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A FITERING STRATEGY FOR IMPROVING CHARACTERISTICS-BASED PORTFOLIOS*

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In this paper, we propose new indexes to measure the predictive power for future returns possessed by firm characteristics and find that the predictive power significantly differs across the cross-section of assets. We also propose a filtering strategy to improve conventional characteristics-based portfolio profits. The new strategy filters out assets with low predictive power. We apply the new strategy to equity data and find that it significantly outperforms the conventional strategy for several well-known firm characteristics. We also find that characteristics-based portfolio profits are not prevalent but rather driven by only a small subset of stocks.

Keywords: Firm Characteristics, Market Anomaly, Sorting, Filtered Sorting
JEL Classification: G11, G12

1. INTRODUCTION

After the capital asset pricing model (CAPM) was proposed as a modern asset pricing model, many prior studies have reported empirical evidences against the CAPM. Those evidences have typically suggested firm characteristics that are used to form profitable portfolios. These characteristics-based portfolios are constructed using a sorting method in which individual assets are sorted based on a chosen firm characteristics and then a long-short portfolio is formed by going long and short on both extremes. The profitability of characteristics-based portfolios implies that firm's current

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characteristics possesses some predictive power for future returns. In this paper, we propose a new predictor variable that is associated with a firm characteristics variable. We then propose a new method called the filtering strategy that uses the new predictor variable for filtering assets to be held in characteristics-based portfolios and show that the filtering strategy can improve the sorting method.

There exists a large literature about improving characteristics-based anomalous profits. For momentum profits as an example, a double sort strategy based on a combination of momentum and reversal signals is examined with respect to commodity futures contracts (Bianchi, Drew, and Fan (2015)) and international equity market indices (Malin and Bornholt (2013)). Balvers and Wu (2006) propose a parametric combination of momentum and mean reversion and apply it into international equity market indices. Rachev, Jašić, Stoyanov, and Fabozzi (2007) and Choi, Kim, and Mitov (2015) modify the momentum strategy by sorting based on reward-risk measures. De Groot, Karstanje, and Zhou (2014) use term-structure information to implement a momentum strategy in commodity futures contracts. Blitz, Huij, and Martens (2011) propose sorting stocks according to their past residuals instead of gross returns to produce more stable momentum profits. Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) propose new momentum strategies to manage momentum crash risks. Suh and Kim (2018) use investor sentiment to improve momentum profits and prescribe decisions to make more (less) investment with an optimistic (pessimistic) sentiment

Our filtering strategy contributes to this literature by proposing a new method to improve characteristics-based anomalous profits. Our method does not uncover new firm characteristics that are used to form profitable portfolios. Instead, it is applicable to quite a broad range of existing such characteristics. This paper is closely related to that by Suh (2019), who also employs the idea of filtered sorting; however, while Suh (2019) applies it into only the currency carry trade strategy, we apply it into multiple characteristics-based portfolios in equity markets. Furthermore, both are quite different in the measurement of the predictive power and other implementations of the filtering strategy.

To construct a new predictor variable, we first view the sorting method as a way of portfolio-assignment forecasting using a chosen characteristics as a predictor variable. We call characteristics-based portfolios the ex ante portfolios which are formed according to the sorts on a current characteristics variable. Next, we consider portfolios which yield maximum long-short portfolio returns. These optimal portfolios are formed by the sorts on realized returns and thus are impossible to be implemented in reality and called the ex post portfolios. We then measure the portfolio assignment error of a sorting method by whether the ex ante portfolio assigned to an individual asset is identical to the ex post portfolio assigned to the asset or not. We name the dummy variable to indicate the portfolio assignment error as the accuracy index which takes one for a correct portfolio assignment and assignment for each of individual assets and at each time.

We find that the proportion of correct portfolio assignments significantly differs across the cross section of assets. Importantly, our finding suggests that some assets more conform to the prediction for a portfolio assignment by a characteristics whereas other assets are less conforming. Further, we argue that portfolio assignment errors arising from a sorting method are predictable. Based on the predictability, we devise a filtering strategy that utilizes current accuracy index levels as forecasts of the expected value of the next period's accuracy of portfolio assignment. Specifically, the filtering strategy only select assets with a high value of the accuracy index at each portfolio formation time. We apply this filtering strategy to several well-known firm characteristics such as size, book-to-market ratio, investment, operating income, momentum, and long term reversal. We find that the filtering strategy offers significant additional returns for all of these characteristics-based portfolios.

We provide several empirical evidence that our new characteristics-based portfolios out-perform conventional portfolios. We statistically confirm that the new portfolios offer higher returns than conventional portfolios in various settings by adjusting risks, controlling for the effect of transaction costs, and varying investment horizons. In order to check the robustness of our results, we consider several alternative methods for forming new characteristics-based portfolios, vary the number of portfolios, perform subperiod analysis, and apply our method to double-sorted portfolios. Our results are robust to the various specification changes Therefore, our new characteristics-based portfolios offer investors greater trade profit opportunities.

The filtering strategy only selects stocks that are highly conforming to the prediction by a characteristics to improve portfolio profits. Contrary to the filtered characteristics-based portfolios, if we select less-conforming stocks, then we may obtain less anomalous profits. We push this idea further and find that we can form filtered zero-profit portfolios with a high proportion of stocks in most cases. This finding suggests that characteristics-based portfolio profits may not be prevalent among stocks but rather be driven by only a small subset of high-conforming stocks. As several firm characteristics have been suggested as empirical proxies for risk factors, this finding has some asset pricing implications. Specifically, as more (fewer) stocks conform to the prediction by a firm characteristics, the explanatory power of the empirical risk factor becomes greater (weaker). Our accuracy index is useful for relating the degree of the heterogeneity of stocks with the explanatory power of the empirical risk factor.

We also find that the distribution of the predictive-power measurements in the long leg of the characteristics-based portfolio differs from that of the short leg. Therefore, the gains of the filtering strategy may asymmetrically come from either the long or short leg. Moreover, we decompose the relative gains of the filtering strategy over the unfiltered one into the long and short legs and find that the profit gains mainly come from the short leg. We develop an aggregate accuracy index by averaging the cross section of the accuracy indexes at each time and find that it is positively correlated with future conventional anomaly returns. This evidence for the predictive power of the aggregate accuracy index is consistent with the results for individual accuracy indexes. This aggregate accuracy index can serve as a new information variable for the return predictability of conventional characteristics-based portfolios.

The remainder of this paper is organized as follows. Section 2 introduces the new filtering strategy for forming characteristics-based portfolios and compares it with the unfiltered strategy. It also provides a theoretical analysis about the predictability of portfolio assignment errors under a sorting method. Section 3 provides several empirical analyses. It first introduces the firm characteristics that are to be studied in our analysis, then explains the data to be used, and presents performance results of the new strategy relative to the conventional one. In addition, it also presents empirical results about the characteristics of the accuracy index, the predictive powers of the aggregate accuracy index, and other complementary analyses for a better understanding of the relative outperformance of the new strategy. In Section 4, we provide results for some robustness checks. We consider the effects of transaction costs on characteristics-based portfolio profits, alternative specifications, subperiod and other analyses. Section 5 concludes the paper.

2. METHODOLOGY

2.1. Unfiltered Characteristics-based Portfolios

To construct characteristics-based portfolios in each month t, we sort all stocks in ascending order based on their month t values for a chosen firm characteristics that is constructed by following prior studies. We form ten equal-weighted portfolios with the stocks belonging to each of these sorts, from the first decile (P^1) to the tenth decile (P^{10}). Every month, a characteristics-based strategy prescribes to form a long-short portfolio by going long in the tenth portfolio and short in the first portfolio if the firm characteristics is positively correlated with future stock returns. For a negative correlation between the characteristics and future stock returns, the long-short portfolio is formed in the reverse direction. The long-short characteristics-based portfolio return at $t+1, R_{t+1}$, is computed as

$$R_{t+1} = \begin{cases} R_{t+1}^{10} - R_{t+1}^{1}, \ \rho > 0 \\ R_{t+1}^{1} - R_{t+1}^{10}, \ \rho < 0 \end{cases}, \tag{1}$$

where R_{t+1}^{10} (R_{t+1}^{1}) denotes the return at time $t+1$ of the tenth (first) decilke portfolio that is formed at t, and ρ represents the ex ante correlation between the characteristics and future stock returns.

