Campbell–Thompson metrics exhibit limited investor gains. Predictability is also small or nonexistent in predicting VW portfolios or the market return. The bottom half of Exhibit 3 combines information from both the 12 Goyal and Welch variables and the accounting variables. Results demonstrate modest predictability; and in all cases, the R^2_{OS} statistics, Campbell–Thompson metrics, Sharpe ratios, and utility gains are smaller than the gains shown in Exhibit 2 from combining forecasts from accounting variables only. Thus, accounting variables forecast industry returns more accurately than macroeconomic and financial variables. Ultimately, however, the investor cares less about predictability performance than whether this predictability translates into profitable long–short portfolio allocations gains. Can accounting variables generate substantial portfolio allocation payoffs consistently over time?

EXHIBIT 3

OOS Results, Macro and Aggregate/Industry Variables, 1990.1–2013.4

	Out-of-Sample Results with Macro Variables				
	R^2_{OS}	R^2_{OS}/S^2	SBK	SCF	$\Delta\gamma$
AVG	1.36	0.214	0.286	0.248	4.40
1/N	1.00	0.061	0.285	0.268	4.72
MKT	1.01	–0.168	0.267	0.274	4.99
	Aggregate-Level and Industry-Level Variables				
	R^2_{OS}	R^2_{OS}/S^2	SBK	SCF	$\Delta\gamma$
AVG	1.53	0.217	0.266	0.286	5.06
1/N	2.34*	0.466	0.267	0.369	7.50
MKT	1.53*	0.548	0.285	0.385	7.58

Notes: The top half of Exhibit 3 shows results from forecasts using a dozen macroeconomic and financial variables from Goyal and Welch [2008] and reports the average (AVG), an equal-weighted portfolio of all 43 industries (1/N), and the market (MKT).

*Note: ** and * indicate significance at the 1% and 5% levels, respectively.*

INDUSTRY-ROTATION PORTFOLIO PERFORMANCE

Pesaran and Timmermann report that

> an alternative approach to evaluating the economic significance of stock market predictability would be to see if the evidence could have been exploited successfully in investment strategies. This can by evaluating portfolio allocation in 'real time,' and see if these portfolios systematically generate excess returns of forecasting performance, such as the directional accuracy (e.g., the proportion of times the sign of excess returns is correctly predicted) of the forecasts. [1995]

Similar to most predictive regression papers, their work forecasts the aggregate market return; as a result, their portfolio allocation strategy forecasts whether the investor should long the market or invest in treasury bills, depending on the sign of the aggregate return forecasts. In our case, OOS industry allocation consists of rotating into industries predicted to perform well and shorting industries predicted to perform poorly.

Exhibit 4 presents the results of various investment strategies. The passive buy-and-hold benchmark strategy is an equal weighting of 1/N industries. The 130/30 long–short strategy shorts the bottom-forecasted decile of industry returns at 30% and rotates the proceeds into the top decile of forecasted industry returns, which is leveraged at 130%. This strategy follows Lo and Patel [2008], who analyze the popularity and performance of such a strategy. J.P. Morgan reports that

> in recent years, 130/30 portfolios have gained traction as useful ways for investors who are seeking to add greater flexibility, diversification, and return potential to their equity holdings. These professionally managed strategies typically short 30% of assets and use the proceeds to increase long positions to 130% of portfolio value. [2014]

To demonstrate the allocation's performance in identifying poorly performing industries, we use a more leveraged 200/100 long–short strategy. This long–short position completely shorts industries (100%) in the bottom-forecasted decile and goes long the top-forecasted decile. We also construct long and short positions using the top and bottom quintile of forecasted industry returns to highlight robustness. Because we have 43 industries, a decile is approximated by four industries and a quintile by nine industries. To highlight the performance over a long period of time, we consider a 30-year OOS period from 1984.1 to 2013.4 and report the consistency of the returns relative to the buy-and-hold by decade. Each decade—1984.1–1993.4, 1994.1–2003.4, and 2004.1–2013.4—highlights different market trends, including a long bull market, tech bubble collapse and financial collapse, followed by a sharp recovery. It is likely that industry predictability changed over these three decades as particular sectors, such as technology and financials, performed well in certain periods and severely underperformed in other periods. Evaluating performance of combination forecasts by decade is thus relevant for understanding overall portfolio performance.

