Can prior information make market anomalies more anomalous? Evidence from common stocks*

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Abstract

In this paper, we propose a new method to improve the conventional market anomaly profits. The new method modifies the conventional anomaly strategy by filtering out equities with low predictability of anomaly attributes for future anomaly profits. We apply the new method into equity data and find that the new method significantly outperforms the conventional method for several well-known anomalies. The additional profits from the new method are largely driven by market inefficiency. Our results also suggest that market anomalies may not be prevalent but rather driven by only a small set of stocks.

Keywords: Market anomaly, Market efficiency, Sorting, Filtered sorting.

JEL classification: G11, G12.

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1 Introduction

Market anomalies refer to significant and persistent deviations of market prices from theoretical equilibrium. The existence of market anomaly may imply market inefficiency or suggest the deficiency of asset pricing models. Prior studies have uncovered many market anomalies and thereby contribute to our understanding about market inefficiency and to the development of asset pricing theory.[1] In this paper, instead of trying to discover new market anomalies, we explore a related but different question: Can prior information make market anomalies more anomalous? We maintain the existing method to find market anomalies but use information contained in the historical performances of the method to deepen anomalous profits. We document that such prior information can make existing market anomalies more anomalous.

Many market anomalies have been uncovered by a sorting method. For example, the so-called size premium refers to anomalous excessive returns of small stocks relative to big stocks. The size premium is conventionally shown by sorting stocks based on firm size known at portfolio formation time. While the sorting method implicitly assumes that the size effect exists pervasively or at least on average, we further hypothesize that the size effect differs across the cross section of stocks. If we effectively filter out stocks which deviate from the predictions by the size premium anomaly and form size portfolios with more conforming stocks, then the size premium would be greater. We name the new method as the "filtered sorting" and the conventional sorting method as the "unfiltered sorting" for contrast. To filter out less conforming stocks, we rely on historical information about the conformity of individual stocks. Therefore, the additional size premium arises from the predictive power of prior information and thus are likely to be related with market inefficiency.

For the size anomaly as an example, we measure the conformity level of individual stocks to the anomaly attribute as the deviation of the assignment of each stock to its ex ante portfolio from the assignment to the ex post portfolio. Here, the ex ante portfolios are formed by sorting on firm size whereas the ex post portfolios are formed by sorting on realized ex post returns. As a stock more conforms to the market anomaly, the assignment

[1] For a more detailed discussion about market anomalies, refer to, for example, Schwert (2003).

to the ex ante portfolio should be closer to the assignment to the ex post portfolio, and the accuracy index would become higher. We call the measure as the "accuracy" index. We select only stocks with high level of accuracy index to form market anomaly portfolios based on historical information about the suggested accuracy index for individual stocks available at each portfolio formation time. We apply this filtered sorting idea into several well-known market anomalies such as anomalies associated with size, book-to-market ratio, investment, operating income, momentum, and long-term reversal. We find significant additional market anomalous returns for all of these anomalies.

To provide empirical evidences for our arguments and to elicit implications, we conduct several analyses. We provide several empirical evidences that our new anomaly portfolios outperform conventional anomaly portfolios. We statistically confirm that the new anomaly portfolios offer higher returns than conventional anomaly portfolios in various settings by adjusting risks, controlling for the effect of transaction costs, and varying investment horizons. To check the robustness of our results, we consider several alternative methods to form anomaly portfolios, vary the number of portfolios, and perform subperiod analysis. Our results are robust to various specification changes. Therefore, our new anomaly portfolios offer investors greater trade profit opportunities. While the existence of additional trade profits from the new method after adjusting risks and net of transaction costs implies market inefficiency, our method to form new anomaly portfolios provides an effective way to exploit such profitable opportunities and thus is valuable for investors.