2.2. Filtered Characteristics-based Portfolios

The filtering strategy consists of two stages to form characteristics-based portfolios. In the first stage, we employ the conventional unfiltered sorting method to assign each of stocks to one of the decile portfolios that are sorted on the characteristics. In the second stage, we assess the predictive power of a chosen characteristics for future returns and then filter out the stocks with low return predictive power from the set of investable stocks. We then form the decile and long-short portfolios using only the filtered stocks. To ease the exposition, we take the size decile portfolios as an example.

To assess the ability of the firm characteristics (size) to predict the return for a one-month holding period, we devise a nonparametric indicator that is called the accuracy index. Intuitively, firm size would possess higher (lower) predictive power for future returns as smaller-sized firms attain higher (lower) future returns. A firm is assigned to one of size deciles based on its current size. The usual size dicile portfolios can be called the ex ante portfolios. We also form the ex post decile portfolios based on realized future returns. We then measure the predictive power of size-sorting by examining whether a firm is assigned to the same sorting-order in the ex ante and the ex post portfolios. A correctly-assigned firm in the smallest (biggest) decile should be assigned to the highest (lowest) realized-future-return decile. The accuracy index is constructed as a dummy variable to indicate whether the size-sorting is a correct assignment or not. Put formally, if a stock j is assigned to ex ante portfolio k at time $t-1$, then the accuracy index for stock j at time t takes a value of one if stock j turns out to belong to ex post portfolio k at time t and zero otherwise. The accuracy index (ACC) is defined as follows:

$$ACC_{j,t} = \begin{cases} 1, \ j \in P_{t-1}^{k}, \ j \in Q_{t}^{k} \\ 0, \ j \in P_{t-1}^{k}, \ j \notin Q_{t}^{k} \end{cases}, \tag{2}$$

where P_{t-1}^{k} and Q_{t}^{k} denote denote the ex ante and ex post portfolio k at time $t-1$, respectively. In order to utilize the historical information about the accuracy index, we form the following moving-average (ACCMA) and recursive (ACCRC) accuracy indexes[1]:

$$ACCMA_{j,t} \equiv \frac{1}{m}\sum_{\tau=0}^{m-1} ACC_{j,t-1,} \tag{3}$$

$$ACCRC_{j,t} \equiv \frac{1}{t-1}\sum_{\tau=0}^{t-2} ACC_{j,t-1}. \tag{4}$$

We then use the accuracy index to filter out stocks that tend to be incorrectly

[1] Although we do not explore alternative methods for the measurement of the predictive power of firm characteristics in this paper, we admit that the alternative methods are also conceivable and potentially perform better. However, we advocate our predictive power measurement because it is a nonparametric index and constructed in a consistent way with the usual sorting method.

assigned. We use historical information available at each month to determine a threshold accuracy index level for the filtering. We apply a hypothetical threshold level to filter out the stocks with accuracy indexes less than the level and obtain the previous *M*-period historical average return of the long-short portfolio including only the filtered stocks. We vary the hypothetical threshold level and find the optimal threshold level that corresponds to the greatest historical long-short portfolio returns. Formally, the threshold level $\overline{\omega_t}$ at each month t is determined to maximize the previous *M*-period historical average return of the long-short portfolio:

$$\overline{\omega_t} \in \underset{\overline{\omega}}{\operatorname{argmax}} \frac{1}{M} \sum_{\tau=1}^{M} R_{t-\tau}\big(S_{t-\tau-1}(\overline{\omega})\big), \tag{5}$$

where $S_t(\overline{\omega})$ indicates the set of assets that are available for investment when the threshold level $\overline{\omega}$ is applied for equity selection. That is, for the ACCMA as an accuracy index,

$$S_t(\overline{\omega}) \equiv S_t^1(\overline{\omega}) \cup S_t^{10}(\overline{\omega}), \tag{6}$$

$$S_t^k(\overline{\omega}) \equiv \{j | j \in P_{t-1}^k, ACCMA_{j,t} \geq (\overline{\omega})\},\ k = 1{,}10. \tag{7}$$

Here $S_t^1(\overline{\omega})$ and $S_t^{10}(\overline{\omega})$ denote the set of filtered assets for the first and the tenth decile portfolios, respectively. $R_\tau\big(S_{\tau-1}(\overline{\omega})\big)$ denotes the long-short portfolio returns with the set of assets $S_{\tau-1}(\overline{\omega})$ at month $\tau - 1$. Notably, the threshold level $\overline{\omega}$ will change over time. The threshold level can be easily found via a grid search over the range [0, 1].

Lastly, the return of the filtered long-short portfolio at month t is computed as

$$R_{Filtered,t+1} = R_{t+1}(S_t(\overline{\omega})) = \begin{cases} R_{t+1}^{10}(S_t^{10}(\overline{\omega})) - R_{t+1}^{1}(S_t^{1}(\overline{\omega})),\ \rho > 0 \\ R_{t+1}^{1}(S_t^{1}(\overline{\omega})) - R_{t+1}^{10}(S_t^{10}(\overline{\omega})),\ \rho < 0 \end{cases}. \tag{8}$$

The filtering strategy prescribes the decisions to dynamically change the set of equities to form long-short portfolios. Note that one-month lagged informations are used for portfolio formation under the filtering strategy. For comparison, $S_t(0)$ denotes the whole set of assets that are available for investment, and thus the return of the unfiltered long-short portfolio at month $t + 1$ (Equation (1)) can be rewritten as follows:

$$R_{Unfiltered,t+1} = R_{t+1}(S_t(0)) = \begin{cases} R_{t+1}^{10}(S_t^{10}(0)) - R_{t+1}^{1}(S_t^{1}(0)),\ \rho > 0 \\ R_{t+1}^{1}(S_t^{1}(0)) - R_{t+1}^{10}(S_t^{10}(0)),\ \rho < 0 \end{cases}. \tag{9}$$

2.3. Predictability of Portfolio Assignment Errors

To understand the predictability of portfolio assignment errors in characteristics-based portfolios, we employ a standard multifactor asset pricing model which specifies an excess return of risky asset i as follows:

$$r_{i,t+1} = \beta_i' F_{t+1} + \epsilon_{i,t+1}, \tag{10}$$

where $r_{i,t+1}$ is an excess return of risky asset i at time $t+1$; F_{t+1} is a $(K \times 1)$ vector of factor portfolio excess returns, β_i is a $(K \times 1)$ vector of factor betas, and $\epsilon_{i,t+1}$ is a random disturbance. The factor portfolio excess returns are assumed to be governed by the following dynamics:

$$F_{t+1} = \alpha + \phi F_t + \varepsilon_{t+1}, \tag{11}$$

where α is a $(K \times 1)$ coefficient vector, ϕ is a $(K \times K)$ coefficient matrix, and ε_{t+1} is a vector of random disturbances.

Investors form their subjective expectation about future risky asset returns based on factor proxy variables such as firm characteristics. Investors' subjective expectation may deviate from a rational expectation either because true risk factors are unknown to investors or because investors are susceptible to various behavioral biases. Specifically, the subjective expectation of risk asset return i is formed as

$$\hat{E}_t r_{i,t+1} = b_i' Z_{i,t}, \tag{12}$$

where $\hat{E}_t r_{i,t+1}$ is the time-t subjective expectation of risky asset return i at time $t+1$, $Z_{i,t}$ is a $(J \times 1)$ vector of characteristics of risky asset i at time t, b_i is a comforming vector of loadings.

The factor portfolio excess returns are partly explained by the characteristics variables. We specify a linear explanatory relation as follows:

$$F_t = \gamma_{i,0} + \gamma_{i,1} Z_{i,t} + u_{i,t}, \tag{13}$$

where $\gamma_{i,0}$ is a $(K \times 1)$ coefficient vector, $\gamma_{i,t}$ is a $(K \times J)$ coefficient matrix, and $u_{i,t}$ is a $(K \times 1)$ vector of random disturbances.

From Equations (10), (11), and (13), we rewrite the excess return of asset i at time $t+1$ as follows:

$$r_{i,t+1} = \beta_i'(\alpha + \gamma_{i,0}) + \beta_i' \gamma_{i,1} Z_{i,t} + \beta_i' u_{i,t} + \beta_i' \varepsilon_{t+1} + \epsilon_{i,t+1}. \tag{14}$$

The above expression shows that the expected excess return is decomposed into two components. The first term of the right hand side in Equation (14) is time-invariant but varies across assets, whereas the second term represents the component affected by characteristics variables $Z_{i,t}$. Importantly, the return predictability possessed by the characteristics variables differs across the cross section of assets because not only the factor betas (β_i) but also the coefficients of the characteristics variables in the relation to factor portfolio excess returns ($\gamma_{i,t}$) differ across assets.