Based on an initial investment of $100 in 1984.1, the VW buy-and-hold portfolio generates a payoff of $944 over 30 years with an average return of 2.3% and a Sharpe ratio of 0.255. Exhibit 4 shows that the top-forecasted decile (quintile) leads to average returns of 3.5% (3.2%), a payoff of $2,609 ($2,341), and Sharpe ratios of .286 (.308). There is also a distinct difference

EXHIBIT 4
Portfolio Allocation Decile and Quintile Strategies, 1984.1–2013.4

	LONG	SHORT	LS^{200}_{100}	LS^{130}_{30}	%L>S	%L>0	$\%LS^{130}_{30}$
Decile Strategy							
% Return	3.5%	0.9%	6.2%	4.3%			
$ Portfolio	$2,609	$145	$9,108	$4,696			
Sharpe Ratio	0.286	0.084	0.305	0.301			
% CF>BH	60%	37%	67%	66%	65%	58%	65%
%1st	60%	33%	65%	68%	75%	58%	65%
%2nd	55%	40%	68%	63%	55%	58%	63%
%3rd	66%	37%	68%	66%	66%	58%	66%
Quintile Strategy							
% Return	3.2%	1.5%	5.0%	3.7%			
$ Portfolio	$2,341	$297	$9,006	$3,788			
Sharpe Ratio	0.308	0.141	0.331	0.326			
% CF>BH	60%	40%	68%	68%	66%	58%	64%
%1st	60%	33%	68%	70%	70%	55%	70%
%2nd	58%	48%	63%	63%	60%	55%	58%
%3rd	63%	37%	71%	68%	68%	61%	63%

Notes: Exhibit 4 presents industry allocation over the past thirty years, where decile (quintile) refers to the strategy that rotates into long positions for the highest 4 (9) forecasted industry returns and shorts industries for the lowest 4 (9) forecasted returns. LS^{130}_{30} $\left(LS^{200}_{100}\right)$ *shorts the lowest-forecasted decile or quintile industries by 30% (100%), investing these proceeds in the industry decile or quintile with the highest forecasted returns. $ Portfolio begin with $100 in 1984.1.*

between the top and bottom-forecasted deciles and quintiles. The short position produces average returns for the forecasted bottom decile (quintile) of 0.9% (1.5%), and a payoff of only $145 ($297). Interestingly, the Sharpe ratios for the quintile are higher than the decile ratios even though the quintile's average return and payoff are lower. This is likely due to greater diversification, because selecting a greater number of industries for the quintile portfolio reduces the overall mean (because the investor is selecting the nine highest forecasted industries instead of the top four), but the portfolio has a lower variance and enjoys more stable returns.

Both the decile and quintile long strategies outperform the benchmark a surprising 60% of the time, generating higher returns in 72 out of 120 quarters. Furthermore, both strategies consistently exceed the benchmark in all three decades, with higher forecasted decile returns 60%, 55% and 66% of the time in the first (%1st), second (%2nd), and third (%3rd) decades, respectively. The short portfolio also consistently identifies poorly performing industries; for example, over the past three decades, the bottom decile underperforms the benchmark 67%, 60%, and 63% of the time, respectively. Results in column 5 show that forecasted returns of the top decile produce average returns greater than the bottom decile two-thirds of the time (e.g., the long portfolio exceeds the short portfolio 65% of the time). These results are remarkably consistent: The top-forecasted decile exceeds the bottom-forecasted decile 75%, 55%, and 66% of the past 120 quarters. Quintile results are similar and reinforce the message that combination forecasts of accounting variables consistently identify both the top and bottom performing industries to go long and to short.

Panel A of Exhibit 5 reinforces these results by illustrating logged payoffs for the long and short industry portfolios. The figure clearly displays noticeable persistent differences in the top and bottom-forecasted decile returns over 30 years—that is, the long decile portfolio frequently outperforms the benchmark and increases over time, whereas the short portfolio underperforms compared to the benchmark and displays no upward trend over 30 years.

The top half of Exhibit 4 also shows substantial average returns and payoffs for the long–short strategies. The 200/100 strategy possesses average returns of 6.2% and 5.0% for the decile and quintile strategies, which are strikingly higher than the benchmark's 2.3%. The payoffs for both strategies exceed $9,000—nearly 10 times the buy-and-hold benchmark. The Sharpe ratios for the decile and quintile approach are 20% and 30% higher than their respective benchmarks. The 130/30 strategy has average returns of 4.3% and 3.7%, with payoffs of $4,696 and $3,788 for decile and quintile portfolios respectively—approximately four to five times the benchmark. Panel B of Exhibit 5 illustrates the logged payoffs for the 130/30 and 200/100 decile portfolios constructed using forecasted accounting variables to consistently beat a buy-and-hold. Both strategies possess distinctly upward sloping lines, particularly since the mid-1990's, and exhibit declines during the bear market of 2000–2002 and financial crisis in 2008. The figures clearly display strong co-movements between the 200/100 and the 130/30 strategies.