We examine whether individual stocks differ with the proposed accuracy index level and find that the accuracy index sufficiently differs across the cross section of stocks. It implies the possibility of effectively sorting out low-accuracy stocks in portfolio formation and also explains the reason why the filtered method works well. In addition, it also suggests the heterogeneity of stocks with respect to a chosen anomaly attribute. Contrary to the filtered anomaly portfolios, if we select low-accuracy stocks, then we may obtain less anomalous portfolios. We push this idea further and find that we can form filtered no-anomaly portfolios with a high proportion of stocks in most cases. This finding suggests that market anomalies may not be prevalent among the cross section of stocks but rather driven by only a small subset of high-accuracy stocks. As some market anomaly attributes have been suggested as empirical proxies for risk factors, this finding also has some asset pricing implications. Specifically, as more (less) stocks are conforming to an anomaly attribute, 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 accuracy level of stocks in the long leg of the anomaly portfolio differs from that of the short leg. Therefore, the gains of the filtered method may asymmetrically come from either the long- or short-leg. Moreover, we decompose the relative gains of the filtered method over the unfiltered one into the long- and short-leg and find that the profit gains mainly come from the short-leg. As short sales are restrictive or costly in reality, the additional anomaly profits may be driven by market inefficiency related with short-sale restrictions.[2]

We develop an aggregate accuracy index by averaging the cross section of 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 measure not only confirms our hypothesis but also proves its validity as a conformity measure. The aggregate accuracy measure also can be used as a new information variable for return predictability of anomaly portfolios.

Out paper is closely related to Suh (2018) who also employs the idea of filtered-sorting; however, while Suh (2018) applies it into only the currency carry trade strategy, we apply it into many anomalies in equity markets. Furthermore, both are quite different in the accuracy measure and other implementations of the filtered-sorting method. This paper is also related to literature about improving anomaly profits.[3] Although our method does not uncover new

[2]This finding is related with Miller's (1977) argument that, with short-sale impediments, overpricing should be more prevalent than underpricing. It implies that anomaly profits are more likely to be found in the short-leg of long-short anomaly portfolios. Our method also finds additional anomaly profits in the short-leg. Relatedly, Stambaugh, Yu, and Yuan (2012) explore empirical implications of the Miller argument on anomlay profits.

[3]For momentum profits as an example, a double sort strategy based on a combination of momentum and reversal signals was examined in commodity futures contracts (Bianchi, Drew, and Fan (2015)) and in international equity market indices (Malin and Bornholt (2013)). Balvers and Wu (2006) proposed a parametric combination of momentum and mean reversion and applied it into international equity market indices. Rachev, Jašić, Stoyanov, and Fabozzi (2007) and Choi, Kim, and Mitov (2015) modified the mo-

market anomalies, our method is applicable to quite a wide range of anomalies and thus indirectly related to literature about uncovering market anomalies.

The rest of this paper is organized as follows. Section 2 introduces the new filtered method to form market-anomaly portfolios and compares it with the unfiltered method. Section 3 provides several empirical analyses. It first introduces the market anomalies to be studied in our analysis and then explains the data to be used, presents performance results of the new method relative to the conventional one. In addition, it also presents empirical results about the characteristics of the accuracy index, predictive powers of the aggregate accuracy index, and other complementary analysis for our better understanding about the relative outperformance of the new method. In Section 4, we provide results for some robustness checks. We consider the effect of transaction costs on anomaly profits, alternative specifications, subperiod and other analyses. Section 5 concludes the paper.