Under the subjective expectation of Equation (12), the forecasting error is expressed as:

$$r_{i,t+1} - \hat{E}_t r_{i,t+1} = \beta_i'(\alpha + \gamma_{i,0}) + (\beta_i'\gamma_{1,t} - b_i')Z_{i,t} + \beta_i' u_{i,t} + \beta_i' \varepsilon_{t+1} + \epsilon_{i,t+1} \quad (15)$$

which shows that the forecasting error also contains the cross-sectional variation term, the characteristics-effect term, and random components. In contrast, under the rational expectation using the true risk factors (i.e., $\hat{E}_t r_{i,t+1} = \beta_i'(\alpha + \phi F_t)$, the forecasting-error predictability disappears. Therefore, the predictability may arise from the deviation of subjective expectations from the rational expectation in this framework.[2]

$$\hat{E}_t r_{i,t+1} = bZ_{i,t}, \quad (16)$$

where $Z_{i,t}$ is a chosen single characteristics variable of stock i at time t, and b is a positive (negative) constant for a positive (negative) ρ, then the subjective expectations can serve as forecasts of the excess returns of stocks that are consistent with the unfiltered sorting strategy. With those forecasts specified by Equation (16), the forecasting error of stock returns is

$$r_{i,t+1} - \hat{E}_t r_{i,t+1} = \beta_i'(\alpha + \gamma_{i,0}) + (\beta_i'\gamma_{i,1} - b)Z_{i,t} + \beta_i' u_{i,t} + \beta_i' \varepsilon_{t+1} + \epsilon_{i,t+1} \quad (17)$$

with the mean squared forecasting error (MSFE) of

$$MSFE_{1,t} = \left[\beta_i'(\alpha + \gamma_{i,0}) + (\beta_i'\gamma_{i,1} - b)Z_{i,t}\right]^2 + \beta_i'\Omega_{u_i}\beta_i + \beta_i'\Omega_\varepsilon\beta_i + \Omega_{\epsilon_i}, \quad (18)$$

where Ω_{u_i}, Ω_ε, Ω_{ϵ_i} denote the conforming (co)variances of $u_{i,t}$, ε_{t+1}, and $\epsilon_{i,t+1}$, respectively.

On the other hand, if the deterministic components of the forecasting error in Equation (17) are known, then the corresponding MSFE becomes

$$MSFE_{2,t} = \beta_i'\Omega_{u_i}\beta_i + \beta_i'\Omega_\varepsilon\beta_i + \Omega_{\epsilon_i} \quad (19)$$

[2] In a similar vein, Lansing, LeRoy, and Ma (2019) employ a consumption-based asset pricing model to show that excess return predictability may stem not only from stochastic volatilities but also from investors' subjective expectations which deviate from rational expectations.

which is lower than the MSFE of Equation (18) with unknown deterministic components. This fact suggests that an efficient estimation of the deterministic components of forecasting errors may improve forecasting.

While the above forecasting error is measured by stock returns, the filtering strategy measures the forecasting error by portfolio assignments.[3] In spite of this difference, the argument that an efficient estimation of the deterministic components of forecasting errors may improve forecasting is still applicable for the forecasting errors in portfolio assignments.

The forecasting error of Equation (17) corresponds to the unfiltered strategy which does not estimate components of a forecasting error or, equivalently, assumes a zero forecasting error. By contrast, the filtering strategy attempts to estimate the forecasting error components of Equation (17). Specifically, the filtering strategy utilizes the accuracy indexes that are historical means of portfolio assignment accuracies and thus are analogous to historical means of (the opposite of) stock return forecasting errors. If this historical mean is more efficient than the benchmark estimate of zero, then the forecasting may be improved.

The first term of the right hand side in Equation (17) shows the existence of cross-sectional variations which are constant over time in forecasting errors. On the other hand, the second term indicates cross-sectional forecasting-error variations which also change over time. The random components in the above forecasting error expression can be mitigated by taking averages of forecasting errors over time. The historical mean of forecasting errors can capture the cross-sectional and time-series variations in the forecasting error of stock returns. Similarly, the accuracy indexes can also capture the cross-sectional and time-series variations in the forecasting errors of portfolio assignments. Notably, compared to the ACCRC index, the ACCMA index is better at capturing time-varying forecasting-error variations (the second term) but worse at mitigating the effects of the random components and estimating time-invariant forecasting-error variations (the first term). Therefore, it will be an empirical issue which of the two indexes performs better.

3. EMPIRICAL ANALYSIS

3.1. Firm Characteristics

For our empirical analysis, we choose six well-known firm characteristics: Size, book-to-market (BM), investment (INV), operating income (OP), momentum (MOM), and long term reversal (LTR). The size effect refers to the fact that small-sized firms

[3] The unfiltered strategy provides portfolio assignments but not specific forecasts of stock returns. To be consistent with the unfiltered strategy, the filtering strategy focuses on portfolio assignment forecasting errors rather than stock return forecasting errors.

tend to earn higher average returns than what are predicted by the CAPM. This size effect was proposed by Banz (1981) and Reinganum (1981).[4] The value premium indicates that firms with high book-to-market ratios have higher average returns than firms with low BM ratios. Stattman (1980), Rosenberg, Reid, and Lanstein (1985) and Chan, Hamao, and Lakonishok (1991) provide empirical evidences for the value premium effect. Fama and French (1992, 1993) include the size and the value premium effects in their three-factor model to account for the cross section of expected stock returns. Novy-Marx (2013) finds that expected profitability is strongly related to average returns. Aharoni, Grundy, and Zeng (2013) document evidence for a relationship between investment and average returns.[5] The effects of profitability (OP) and investment (INV) on average returns are incorporated into the Fama-French (2015) five-factor model. The momentum effect shows that past returns (during the previous 6-12 months) are positively correlated with future returns and thus buying past winners and selling past losers tends to generate positive profits. A large body of literature documents significantly positive and pervasive momentum profits.[6] The long term reversal effects are documented by DeBondt and Thaler (1985). They indicate that past returns (during the previous 3-5 years) are negatively correlated with future returns, and a contrarian strategy of selling past winners and buying past losers tends to generate positive profits.

3.2. Data and Variables

We will apply the unfiltered and filtering strategies to the U.S. individual stocks. We use all common stocks (share codes 10 and 11) that are listed in the New York and American Stock Exchanges. The sample time period is from January 1963 to December 2017. We delete all stocks that are priced less than $5 at the beginning of the holding period. We also exclude stocks that belong to the smallest decile, which are sorted with

[4] Refer to, for example, Schwert (1983) for other subsequent studies on the size effect.

[5] For anomalies related with investment and pro.tability, refer to also Haugen and Baker (1996), Cohen, Gompers, and Vuolteenaho (2002), Fairfield, Whisenant, and Yohn (2003), Titman, Wei, and Xie (2004), and Fama and French (2006, 2008).

[6] For example, Jegadeesh and Titman (1993) and Asness (1994) sort .rms on the basis of three- to 12-month past returns and documented the momentum pro.ts in U.S. common stock returns from 1965 to 1989. Jegadeesh and Titman (2001) also document momentum pro.ts in a later period from 1990 to 1998. Israeland Moskowitz (2013) extend the period from 1927 to 1965 and from 1990 to 2012. Momentum profits are also documented in industry portfolios (Moskowitz and Grinblatt (1999)), in developed and emerging equity markets (Rouwenhorst (1998, 1999)), in country indices (Asness, Liew, and Stevens (1997)), in currencies (Okunev and White (2003)), in commodities (Erb and Harvey (2006)), and in exchange traded futures contracts (Moskowitz, Ooi, and Pedersen (2012)). Asness, Moskowitz, and Pedersen (2013) also report evidence for momentum pro.t across multiple markets and asset classes.

NYSE breakpoints. Our data selection criteria are consistent with prior studies (e.g., Jegadeesh and Titman (1993) and Han, Zhou, and Zhu (2016)).[7]

The characteristics variables are constructed by following prior studies. We follow Fama and French (1992, 1993) to construct the size and BM variables and Fama and French (2015) to construct the INV and OP variables.[8] Prior returns from month $t-2$ to $t-12$ and from month $t-13$ to $t-60$ are used in month t for the MOM and LTR variables, respectively.

3.3. The Cross Section of Accuracy Indexes

We propose the new index to measure portfolio assignment accuracies in the conventional sorting strategy. If a characteristics variable does not possess any forecasting power, the accuracy index would have the mean value of one-tenth for decile portfolios. Figure 1 shows the empirical distributions of the individual accuracy indexes (ACCs) that are averaged over the sample period for each of the six firm characteristics and for all (All), the first (P^1) and the tenth (P^{10}) decile portfolios.