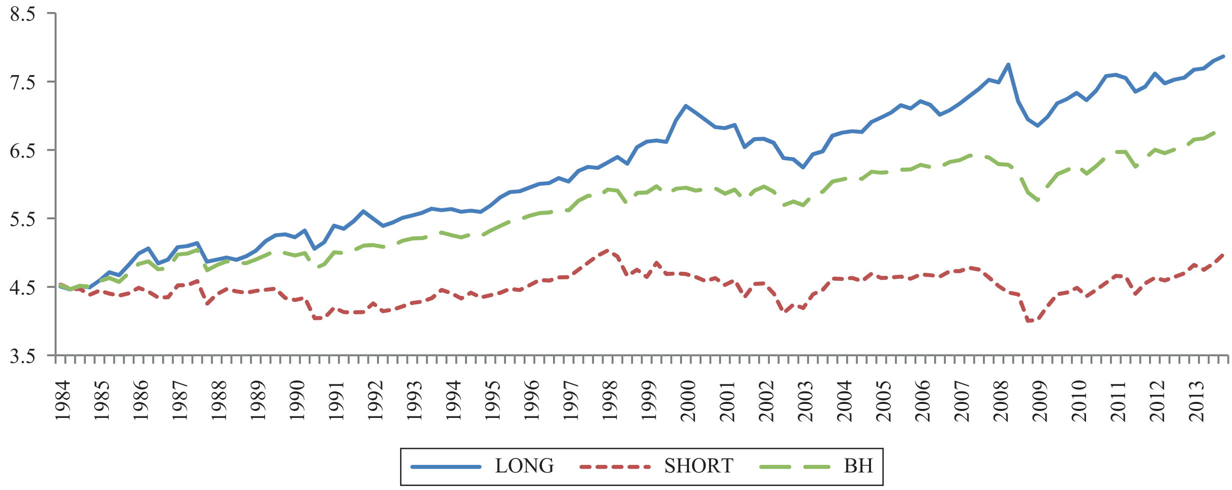
As shown in Exhibit 4, the Sharpe ratios for the 130/30 strategy are roughly equivalent to the 200/100 strategy; this is because the 130/30 strategy provides more stable, but lower average returns. Both the 200/100 and 130/30 strategies outpace the benchmark and also generate returns greater than zero (column 7) approximately two-thirds of the time, which implies that both long–short strategies deliver higher returns twice as often as the benchmark. This is an impressive record given the difficulty of forecasting returns over time.

Exhibit 6 reports details concerning industry selection and portfolio construction for the 20 highest and lowest forecasted industries to assess the ability of the combination forecasts to select industries with the highest and lowest returns. Results in column 1 show that eight of the top ten forecasted industries possess average returns greater than the buy-and-hold; column 4 shows a similar performance for the short strategy—7/10 of the lowest performing industries generate returns less than the buy-and-hold. The top five forecasted industries generate returns that outperform the benchmark more than 50% of the time, and 4/5 industries possess payoffs greater than the benchmark's $944. Column 5 reveals that 9/9 industries selected to short deliver payoffs less than $944, and 17/20 industries are less than the benchmark; this implies a particularly successful ability to identify poorly performing industries to short.

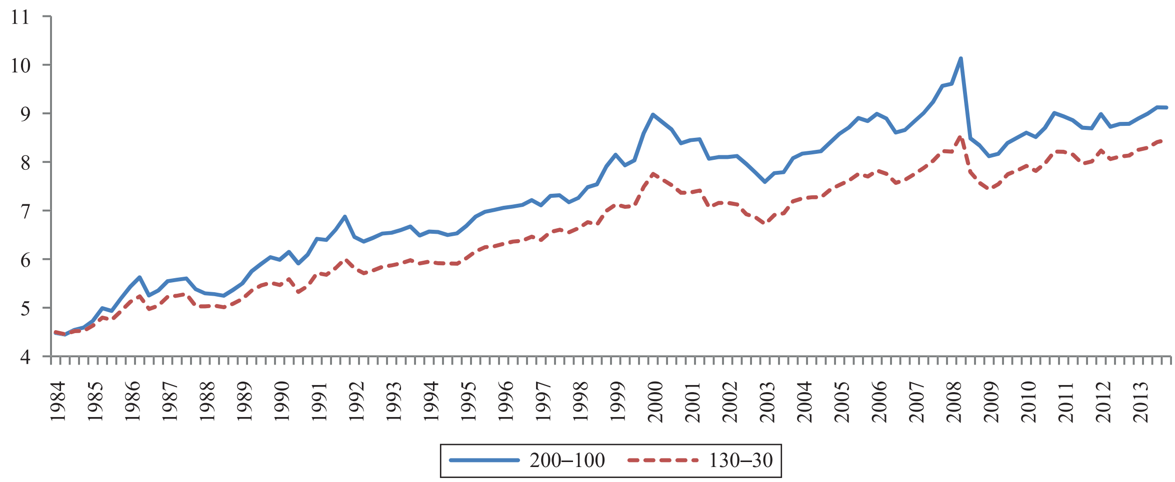
The bottom portion of Exhibit 6 forms portfolios from the top and bottom 5, 10, 15 and 20 industries. Results show that portfolios constructed from the top 5, 10, 15, and 20 industries outperform the benchmark 59%, 59%, 63%, and 63% of the time; these percent-