For all stocks, the average accuracy index is dispersed and roughly centered around the no-predictive- power value (0.1). While a significant portion of stocks exhibit a higher accuracy index level than one-tenth, another significant portion of stocks exhibit a lower accuracy index level than one-tenth. Interestingly, the accuracy index for stocks belonging to the first or the tenth decile portfolios are distributed quite differently from that of all stocks. Specifically, the proportion of stocks with high accuracy in the extreme portfolios is higher than that in all stocks. This result shows that the predictive power of a firm characteristics differs across the cross section of stocks. The filtering strategy relies on the assumption that the predictive power of firm characteristics to forecast future returns sufficiently differs across stocks, and this result implies that the assumption holds for well-known firm characteristics.

3.4. Portfolio Performance

In this subsection, we compare the portfolio performances of both strategies in various ways.

Summary statistics. Figure 2 shows the cumulative returns of the filtered and the unfiltered portfolios for each of the six firm characteristics over the sample period. Remarkably, the filtering strategy shows the cumulative returns have grown much faster than those of the unfiltered strategy in all cases.

[7] All of the conventional characteristics-based portfolio return data in our analysis are available at Kenneth French's data library. We closely follow the method to generate those portfolios.

[8] The Internet Appendix provides detailed explanation about the construction of these variables.

Table 1 presents the summary statistics of the profits from both strategies. The conventional characteristics-based portfolios generate significantly positive and high mean returns (ranging from 0.41% to 1.36% per month) in all cases, which is consistent with the literature on the profitability of those portfolios. Notably, the filtering strategy yields much higher mean returns (ranging from 0.77% to 1.99% per month) than the unfiltered strategy in all cases. Although the filtering strategy yields higher volatilities than the unfiltered strategy, the Sharpe ratios of the filtering strategy (ranging from 0.36 to 0.85) are higher than those of the unfiltered strategy (ranging from 0.30 to 0.76) in all cases (except the MOM). Interestingly, the filtered portfolio profits tend to be less skewed and thinner tailed than the unfiltered portfolio profits in most cases. The filtering strategy uses only a small portion (ranging from 9.1% to 16.9%) of stocks to form filtered portfolios. Table 2 shows the correlation coefficients between the filtered and unfiltered portfolio profits. As expected, the filtered portfolio profits are highly correlated with the unfiltered portfolio profits; however, the correlation coefficients between the filtered profits and the corresponding unfiltered profits range from 0.451 to 0.745, and thus they are far from being perfectly correlated.

Table 1. Summary Statistic

	Portfolios					
	Size	BM	INV	OP	MOM	LTR
	Unfiltered					
Mean	0.409	0.587	0.780	0.740	1.357	0.531
(t-value)	**2.173**	**3.122**	**5.206**	**3.781**	**5.600**	**3.417**
Median	0.251	0.300	0.546	0.675	1.463	0.308
SD	4.779	4.776	3.839	5.016	6.158	3.802
SR	0.296	0.425	0.704	0.511	0.763	0.484
Skew	1.170	0.179	0.804	-0.124	-0.479	0.550
Kurtosis	15.723	10.307	6.048	14.362	10.365	5.817
	Filtered					
Mean	0.769	1.588	1.604	1.957	1.986	1.148
(t-value)	**2.630**	**5.026**	**5.606**	**6.290**	**5.481**	**3.606**
Median	0.528	1.429	1.071	1.576	1.681	0.834
SD	7.434	8.030	7.335	7.976	9.208	7.785
SR	0.358	0.685	0.758	0.850	0.747	0.511
Skew	0.766	-0.310	0.212	-0.293	0.155	0.079
Kurtosis	7.983	6.441	4.881	6.185	7.059	5.291
Proportion	11.995	10.769	9.135	9.327	11.242	16.867

Notes: This table shows the summary statistics of the unfiltered and the filtered portfolio profits for each of the six firm characteristics, including mean, median, standard deviation (SD), skewness, kurtosis, and the Sharpe ratio (SR) of the average monthly return over the sample period. Bold-faced t-values indicate the 5% significance. The proportion (%) of stocks selected in the filtered portfolios to available stocks (Proportion) is also provided.

Table 2. Correlation

		Unfiltered					
		Size	BM	INV	OP	MOM	LTR
Unfiltered	Size	1.000					
	BM	-0.297	1.000				
	INV	-0.214	0.728	1.000			
	OP	-0.429	0.490	0.343	1.000		
	MOM	0.291	-0.431	-0.169	-0.147	1.000	
	LTR	0.265	0.378	0.469	-0.056	0.112	1.000
Filtered	Size	0.733	-0.269	-0.193	-0.262	0.389	0.167
	BM	-0.285	0.656	0.517	0.440	-0.096	0.241
	INV	0.023	0.163	0.451	-0.017	0.159	0.219
	OP	0.243	0.265	0.250	0.621	0.159	-0.037
	MOM	0.215	-0.290	-0.093	-0.104	0.745	0.046
	LTR	0.224	-0.038	0.117	-0.122	0.384	0.570
		Filtered					
		Size	BM	INV	OP	MOM	LTR
Filtered	Size	1.000					
	BM	-0.190	1.000				
	INV	0.031	0.226	1.000			
	OP	-0.140	0.328	0.140	1.000		
	MOM	0.362	-0.002	0.183	0.075	1.000	
	LTR	0.216	0.057	0.128	-0.074	0.223	1.000

Risk-adjusted returns. We examine whether the higher profits of the filtering strategy simply reflect more loadings on economic risk factors. To account for the effect of risk-taking on the filtered portfolio profits, we compute the risk-adjusted filtered portfolio profits based on widely used asset pricing models: the CAPM, the Fama-French (1992, 1993) 3-factor model (FF3), the Fama-French-Carhart 4-factor model (FF3+Mom), the Fama-French (2015) 5-factor model (FF5), and FF5 plus Carhart's (1997) momentum factor model (FF5-+Mom). Table 3 presents the risk-adjusted filtered portfolio profits and the risk-adjusted profit differences between the filtered and the unfiltered portfolios. While the risk-adjusted returns of the filtering strategy are significantly positive in most cases, the risk-adjusted returns of the filtering strategy are much greater than those of the unfiltered strategy. The difference between the risk-adjusted returns of both strategies is positive and highly significant in most cases. This result implies that the higher returns of the filtering strategy (relative to the unfiltered strategy) remain robust to these risk-adjustments.

Investment horizon. One-period analysis holds true for multiple periods only under some restrictive assumptions.[9] In general (and realistic) situations, it would be desirable to measure the performance over an appropriate horizon. In that sense, it would be

[9] For example, if returns follow an identically and independently normal distribution, then a one-period analysis can also hold for multiple periods. However, as Table 1 suggests, one-period returns are not normally distributed but have fat tails.

legitimate to compare the cumulative returns of both strategies, as shown in Figure 2, if an investor's investment horizon coincides with the sample period. However, this investment horizon seems unrealistically too long. On the other hand, a one-month horizon seems too short, which is how performances are measured and shown in Table 1. Although there are various investment horizons, we will consider a 10-year horizon to deliver more realistic results in this analysis. Figure 3 shows the time trend of 10-year rolling cumulative returns of both the filtered and the unfiltered strategies. With a 10-year horizon, the filtering strategy delivers better performance than the unfiltered strategy in most periods and most cases.