Exhibit 5
Portfolio Payoffs, 1984.1–2013.4

Panel A: Portfolio Payoffs, Industry Portfolios



Panel B: Portfolio Payoffs, Long-Short Strategies



Note: The log of portfolio values, or payoffs, are depicted from 1984.1 through 2013.4.

ages are considerably higher than the individual results in the top half of the exhibit and imply that diversification increases the likelihood that the portfolio's return exceeds the benchmark. Portfolio allocation that selects portfolios of 10, 15, and 20 industries with the lowest predicted returns successfully underperforms the benchmark 67%, 79%, and 75% of the time—a remarkably high percentage that further highlights the consistency in identifying poorly performing industries.

Additionally, the long–short payoffs exhibit wide divergences. For instance, for 5- and 10-industry portfolios, the long payoffs are $2,790 and $1,900, while the short payoffs are $208 and $396—implying that the long portfolios are approximately 13 and 5 times their respective short portfolios. Overall, results reveal that combination forecasts reliably select long and short industry portfolios that consistently outperform the buy-and-hold strategy.

Exhibit 6
Individual Industry Portfolio Performance, 1984.1–2013.4

	Individual Industry Performance					
	LONG			SHORT		
IND	Mean Return	Payoff	%IND>BH	Mean Return	Payoff	%IND<BH
BH	2.3%	$944				
1	**3.3%**	$867	55%	*0.8%*	*$58*	*59%*
2	**3.6%**	**$1,712**	**56%**	*0.6%*	*$76*	*57%*
3	**3.7%**	**$1,960**	**54%**	*0.6%*	*$103*	*66%*
4	**3.6%**	**$2,434**	**53%**	*1.6%*	*$298*	*58%*
5	**3.2%**	**$2,021**	**54%**	*2.2%*	*$618*	49 %
6	1.2%	$163	41%	*1.4%*	*$182*	*53%*
7	**3.1%**	**$1,660**	**53%**	*2.7%*	*$923*	50 %
8	**4.1%**	**$5,401**	**59%**	*1.8%*	*$343*	*56%*
9	1.7%	$384	45%	*2.4%*	*$785*	48 %
10	**2.4%**	**$735**	**49%**	*2.8%*	$1,072	47 %
11	**2.5%**	**$959**	**51%**	*2.1%*	*$645*	50 %
12	1.7%	$335	50%	*2.6%*	$1,076	*55%*
13	1.4%	$1,319	46%	*2.1%*	*$468*	*52%*
14	2.2%	$623	46%	*2.7%*	$1,074	*51%*
15	1.9%	$1,638	53%	*2.0%*	*$540*	*54%*
16	**2.6%**	**$1,236**	**57%**	*2.0%*	*$478*	*54%*
17	1.9%	$4,217	48%	*2.3%*	*$793*	50 %
18	**2.5%**	**$491**	**43%**	*2.5%*	*$922*	*53%*
19	2.1%	$2,308	57%	*2.3%*	*$755*	48 %
20	**2.8%**	**$903**	**48%**	*2.6%*	*$926*	48 %
#<10	8	6	52%	8	9	54%
#<20	12	12	50%	12	17	52%

	Industry Portfolio Performance					
	LONG			SHORT		
PORT	Sharpe	Payoff	%Port>BH	Sharpe	Payoff	%Port<BH
5	0.302	$2,790	59%	0.112	$208	62%
10	0.301	$1,900	59%	0.165	$396	67%
15	0.290	$1,461	63%	0.187	$593	79%
20	0.292	$1,438	63%	0.207	$492	75%

Notes: In the top panel, statistics for the 20 industries predicted to perform the best (worst) are shown under the heading LONG (SHORT). "BH" represents the benchmark portfolio and bold (italics) indicates industries that outperform (underperform) the benchmark. The bottom panel constructs portfolios with varying numbers of industries. %IND>BH indicates percentage of quarters that the combination forecast outperforms the benchmark.

Portfolio Performance and Alternative Specifications

Exhibit 7 presents a portfolio scheme that selects the highest and lowest decile and quintile of industries for the first quarter of each year and then holds this portfolio for one year. The yearly rotation strategy substantially outperforms the buy-and-hold in terms of return and dollar payoff, but not the quarterly allocation strategy in Exhibit 4. For instance, the highest forecasted decile returns generate an average return of 3.0% and a payoff of $1,201, compared to the benchmark's return of 2.3% and $944 payoff. The 200/100 and 130/30 long–short strategies generate returns 66% and 68% greater than the benchmark, and generate annual returns that consistently exceed the benchmark 64% of the time over the past 30 years.

Following Nichols and Wahlen [2004], we evaluate a portfolio strategy that adjusts for size. They label this method "cumulative abnormal returns" because it subtracts the returns from the size-decile to which the industry belongs (which is obtained from the French library under "Portfolios formed on size"). This implies

Exhibit 7

Annual Rotation Performance and Abnormal Returns, 1984.1–2013.4

	LONG	SHORT	LS^{200}_{100}	LS^{130}_{30}	%L>S	%L>0	%LS^{130}_{30}>0
Panel A: Annual Rotation Performance							
Decile							
% Return	3.0%	1.3%	4.6%	3.5%			
$ Portfolio	$1,201	$242	$1,242	$1,487			
Sharpe Ratio	0.230	0.124	0.225	0.232			
% CF>BH	58%	38%	66%	68%	58%	61%	64%
%1st	63%	40%	68%	65%	65%	58%	65%
%2nd	55%	40%	68%	70%	58%	63%	58%
%3rd	55%	34%	68%	65%	63%	63%	65%
Quintile							
% Return	2.9%	2.1%	3.6%	3.1%			
$ Portfolio	$1,567	$664	$2,098	$1,820			
Sharpe Ratio	0.278	0.207	0.252	0.275			
% CF>BH	56%	43%	64%	68%	58%	62%	66%
%1st	55%	35%	60%	65%	65%	60%	65%
%2nd	55%	50%	63%	63%	55%	63%	55%
%3rd	58%	45%	60%	68%	55%	61%	73%
Panel B: Abnormal Returns							
Decile							
% Return	1.7%	–0.8%	4.3%	2.5%			
$ Portfolio	$234	$14	$897	$419			
Sharpe Ratio	0.122	–0.067	0.199	0.156			
% CF>BH	59%	36%	60%	62%	63%	53%	60%
%1st	63%	33%	63%	65%	70%	50%	63%
%2nd	50%	43%	53%	55%	58%	53%	53%
%3rd	66%	32%	66%	63%	61%	55%	63%
Quintile							
% Return	1.6%	0.0%	3.2%	2.1%			
$ Portfolio	$258	$35	$921	$408			
Sharpe Ratio	0.128	–0.004	0.196	0.156			
% CF>BH	56%	48%	62%	60%	61%	53%	60%
%1st	55%	38%	65%	65%	70%	48%	68%
%2nd	55%	55%	55%	55%	48%	50%	55%
%3rd	58%	47%	63%	58%	66%	58%	55%

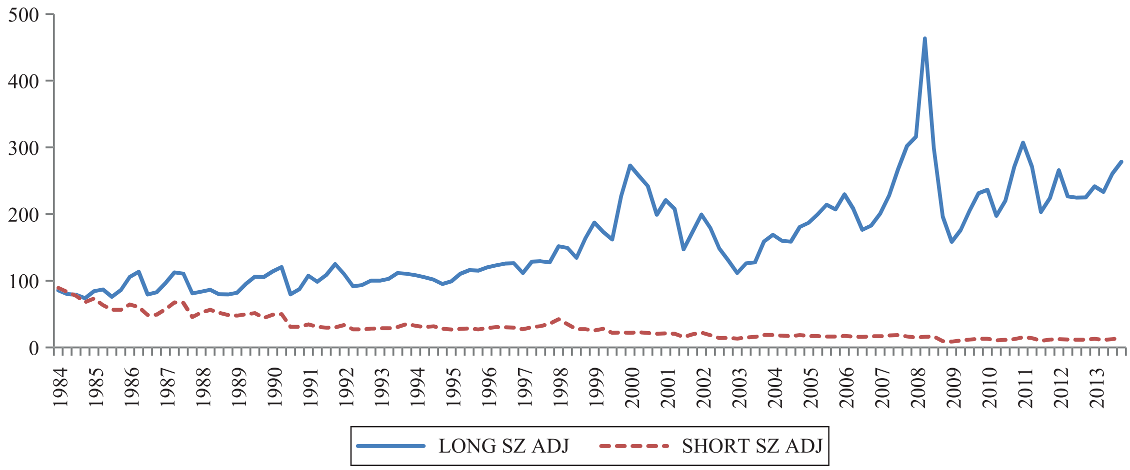
Notes: Panel A reports results for an annual rotation strategy that selects the top and bottom decile and quintile of industries as of the first quarter of each calendar year, and holds the portfolio for one year. Panel B follows Nichols and Wahlen [2004] and reports "cumulative abnormal returns" that are found by subtracting the returns from the corresponding size decile to which the industry belongs.