Table 3. Risk-adjusted Returns

Model	Portfolios					
	Size	BM	INV	OP	MOM	LTR
	Filtered profits: alpha					
CAMP	0.68	1.87	1.70	2.03	2.05	1.22
FF3	0.58	1.39	1.51	1.93	2.30	1.09
FF3+Mom	0.05	1.31	1.25	1.77	1.06	0.54
FF5	0.46	0.98	1.54	1.17	2.10	0.96
FF5+Mom	0.03	0.96	1.32	1.12	1.07	0.54
	Filtered profits: t-value					
CAMP	**2.31**	**6.16**	**6.15**	**6.41**	**5.42**	**3.90**
FF3	**2.52**	**5.44**	**5.41**	**5.88**	**5.76**	**3.53**
FF3+Mom	0.23	**4.97**	**4.48**	**5.44**	**3.46**	1.75
FF5	1.74	**3.77**	**5.24**	**4.12**	**4.33**	**3.24**
FF5+Mom	0.13	**3.61**	**4.57**	**3.97**	**3.43**	1.86
	Filtered profits - unfiltered profits: alpha					
CAMP	0.41	1.10	0.75	1.18	0.65	0.62
FF3	0.49	1.16	0.93	1.25	0.68	0.82
FF3+Mom	0.20	0.85	0.64	1.09	0.60	0.40
FF5	0.34	0.94	1.14	1.13	0.59	0.78
FF5+Mom	0.11	0.70	0.87	1.01	0.53	0.44
	Filtered profits - unfiltered profits: t-value					
CAMP	**2.16**	**4.92**	**3.04**	**4.78**	**2.58**	**2.35**
FF3	**2.56**	**5.15**	**3.81**	**4.89**	**2.67**	**3.36**
FF3+Mom	1.03	**3.82**	**2.61**	**4.26**	**2.28**	1.63
FF5	1.63	**4.02**	**4.51**	**4.18**	**2..23**	**3.09**
FF5+Mom	0.53	**3.06**	**3.4**	**3.75**	**2.00**	1.83

Notes: This table shows the results about the risk adjustment not only for characteristics-based profits of the filtering strategy but also for characteristics-based profit differences between the filtered and the unfiltered portfolios. The risk adjustment is based on the CAPM, the Fama-French 3-factor model (FF3), the Fama-French-Carhart 4-factor model (FF3+Mom), the Fama-French 5-factor model (FF5), and FF5 plus Carhart's momentum factor model (FF5+Mom). The risk-adjusted alpha indicates a monthly return in percentage. The t-values of the alpha are calculated using Newey-West (1987) standard errors. Bold-faced t-values indicate the 5% significance.

Hypothesis tests. Figure 4 illustrates the empirical densities of both types of portfolio profits over a 10-year horizon. The unfiltered strategy yields positive returns in most cases. While the filtered profits tend to be more dispersed than the unfiltered returns, they are distributed over a much higher range than the unfiltered returns in all cases. Although the Sharpe ratio (SR) has been popularly used as a performance measure, it does not distinguish between a downside risk and an upside potential, and it unduly penalizes high volatility, even when it is associated with positive and high returns, which is not a risk but is rather a potential gain. To account for this, we not only use the SR but also the following measures for formal hypothesis tests: the Sortino ratio (SO), the upside potential ratio (UP), and the omega ratio (OM). The SO penalizes only downside risk. The UP penalizes upside gains (relative to a target return) with downside risk. The OM measures the ratio of the upside gains to the downside losses relative to a target return. The Internet Appendix[10] provides detailed explanations of these measures.

Based on these measures, we formally test the null hypothesis that both strategies perform equally against the alternative hypothesis that the filtering strategy performs better than the unfiltered strategy. The p-value is calculated using a bootstrapping method.[11] Table A1 (of the Internet Appendix) presents the hypothesis testing results based on the four performance measures with a 10-year horizon. For the performance comparison, we set the target return as the mean return of the unfiltered strategy, with which the SO is zero, and the OM is one for the unfiltered strategy. The SR of the filtering strategy is significantly higher than that of the unfiltered strategy for all cases (except the MOM). Moreover, the results based on the other three performance measures significantly reject the null hypothesis and support the alternative hypothesis for all cases. That is, the filtering strategy outperforms the unfiltered strategy by providing significant relative upside gains.

3.5. Aggregate Accuracy Index

We expect that if the proposed accuracy index effectively captures the predictive power of a firm characteristics, the portfolio profits tend to be higher in high accuracy-index periods. To support the validity of the accuracy index, we examine whether the accuracy index can well explain time variations in portfolio profits. We construct the aggregate accuracy indexes by averaging the cross section of the accuracy indexes at each time. We then perform the following linear explanatory regression:

$$R_t = \alpha + \beta_1 ACCAG_{long,t} + \beta_2 ACCAG_{short,t} + \epsilon_{t+1}, \quad (20)$$

[10] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3874684.

[11] We employ a block bootstrapping method to account for potential serial dependence. We also conduct a bootstrapping method assuming serial independence as a robustness check. We find that both results are qualitatively similar in our analysis.

where R_t denotes a chosen unfiltered long-short portfolio profit at time t, $ACCAG_{long,t}$ and $ACCAG_{short,t}$ indicate the aggregate accuracy indexes by averaging the cross section of the accuracyindexes ($ACCMA_{j,t}$) belonging to the long and the short leg portfolios, respectively. As Table 4 shows, the regression results imply that an increase in accuracy in both the long and short legs translate to an increase in the portfolio profits with R-squares ranging from 35% to 59%.

We further investigate whether the aggregate accuracy indexes possess any forecasting power for future unfiltered portfolio profits. For that purpose, we conduct the following linear forecasting regression:

$$R_{t=1} = \alpha + \beta_1 ACCAG_{long,t} + \beta_2 ACCAG_{short,t} + \epsilon_{t+1}. \quad (21)$$

Table 4 also shows the forecasting regression results. Notably, the current aggregate accuracy indexes are positively correlated with future portfolio profits, and the forecasting powers are significant in some cases. For example, the short-leg aggregate accuracy index possesses significant forecasting powers for the Size, INV, OP, and LTR portfolio profits while the long-leg aggregate accuracy index possesses significant forecasting power for the BM portfolio profits. For the MOM portfolio profits, the long- and short-leg accuracy indexes are positively but insignificantly correlated with future portfolio profits.

Table 4. Explanatory and predictive powers of the aggregate accuracy index for unfiltered portfolio profits

Unfiltered portfolio		Explanatory				Forecast			
		Const	Long	Short	R^2	Const	Long	Short	R^2
Size	Coef	-0.081	42.092	72.599	0.594	-0.007	3.134	16.074	0.016
	(t-value)	-10.567	8.114	13.931		-0.803	0.414	2.637	
BM	Coef	-0.091	56.659	37.562	0.550	-0.016	10.702	9.896	0.027
	(t-value)	-9.579	9.189	7.404		-1.902	2.014	1.407	
INV	Coef	-0.052	6.868	34.646	0.467	-0.013	0.582	13.012	0.061
	(t-value)	-9.496	1.352	11.871		-2.104	0.133	3.363	
OP	Coef	-0.072	43.814	26.811	0.348	-0.015	11.032	8.458	0.029
	(t-value)	-4.440	3.181	6.449		-2.274	1.560	2.258	
MOM	Coef	-0.100	49.993	32.212	0.492	0.006	2.010	3.663	0.002
	(t-value)	-8.848	7.800	6.693		0.650	0.366	0.745	
LTR	Coef	-0.079	44.627	52.361	0.473	-0.007	-1.316	15.682	0.018
	(t-value)	-13.800	8.207	10.225		-1.185	-0.279	3.069	

Notes: This table shows the results for the regressions of unfiltered portfolio profits on the aggregate accuracy index for each of the six characteristics. The unfiltered portfolio profits in month $t+1$ are regressed on month $t+1$ ("Explanatory") or month t ("Forecast") aggregate accuracy indexes for long and short decile portfolios. The t-values are calculated using Newey-West (1987) standard errors, and bold-faced t-values indicate the 5% significance.

Table 5. Accuracy State and Portfolio Profits

Unfiltered portfolio		Accuracy state				
		low	middle	high	h-l	(t-value)
		A. Explanatory regression				
Size	long	-2.44	0.41	3.07	5.50	**12.09**
	short	-2.73	0.30	4.16	6.90	**12.44**
BM	long	-2.19	0.15	3.90	6.09	**8.88**
	short	-1.59	-0.38	3.63	5.22	**8.79**
INV	long	-0.78	0.49	2.71	3.48	**7.83**
	short	-1.49	0.39	3.46	4.95	**10.04**
OP	long	-1.71	0.86	2.99	4.71	**4.67**
	short	-0.91	-0.14	3.57	4.48	**6.58**
MOM	long	-2.71	1.25	5.63	8.34	**6.58**
	short	-2.47	1.51	4.79	7.26	**8.82**
LTR	long	-1.94	-0.05	2.81	4.74	**11.06**
	short	-1.73	-0.03	2.86	4.59	**11.76**
		B. Forecasting regression				
Size	long	0.09	0.64	0.48	0.39	**0.76**
	short	-0.43	0.51	1.26	1.69	**3.61**
BM	long	0.19	0.18	1.40	1.22	**2.48**
	short	-0.20	0.59	1.28	1.22	**3.10**
INV	long	0.38	0.85	1.09	0.71	**1.61**
	short	0.28	0.44	1.66	1.38	**3.09**
OP	long	0.22	0.67	1.40	1.18	**2.12**
	short	0.42	0.42	1.47	1.04	**1.88**
MOM	long	0.85	1.88	1.27	0.42	**0.59**
	short	0.97	1.43	1.63	0.66	**0.97**
LTR	long	0.35	0.44	0.76	0.41	**1.00**
	short	0.11	0.26	1.18	1.07	**2.47**

Notes: This table shows monthly unfiltered portfolio returns (%) in month $t+1$ according to month $t+1$ ("Explanatory") or month t ("Forecast") accuracy state for each of the six firm characteristics. Based on the aggregate accuracy index level, the accuracy state is classified into three states: high (top 30%), middle (middle 40%), and low (bottom 30%). The return differences ("h-l") of unfiltered portfolios between the "high" and "low" states and their t-values are also provided. Bold-faced t-values indicate the 5% significance.

We also classify the sample period into three states of accuracy based on the aggregate long- and short-leg accuracy indexes: high (top 30%), middle (middle 40%), and low (bottom 30%). We calculate the monthly unfiltered portfolio profits for each of the accuracy states. We also consider the contemporaneous (explanatory) and one-month lagged (forecasting) state classifications. Table 5 provides the results that characteristics-based profits are monotonically aligned with the accuracy state. Further, the portfolio profits are significantly higher in high accuracy states than in low accuracy states not only under the contemporaneous but also under the one-month lagged classifications. The Internet Appendix (Table A2) also provides the results for two alternative classifications: the top 20% and bottom 20%, and the top 40% and bottom 40%. The results with the alternative thresholds qualitatively remain the same. In sum, the results from both the regressions and the accuracy classification suggest that the aggregate accuracy indexes possess not only explanatory power but also predictive power for characteristics-based portfolio profits.

3.6. Characteristics of the Filtered Stocks

Do filtered stocks differ from other stocks with respect to firm characteristics? To investigate this issue, we first compute ranks of stocks in the long or short leg with respect to each of the six firm characteristics and normalize the rank to conform to the usual sorting direction and to take values from zero to one; thus the average rank of all stocks in the long or short leg is 0.5. Next, we compute the average of the normalized ranks of filtered stocks with respect to each characteristics and examine its deviation from 0.5. If the filtering is strongly correlated with a firm characteristics, then the outperformance of the filtered portfolio mainly comes from a smaller set of more extreme stocks with respect to the characteristics. Under the null hypothesis of no-correlation, the relative ranks of filtered stocks with respect to a frm characteristics should be uniformly distributed.

Table 6. Characteristics of Filtered Stocks

Filtered portfolio		Characteristics					
		Size	BM	INV	OP	MOM	LTR
Size	long	0.499	0.511	0.525	0.521	0.532	0.562
	short	0.494	0.498	0.508	0.515	0.505	0.518
BM	long	0.490	0.510	0.519	0.527	0.522	0.566
	short	0.484	0.506	0.530	0.522	0.542	0.602
INV	long	0.476	0.498	0.497	0.524	0.528	0.582
	short	0.506	0.507	0.521	0.502	0.563	0.591
OP	long	0.488	0.532	0.545	0.513	0.575	0.601
	short	0.505	0.496	0.537	0.502	0.543	0.580
MOM	long	0.480	0.490	0.534	0.512	0.514	0.592
	short	0.486	0.507	0.530	0.514	0.494	0.591
LTR	long	0.467	0.490	0.523	0.513	0.522	0.491
	short	0.492	0.509	0.516	0.511	0.505	0.520

Notes: This table shows the average ranks of filtered stocks in the long or short leg relative to unfiltered stocks with respect to each of the six firm characteristics. The ranks of unfiltered stocks are normalized to conform to the usual sorting direction and to take values from zero to one. Note that the average rank of unfiltered stocks is 0.5.

Table 6 shows the average rank of filtered stocks in the long or short leg with respect to each of the six characteristics. To provide more detailed information, the Internet Appendix (Figures A1 to A6) demonstrates empirical distributions of relative ranks of filtered stocks. The results show that filtered stocks are not significantly tilted toward any firm characteristics. Using the Size as an example, filtered stocks in the long leg have relative average ranks of 0.499, 0.511, 0.525, 0.521, 0.532, and 0.562 for characteristics of Size, BM, INV OP, MOM, LTR, respectively. These deviations from the benchmark value of 0.5 are small. The averages of relative ranks in the short leg also show similar-sized deviations. As Figure A1 (of the Internet Appendix) illustrates, while the relative ranks of the filtered stocks in the Size portfolio are largely uniformly distributed in the long and short legs and for non-time-series characteristics (Size, BM, INV, and OP), they are a bit more tilted for time-series characteristics (MOM and LTR).

Table 7. Return Contributions by Risk Factors

Factors	Characteristics					
	Size	BM	INV	OP	MOM	LTR
A. Coefficient estimates						
Alpha	0.11	0.70	0.87	1.01	0.54	0.44
Mkt-RF	-0.05	-0.04	0.01	0.11	-0.01	0.01
SMB	0.13	-0.21	0.07	0.00	0.09	-0.19
HML	-0.15	0.00	-0.19	-0.28	-0.06	-0.41
RMW	0.24	0.38	-0.56	-0.56	0.14	-0.20
CMA	0.12	0.17	-0.32	0.26	0.17	0.08
Mom	0.32	0.33	0.37	0.16	0.08	0.49
LT Rev	-0.01	0.05	-0.02	0.14	-0.15	0.24
B. t-value						
Alpha	0.53	**3.05**	**3.46**	**3.73**	**2.01**	1.82
Mkt-RF	-1.06	-0.59	0.14	1.66	-0.17	0.19
SMB	1.81	**-2.20**	0.64	-0.03	0.83	-1.86
HML	-1.51	-0.02	-1.33	**-2.09**	-0.42	**-2.57**
RMW	**2.23**	**2.40**	**-3.63**	0.89	0.71	-1.52
CMA	0.71	0.94	-1.39	1.17	0.71	0.42
Mom	**6.19**	**4.79**	**5.04**	1.94	1.00	**7.19**
LT Rev	-0.11	0.40	-0.15	0.85	-0.94	1.69
C. Return contribution						
Alpha	0.11	0.70	0.87	1.01	0.54	0.44
Mkt-RF	-0.03	-0.02	0.01	0.06	-0.01	0.01
SMB	0.03	-0.05	0.02	0.00	0.02	-0.05
HML	-0.05	0.00	-0.07	-0.10	-0.02	-0.14
RMW	0.06	0.09	-0.14	0.04	0.03	-0.05
CMA	0.03	0.05	-0.09	0.08	0.05	0.02
Mom	0.21	0.22	0.24	0.10	0.05	0.32
LT Rev	0.00	0.01	-0.01	0.04	-0.04	0.06

Notes: This table shows the results of regressions of return differences between the filtered and the unfiltered portfolios on the FF5 (the market factor “Mkt-RF”, the size factor “SMB”, the book-to-market factor “HML”, the profitability factor “RMW”, and the investment factor “INV”), the momentum factor (“Mom”), and the long-term reversal factor (“LT Rev”). The return contribution is computed by the regression coefficient times the average risk premium of the corresponding risk factor. The alphas and returns are monthly returns in percentage. The t-values of the alpha and coefficient are calculated using Newey-West (1987) standard errors. Bold-faced t-values indicate the 5% significance.

To examine the effects of tilted characteristics in the filtering strategy on portfolio returns, we run time-series regressions of return differences between the filtered and the unfiltered portfolios on the FF5 plus the momentum (Mom) and the long-term reversal (LT Rev) factors. We then use the coefficient estimates to decompose the return differenc tributions by risk factors. Table 7 shows the regression results and the return contributions. While the rank deviations in the characteristics of MOM and LTR are relatively large, the LT Rev factor is insignificant in the regressions. The Mom factor significantly affects the outperformance of the filtered portfolios of the Size, BM, INV, and LET. The Mom factor also contributes to increase monthly returns of the Size, BM, INV, and LTR filtered portfolios by 0.21%, 0.22%, 0.24%, and 0.32% points, respectively. The profitability factor (RMW) positively affects the filtered Size and BM portfolio profits but negatively affects the filtered INV portfolio profits with small-sized return contributions. The size factor (SMB) and the book-to-market factor (HML) negatively affect some filtered portfolio profits. After controlling for the effects of risk factors, portfolio alphas of the filtered portfolios over the unfiltered portfolios are significant and large-sized in four cases (except for the Size and LTR portfolios). In sum, although the filtering strategy may introduce a tilting in firm characteristics, the tilting is not a main reason for the outperformance of the filtered portfolios.