that the average industry portfolio has a cumulative abnormal return of approximately zero; therefore, a successful long position after 30 years induces an average return greater than zero and a payoff greater than $100; conversely, a successful short strategy identifies industry returns less than zero and a payoff less than $100. Inspection of Exhibit 7, Panel B (bottom panel) shows that the top-forecasted decile delivers an abnormal return of 1.7% compared to the bottom decile of –0.8%. The long position generates average returns greater than the short (%L > S) in all three decades.

Exhibit 8 illustrates the top (long) and bottom (short) forecasted abnormal (size-adjusted) returns—or more precisely, abnormal payoffs. The long strategy clearly illustrates positive average returns over most of the sample (59% of the time the slope is increasing) and a

EXHIBIT 8

Size-Adjusted Portfolio Payoffs, 1984.1–2013.4



Note: Size-adjusted (SZ ADJ) portfolio payoffs are determined by subtracting the portfolio payoffs from the corresponding size-decile to which each industry belongs.

payoff of $234. In contrast, the short strategy has a negative slope over 64% of the time and has average returns well below zero (–0.8%); the payoff is only $14 and implies a loss of 86% of its value. The figure is similar in spirit to the approach of Ball and Brown [1968] and Beaver Clarke, and Wright [1979] that examined value relevance. Their work identifies the top and bottom decile of earnings by firm and plots the returns of these firms. Firms are value relevant if returns of the top and bottom decile of earnings sharply increase and decrease, respectively, revealing a large difference between the two returns.

There is, however, one key difference between the value-relevant approach and our procedure. Our method is an implementable real-time portfolio allocation strategy—because it employs forecasts, not actual accounting variables. Exhibit 5 shows that the top and bottom deciles of forecasted industry returns display considerable differences that grow over time; by 2013.4, the top decile exceeds the bottom decile by more than 16 times. A 200/100 strategy yields an excess return of 4.3% and a payoff of $897, which is approximately nine times the buy-and-hold, and also consistently delivers positive returns over three decades. Inspection by decade highlights that the portfolio allocation outperforms the benchmark by a wide margin in all three decades.

How does the inclusion of alternative combination forecast specifications affect industry portfolio allocation? Exhibit 9 analyzes the robustness of our results using the highest and lowest deciles. Panel A (top) presents a portfolio allocation that combines forecasts from a dozen macroeconomic/financial variables used in Exhibit 3. Portfolio results show that while macroeconomic and financial variables outperform the buy-and-hold, they do not beat allocation methods using accounting variables. For instance, for the 200/100 strategy, the average returns, payoffs, and Sharpe ratios are 5.3%, $3,159 and 0.254, which are considerably less than 6.2%, $9,108 and 0.305 (reported in Exhibit 4).

To assess the importance of industry accounting variables, we report portfolio allocation using only aggregate accounting variables. Results in Exhibit 9, Panel B, reveal a payoff of $4,891 and a Sharpe ratio of 0.273. These values are lower than those found in Exhibit 4, and thus we see that industry-specific accounting variables possess useful information for identifying industry expected returns and constructing industry portfolios.

Panels C and D of Exhibit 9 examine a subset of aggregate and industry accounting variables. Panel C combines information from only industry and aggregate earnings and book-to-market ratios; we group these variables because both are traditional return predictors. Results show that the payoff and Sharpe ratios are $3,704 and .269; hence, information from accruals, and investment and gross profits affects portfolio allocation and substantially boosts industry returns. Panel

EXHIBIT 9

Alternative Portfolio Specifications, 1984.1–2013.4

	LONG	SHORT	LS^{200}_{100}	LS^{130}_{30}	%L>S	%L>0	$\%LS^{130}_{30}>0$
Panel A: Macroeconomic Variables Only							
% Return	3.3%	1.2%	5.3%	3.9%			
$ Portfolio	$1,663	$210	$3,159	$2,382			
Sharpe Ratio	0.249	0.113	0.254	0.256			
% CF>BH	58%	41%	61%	63%	60%	60%	63%
Panel B: Aggregate Accounting Only							
% Return	3.3 %	1.2 %	5.5 %	4.0 %			
$ Portfolio	$2,172	$185	$4,891	$3,369			
Sharpe Ratio	0.279	0.103	0.273	0.285			
% CF>BH	58 %	43 %	64 %	66 %	62 %	57 %	65 %
Panel C: Earnings and Book-to-Market							
% Return	2.8 %	1.3 %	4.4 %	3.3 %			
$ Portfolio	$1,251	$231	$3,704	$1,844			
Sharpe Ratio	0.242	0.120	0.269	0.257			
% CF>BH	53 %	43 %	67 %	65 %	63 %	58 %	64 %
Panel D: Investment and Gross Profits							
% Return	3.2 %	1.7 %	4.7 %	3.6 %			
$ Portfolio	$2,117	$331	$4,891	$3,010			
Sharpe Ratio	0.290	0.146	0.269	0.293			
% CF>BH	53 %	44 %	63 %	63 %	56 %	62 %	61 %
Panel E: Accounting and Macroeconomic Variables							
% Return	3.3 %	1.2 %	5.5 %	4.0 %			
$ Portfolio	$2,684	$213	$9,490	$4,881			
Sharpe Ratio	0.318	0.115	0.355	0.342			
% CF>BH	67 %	38 %	67 %	% 68 %	66 %	59 %	67 %

Notes: Exhibit 9 presents portfolio allocation results using alternative combination forecast specifications. Panel A uses a dozen financial variables from Goyal and Welch [2008], whereas Panel B combines only the five aggregate accounting variables. Panels C and D employ subsets of the accounting variables, and Panel E combines both a dozen aggregate financial variables and accounting variables.

D presents forecasts that combine investment and gross profits; these accounting variables are recent additions to the Fama and French [2015] five-factor model and are not traditional return predictors in the time-series literature. The long payoff is nearly seven times greater than the short, and the 130/30 (200/100) outperforms the benchmark by a factor of three (five). Results demonstrate that both earnings and book-to-market, as well as investment and gross profits, lead to economic gains in portfolio allocation—but these gains are larger when forecasts from all these variables along with accruals are combined together.

We also examine the role of accruals and investment and profits, because all three variables are not traditional return predictors; 130/30 (200/100) results reveal payoffs five (eight) times the benchmark. Lastly, we combine forecasts from the dozen macroeconomic/financial variables and our 10 accounting variables. These results, in contrast, exhibit a small improvement in terminal payment compared to the accounting results.

Exhibit 10 investigates the magnitude of alpha after controlling for the three Fama and French [1993] risk factors. We regress the decile portfolio performance over the past 120 quarters against the excess return of the market (MKT), the small-minus-big (SMB), and the high-minus-low (HML) factors. Annualized alphas for the long position (top-forecasted decile) equal 6.7%, and statistically are very significant. Alphas for the short are negative and imply that the SHORT strategy accurately selects poorly performing industries. The 200/100 and 130/30 strategies generate very significant and economically sizable alphas, equaling 19.4% and 10.5%, respectively.

Exhibit 10

Fama–French Three-Factor Model, 1984.1–2013.4

	LONG	SHORT	LS_{100}^{200}	LS_{30}^{130}
α	6.68**	–5.73**	19.44**	10.51**
MKT	1.07**	1.04**	1.16**	1.10**
SMB	0.18*	0.45*	–0.28	0.04
HML	–0.31	0.59**	–1.03**	–0.53*
R^2	68%	77%	38%	55%

Notes: Exhibit 10 presents results from the Fama–French three-factor model. Combination forecast estimates are regressed against the market excess return (MKT), SMB, and HML.

*Note: ** and * indicate significance at the 1% and 5% levels, respectively.*

Inspection of Exhibits 4, 6, 7 and 9 reveals several characteristics of the gradual diffusion of information. First, gradual diffusion of information implies that quarterly rotations generate higher returns than annual rotations; because by quarters 2, 3, or 4, much of the information will have diffused into returns. Additionally, if we employ an additional quarter lag on the accounting variables to allow time for the return to reflect accounting information, the payoff for a 200/100 strategy markedly decreases to $1,699.

Second, "bad news travels slowly" implies that portfolio allocation should be more accurate for poorly performing industries. Results from Exhibit 6, for instance, show that 9/10 and 17 of 20 of the bottom industry payoffs and average returns are consistently less than the buy-and-hold (%IND < BH); these results highlight a remarkable ability to identify industries subject to bad news. The percentage of the bottom 10, 15, and 20 are 67%, 79% and 75%, respectively, and also support the ability to identify industries that perform worse than the benchmark. Furthermore, the success of the long–short 200/100 relies heavily on the accuracy of the short strategy (which yields returns less than the buy-and-hold over 30 years twice as often).