3.7 Characteristics-based Zero-profit Portfolios

Contrary to the filtered profitable portfolios, if we select stocks with low accuracy, then we may obtain less profitable portfolios. We select the stocks with accuracies that belong to bottom x-percentile. We vary the bottom x-percentile from the bottom 90th to 10th percentile, decreasing it by 10 percentile points each step and see whether the long-short portfolio return becomes insignificant at the 5% level.

Table 8. Zero-profit Portfolios

	Model	Bottom x-percentile					
		Size	BM	INV	OP	MOM	LTR
Return		10	60	30	<10	<10	50
Risk-adjusted alpha	CAMP	90	10	30	10	<10	<10
	FF3	90	90	50	70	<10	90
	FF3+Mom	90	60	30	<10	<10	90
	FF5	90	90	70	90	<10	90
	FF5+Mom	90	80	50	90	<10	90

Notes: This table shows the results of forming zero-profit portfolios by selecting stocks of which accuracy belongs to bottom x-percentile. The bottom x-percentile varies from the bottom 90th to 10th, decreasing by 10 percentile points each step. The zero-profit is defined by the event that the long-short portfolio return becomes insignificant at the 5% level. The bottom x-percentiles are provided in the table.

Table 8 shows the results of forming these zero-profit portfolios. We use the returns or risk-adjusted alphas of the long-short port-folios to judge the zero-profit portfolios. Using Size as an example, while the Size long-short portfolio returns remain significant with only the bottom 10% of stocks, the corresponding alphas are significant with the bottom 90% of stocks. After the risk adjustment, more stocks tend to be included in the zero-profit portfolios. Notably, a high proportion of stocks do not deliver anomalous returns in most cases (except for the MOM). This result suggests that characteristics-based anomalous profits may not be prevalent among the cross section of stocks but rather be driven by only a small subset of high-accuracy stocks.

3.8. Additional Analyses

In this subsection, we perform several complementary analyses. Long leg vs. short leg, As characteristics-based portfolios consist of long and short legs, we decompose the relative gains of the filtered portfolio profits over the unfiltered ones into the two legs. Table 9 shows the results for the decomposition. The profit differences between the filtered and the unfiltered portfolios are positive and statistically significant for all characteristics (except the Size). These profit gains mainly come from the short leg.

Table 9. Profit Differences in the Long and Short Legs

Model	Filtered profits - unfiltered profits					
	Size	BM	INV	OP	MOM	LTR
Difference	0.361	1.002	0.824	1.217	0.629	0.617
(t-value)	1.806	**4.168**	**3.200**	**4.976**	**2.617**	**2.347**
Long-leg	0.297	0.094	-0.078	0.471	0.092	0.008
(t-value)	1.628	0.674	-0.370	**2.933**	0.475	0.044
Short-leg	0.064	0.908	0.902	0.747	0.537	0.608
(t-value)	0.526	**3.949**	**4.921**	**3.548**	**3.064**	**3.275**

Notes: This table shows the decomposition of the profit differences between the filtered and the unfiltered portfolios into the long and the short legs of the long-short portfolios. The returns are monthly returns in percentage. Bold-faced t-values indicate the 5% significance.

As Figure 1 shows, the accuracy index for stocks belonging to the first decile portfolios shows distributions that are different from those of stocks in the tenth decile portfolios. This difference in accuracy may be related to the relative gains from short legs. As Miller (1977) argues and Stambaugh, Yu, and Yuan (2012) provide supportive evidence, anomaly ally profits are more likely to be found in the short leg of long-short portfolios with short sales impediments. The profit decomposition result suggests that the filtering strategy deepens further the profits in the short leg rather than those in the long leg.

Controlling for correlation. As Table 2 shows, the filtered portfolio profits are highly correlated with the unfiltered portfolio profits. We investigate whether the outperformance of the filtered profits can survive even after controlling for a strong correlation between both profits. For that purpose, we regress the filtered profits on the long and the short legs of the unfiltered profits. Table A3 (of the Internet Appendix) shows the regression results. In most cases, the filtered profits tend to be more sensitive to changes in both the long and the short legs of the unfiltered profits; however, the filtered profits show significantly positive profits, even after controlling for this sensitive responsiveness.

Monotonicity. Table A4 (of the Internet Appendix) shows monthly returns of the decile portfolios for the unfiltered and the filtered portfolios. The unfiltered portfolio returns are largely monotonically aligned. This monotonicity implies that the firm characteristics systematically affects portfolio returns. The return monotonicity is also largely maintained for the filtered portfolios. To provide a complementary analysis, we also construct a fixed-accuracy filtered portfolio by applying a fixed threshold level for the accuracy index to select stocks. We vary the accuracy threshold and see whether the monotonicity is still maintained. Specifically, we select stocks according to the following four filtering rules: accuracy index rank range of [0, 100], [30, 100], [60, 100], and [90, 100] percentiles. Table A5 (of the Internet Appendix) shows that while applying a higher accuracy threshold for filtering stocks generates higher portfolio profits, decile portfolios exhibit largely monotonic profits.

4. ROBUSTNESS

To check the robustness of the results, we conduct several analyses in this section.

4.1. Value-weighted Portfolios

We form valued-weighted portfolios for the unfiltered and the filtering strategies and investigate whether the filtered portfolios still outperform the corresponding unfiltered portfolios. Table A6 (of the Internet Appendix) presents the summary statistics of the portfolio performances for both strategies and for each of the six firm characteristics. The Internet Appendix also shows their cumulative returns (Figure A7) and 10-year rolling cumulative returns (Figure A8). These results confirm that the filtering strategy also works well for valued-weighted portfolios. Interestingly, compared to equal-weighted portfolios, the outperformance of the filtering strategy is greater for valued-weighted portfolios in many cases.

4.2. Alternative Specifications

In addition to the benchmark specification for the filtering strategy, several variants are also conceivable. An alternative accuracy index (ACC2) is devised as follows:

$$ACC2_{j,t} = \frac{|k-l|}{\sum_{i=1}^{10}|k-l|}, \quad j \in P_{t-1}^{k},\ j \in Q_{t}^{l}, \tag{22}$$

Note that this alternative accuracy index measures the relative ratio of the deviation between the ex ante and the ex post portfolios. Based on the alternative accuracy index, we form the moving-average and recursive accuracy indexes, which are denoted as ACC2MA and ACC2RC, respectively. In addition, we consider alternative ways in determining the threshold level for stock selection. The benchmark method (expressed in Equation (5)) maximizes the previous M-period historical average return of the long-short portfolio, which we denote as (ma $= 1$) and (SR $= 0$).[12] Alternatively, we use the following variants. If we use all of the available historical returns instead of the previous M-period returns, then we denote it as (ma $= 0$). If we maximize an empirical Sharpe ratio instead of long-short portfolio returns, then we denote it as (SR $= 1$).

Table A7 (of the Internet Appendix) presents the profit differences between the filtering and the unfiltered strategies for various specifications and for each anomaly. The Internet Appendix (Figures A9 to A14) shows the cumulative profits of the filtering and the unfiltered strategies for various specifications and for each characteristics. Using all historical returns (ma $= 0$) instead of only recent returns (ma $= 1$) leads to inferior performances in all cases.

Maximizing the empirical Sharpe ratio (SR $= 1$) instead of long-short portfolio returns (SR $= 0$) also yields inferior performances. In most cases, the recursive accuracy index (ACCRC) delivers inferior portfolio profits. Employing the alternative accuracy index (ACC2) improves the performance in some cases but diminishes it in other cases. Despite theses performance changes for the filtering strategy, the performance comparisons between the two strategies confirm that the relative outperformance of the filtering strategy over the unfiltered one largely withstand these specification changes.

4.3. Accuracy-weighted Portfolios

Instead of equal-weighted portfolios, we form portfolios with the normalized accuracy index as the weight.[13] These accuracy-weighted portfolios assign weights that are proportional to the accuracy index (ACCMA). We investigate whether such accuracy-weighted portfolios result in superior performances compared to equal-weighted portfolios. The superior performances of the accuracy-weighted portfolios would be consistent with the outperformance of the filtered portfolios. Table A8 (Panel A) (of the Internet Appendix) shows the summary statistics of the profit difference between the accuracy-weighted portfolios and the equal weighted portfolios.

[12] We employ a 5-year moving window not only for the calculation of the historical mean of portfolio returns or the empirical Sharpe ratio (M $= 60$) but also for the moving-average accuracy index (m $= 60$).

[13] The cross section of the accuracy indexes is summed to one at each time.