Third, we conducted predictability and portfolio allocation for equal-weighted (EW) industries (results available upon request). VW industries place greater weight on market capitalization, and hence their industries tend to be bigger than EW industries. Because EW industries are smaller, they receive less analyst coverage and information generally diffuses more slowly—thus making portfolio allocation more profitable. Results highlight an EW payoff for the 200/100 deciles of $55,863 compared to the VW payoff of $9,108. Furthermore, of the 20 EW industries identified to short, all 20 EW industries underperform the benchmark. These results highlight that bad news travels slowly, particularly for industries that receive little attention.

CONCLUSION

Out-of-sample forecast methods that combine information from industry-level and aggregate accruals, book-to-market, earnings, and investment and gross profits data document significant predictability of industry excess returns. We use these industry forecasts to construct portfolios that rotate into industries forecasted to perform well and short industries forecasted to perform poorly. Long–short positions deliver portfolio payoffs nearly nine times the benchmark, and their relatively large Sharpe ratios indicate the performance increases are not driven primarily by risk. Portfolio allocation allowing for size-adjusted returns generate a long position with payoffs sixteen times the short position. Additionally, combining information from accounting variables generates average returns, Sharpe ratios, utility gains, and portfolio payoffs that outperform traditional macroeconomic and financial predictors.

Overall, portfolio allocation results show that combination forecasts of accounting variables consistently outperform a buy-and-hold strategy over the last three decades. Average returns for industries selected to go long are consistently above the buy-and-hold portfolio in all three decades, while average returns in the bottom-forecasted decile of industries are consistently below the buy-and-hold portfolio. Long–short positions in all three decades generate returns substantially above the benchmark 67% of the time. Thus, combination forecasts generated from accounting variables consistently and substantially beat the buy-and-hold benchmark.

ENDNOTES

[1]Frankel and Lee [1998] and Kothari [2001] also posit that "price convergence to value is a much slower process than prior evidence suggests" and can take up to three years. Ou and Penman [1989] argue that "stock prices only slowly gravitate towards fundamental values," and "analysis of published financial statements can discover values that are not reflected in stock prices," leaving the door open for accounting data to forecast stock returns.

[2]Additional variables include the aggregate earning-to-price ratio, yield curve, default ratio, nominal interest rates (Campbell [1987] and Ang and Bekaert [2007]), inflation rate (Campbell and Vuolteenaho [2004]), default spreads (Fama and French [1989]) and corporate issuance activity (Baker and Wurgler [2000]).

[3]One exception is a recent paper by Kong et al. [2011] showing that lagged size and value-sorted portfolios forecast the performance of size and value-sorted portfolios. They then develop a portfolio allocation scheme that selects industries with the highest forecasted returns to go long, and short industries with the lowest forecasted returns. This allocation strategy is shown to generate substantially large economic gains.

[4]Principal component analysis of the 43 industries indicates that 13 (19) industries represent 90% (95%) of industry movements; hence, although there are co-movements, considerable diversity across industry returns also occurs; for example, the average correlation is less than 60%.

[5]Kahneman [1973] pioneered the limited cognitive resources approach, and additional works include Hirshleifer and Teoh [2003] and Peng and Xiong [2006], who model investor inattention and show its return implications. Recent work by Rapach and Zhou [2013] uses a gradual diffusion model to explain why U.S. stock returns lead other countries' returns.

[6]The dropped industries of Smoke, Clothes, Textiles, Ships, Aero, and Gold are industries with few firms, and their quarterly accounting data are not consistently available throughout the sample.

[7]Bossaerts and Hillion [1999] find that the parameters of the best prediction models change over time; similarly, Ang and Bekaert [2007] and Dangl and Halling [2012] demonstrate substantial parameter instability for return prediction models.

[8]We also consider an approximate Bayesian model averaging (ABMA) method that combines weights, as well as a simple average. Results are found to be qualitatively similar and are available upon request.

[9]These variables include the aggregate book-to-market ratio, dividend-price ratio, dividend-payout ratio, stock variance, earnings-to-price ratio, net equity expansion, Treasury bill rate, long-term yield, default yield spread, inflation, consumption-income ratio, and investment-to-capital ratio. See Goyal's website at www.hec.unil.ch/agoyal. For conciseness, we present the average R_{OS}^2 statistics, Campbell–Thompson metrics, Sharpe ratios, and utility gains. The variables are lagged only one quarter; that is, we do not add the extra quarter lead because market variables are reported with little delay.

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