The Internet Appendix (Figure A15) provides the cumulative profits of the accuracy-weighted portfolios for the filtering and the unfiltered strategies and for each of the six firm characteristics. The accuracy-weighted portfolios result in higher profits than the equal-weighted portfolios in all cases, and the differences in the returns are statistically significant in most cases. We also apply the accuracy-weighting to value-weighted portfolios. As Table A8 (Panel B) shows, we obtain similar results for the accuracy-value-weighted portfolios.

4.4. Quintile Portfolios

In addition to decile portfolios, we also form quintile portfolios and examine whether the filtering strategy can still render superior performances. Table A9 (of the Internet Appendix) presents the summary statistics of the performances of quintile portfolios under both strategies. The Internet Appendix (Figure A16) shows the cumulative profits of quintile portfolios for the filtering and the unfiltered strategies and for each characteristics. Consistent with the results for decile portfolios, the filtering strategy still outperforms the unfiltered strategy with quintile portfolios for each of the characteristics. The Internet Appendix (Table A10) also shows the returns of quintile portfolios for both strategies. The quintile portfolio returns are largely monotonically aligned for both strategies and in all characteristics cases. In sum the outperformance of the filtering strategy is robust to changes in the number of sorted portfolios.

4.5. Subperiod Analysis

We investigate whether the outperformance of the filtering strategy persists or exists only for specific subperiods. Figure 5 shows the portfolio profits of both strategies over a decade for each of the characteristics. The size of the outperformance of the filtering strategy over the unfiltered strategy varies with subperiods and characteristics; however, the outperformance of the filtering strategy largely persists over decades.

4.6. Transaction Costs

Table 10 shows the turnover ratios in percentages for a monthly portfolio rebalancing. Although the turnover ratio differs with portfolios, the filtering strategy consistently requires more trading than the unfiltered strategy. To investigate whether the outperformance of the filtering strategy remains after accounting for the effect of higher transaction costs, we compute the break-even costs to render zero return or risk-adjusted alpha. We use the Fama-French 3-factors for the risk adjustment. The relative outperformance of the filtering strategy would be nullified only with unrealistically high transaction costs, ranging from 0.36% to 0.99% (for return) or from 0.49% to 1.01% (for risk-adjusted alpha). This result confirms the outperformance of the filtering strategy, even in the presence of transaction costs.

Table 10. Transaction Costs

		Profits	Portfolios					
			Size	BM	INV	OP	MOM	LTR
Turnover (%)		Unfiltered	51.53	31.21	46.72	37.01	125.90	70.36
		Filtered	152.23	153.15	164.93	160.55	195.96	176.72
BE costs (%)	Return	Unfiltered	0.79	1.88	1.67	2.00	1.08	0.76
		Filtered	0.51	1.04	0.97	1.22	1.01	0.65
		Filtered - Unfiltered	0.36	0.82	0.70	0.99	0.90	0.58
	Alpha	Unfiltered	0.16	0.72	1.24	1.86	1.28	0.38
		Filtered	0.38	0.91	0.92	1.20	1.17	0.62
		Filtered - Unfiltered	0.49	0.95	0.79	1.01	0.97	0.77

Notes: This table shows the turnover ratios in percentage for the filtering and the unfiltered strategies. The break-even (BE) costs are also reported in percentage. The BE costs refer to the transaction costs to render zero portfolio return or risk-adjusted alpha. The Fama-French 3-factors are used for the risk adjustment.

4.7. Double-sorted Portfolios

We investigate whether the filtering strategy is applicable to double-sorted portfolios and whether it can still improve portfolio performance. To combine the filtering strategy with a double-sorting method, we construct individual accuracy indexes for each of the two sorting variables. By construction, the accuracy index ranges between zero and one.

We then form a composite accuracy index as a product of the two associated accuracy indexes for each of individual stocks. The composite accuracy index also ranges between zero and one and can effectively summarize accuracy components. We can apply the filtering strategy to double-sorted portfolios using the composite accuracy index. Table 11 shows the results of the filtering strategy applied to double-sorted portfolios. We form 5x5 equal-weighted portfolios by sorting on Size and then sorting the size quintiles by each of the other five characteristics (BM, INV, OP, MOM, or LTR). Therefore, we will consider five kinds of double-sorted portfolios. The long leg of the portfolio consists of the smallest Size with the highest BM, the lowest INV, the highest OP, the highest MOM, or the lowest LTR, while the corresponding short leg takes the opposite position. The filtering strategy shows superior performances, compared to the unfiltered one. The profit differences between the filtered and unfiltered strategies are positive for all cases, although they are statistically insignificant in some cases ($\text{Size} \times \text{OP}$ and $\text{Size} \times \text{LTR}$). We obtain similar results for risk-adjusted alphas. As more portfolios are formed (25 instead of 10 in our analysis), each portfolio contains less stocks, thus the advantage of the filtering could be smaller. The filtering strategy can still, however, significantly improve double-sorted portfolios in many cases.

Table 11. Double-sorted Portfolios

	Size-by-				
	BM	INV	OP	MOM	LTR
			A. Unfiltered profits		
Mean	0.474	0.536	0.879	1.115	0.582
(t-value)	**2.654**	**2.818**	**4.010**	**4.126**	**2.796**
			B. Filtered profits		
Mean	1.299	1.295	1.273	1.865	0.941
(t-value)	**3.634**	**3.181**	**2.663**	**3.996**	**2.171**
			C. Filtered profits - unfiltered profits		
Mean	0.825	0.759	0.393	0.750	0.359
(t-value)	**2.666**	**2.104**	0.942	**2.183**	0.955
			D. Filtered profits - unfiltered profits: alpha		
CAMP	0.955	0.856	0.490	0.911	0.461
FF3	1.048	1.237	0.549	0.915	0.760
FF3+Mom	0.543	0.633	0.238	0.524	0.189
FF5	0.733	1.109	0.604	0.711	0.618
FF5+Mom	0.338	0.612	0.334	0.399	0.163
			E. Filtered profits - unfiltered profits: t-value		
CAMP	**3.077**	**2.541**	1.188	2.671	1.245
FF3	**3.417**	**3.576**	1.276	**2.675**	**1.985**
FF3+Mom	1.717	1.889	0.555	1.386	0.501
FF5	**2.414**	**3.191**	1.360	1.810	1.614
FF5+Mom	1.064	1.821	0.759	0.987	0.422

Notes: This table shows the results of applying the filtering strategy to double-sorted portfolios. We form 5×5 equal-weighted portfolios by sorting on Size and then sorting the size quintiles by each of the other five characteristics (BM, INV, OP, MOM, or LTR). The long leg of the portfolio consists of the smallest Size with the highest BM, the lowest INV, the highest OP, the highest MOM, or the lowest LTR, while the corresponding short leg takes the opposite position. Panel A shows monthly returns (in percentage) of the long-short portfolios. We compute accuracy indexes for individual stocks by forming quintile ex ante and ex post portfolios based on each of characteristics. The composite accuracy index for double-sorted portfolios is formed as a product of the associated two accuracy indexes. We obtain filtered profits for double-sorted portfolios by using the composite accuracy index. Panel B shows monthly returns of the filtered strategy for double-sorted portfolios. Panel C shows the profit differences between the unfiltered and the filtered strategies. Panels D and E shows the risk-adjusted alphas and their t-values of the profit differences between the two strategies. The risk adjustment is based on the CAPM, the Fama-French 3-factor model (FF3), the Fama-French-Carhart 4-factor model (FF3+Mom), the Fama-French 5-factor model (FF5), and FF5 plus Carhart's momentum factor model (FF5+Mom). The risk-adjusted alpha indicates a monthly return in percentage. The t-values of the alpha are calculated using Newey-West (1987) standard errors. Bold-faced t-values indicate the 5% significance.

5. CONCLUSION

In this paper, we propose a new index for the measurement of the predictive power for future stock returns possessed by firm characteristics for individual stocks and also a new filtering strategy in which the index is used to filter out stocks with low predictive power in constructing portfolios. We find that the predictive power differs across the cross section of stocks. This filtering strategy significantly improves portfolio profits for several well-known firm characteristics. Our new method provides an effective way to exploit such profitable opportunities and thus is valuable for investors. We also proceed in the opposite direction and form filtered zero-profit portfolios. The results imply that characteristics-based anomalous profits may not be prevalent but rather be driven by only a small set of stocks. In addition, we find that the profit gains from the new method mainly come from the short leg. This result suggests that the filtering strategy deepens further the profits in the short leg rather than those in the long leg.

While this paper shows that the new method is applicable to several well-known characteristics in equity markets, it can be used for other characteristics, for other asset classes, and in other asset markets. This extension would be worthwhile to explore in future research.

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