2 Methodology

2.1 Unfiltered market-anomaly portfolios

To construct market anomaly portfolios, we sort all stocks in ascending order based on their month $t-1$ value for a chosen market anomaly attribute variable in each month t. We allow one month between the end of the formation period and the beginning of the holding period, which helps to avoid microstructure biases. We form ten equal-weighted portfolios with stocks belonging to each of these sorts, from the first decile (P^1) to the tenth decile (P^{10}). Every month, a market anomaly strategy prescribes to form a long-short portfolio by going long in the tenth portfolio and short in the first portfolio if the market anomaly attribute variable is positively correlated with future stock returns. For a negative correlation

mentum strategy by sorting based on reward-risk measures. De Groot, Karstanje, and Zhou (2014) used term-structure information to implement momentum strategy in commodity futures contracts. Blitz, Huij, and Martens (2011) proposed 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) proposed new momentum strategies to manage momentum crash risks. Suh and Kim (2018) used investor sentiment to improve momentum profits and prescribes decisions to make more (less) investment with optimistic (pessimistic) sentiment.

between the attribute variable and future stock returns, the long-short portfolio is formed in the reverse direction. The long-short market anomaly portfolio return at t, R_t, is computed as

$$R_t = \begin{cases} R_t^{10} - R_t^1, & \rho > 0 \\ R_t^1 - R_t^{10}, & \rho < 0 \end{cases}, \tag{1}$$

where R_t^{10} (R_t^1) denotes the return at time t of the tenth (first) decile portfolio which is formed at $t-1$, and ρ indicates an ex ante correlation between the attribute variable and future stock returns.

2.2 Filtered market-anomaly portfolios

The filtered-sorting strategy consists of two stages to form market anomaly portfolios. In the first stage, we employ the conventional unfiltered sorting method to assign each of stocks to one of decile portfolios sorted on the market anomaly attribute variable. In the second stage, we assess the predictive power of a chosen market anomaly attribute variable for future returns and then filter out stocks with low return predictive power from the set of investable stocks. We then form decile and long-short portfolios using only the filtered stocks.

To assess the ability of the market anomaly attribute variable to predict the return for one-month holding period, we devise a nonparametric indicator called as the *accuracy index*. The accuracy index is a dummy variable to indicate whether the market anomaly attribute variable correctly assigns stocks to their optimal decile portfolios. The optimal decile portfolios would be formed by sorting on ex post realized returns in which sense we name them as *ex post* portfolios. The maximum long-short portfolio return could be obtained by this ex post long-short portfolio. In contrast, the usual long-short portfolio can be called as *ex ante* portfolio. If a stock j is assigned to ex ante portfolio k at time t, then the accuracy index for stock j at time t takes one if stock j's ex post portfolio also turns out to be portfolio k and zero otherwise. The accuracy index (ACC) is formally defined as follows:

$$ACC_{j,t} = \begin{cases} 1, & j \in P_t^k, j \in Q_t^k, \\ 0, & j \in P_t^k, j \notin Q_t^k, \end{cases}, \tag{2}$$

where P_t^k and Q_t^k denote ex ante and ex post portfolio k at time t, respectively. To utilize historical information about the accuracy index, we form the following moving-average (ACCMA) and recursive (ACCRC) accuracy indexes:

$$\begin{aligned} ACCMA_{j,t} &\equiv \frac{1}{m}\sum_{\tau=0}^{m-1} ACC_{j,t-\tau}, \quad (3) \\ ACCRC_{j,t} &\equiv \frac{1}{t}\sum_{\tau=0}^{t-1} ACC_{j,t-\tau}. \quad (4) \end{aligned}$$

We then filter out stocks with the accuracy index less than a threshold level $\overline{\omega}_t$ at each month t. We use historical long-short portfolio returns to determine the threshold level for stock selection. Formally, the threshold level $\overline{\omega}_t$ at each month t, is determined as a level to maximize the previous $M-$period historical average return of the long-short portfolio:

$$\overline{\omega}_t \in \arg\max_{\overline{\omega}} \frac{1}{M}\sum_{\tau=1}^{M} R_{t-\tau}\left(S_{t-\tau}\left(\overline{\omega}\right)\right), \quad (5)$$

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

$$\begin{aligned} S_t\left(\overline{\omega}\right) &\equiv S_t^1\left(\overline{\omega}\right) \cup S_t^{10}\left(\overline{\omega}\right), \quad (6) \\ S_t^k\left(\overline{\omega}\right) &\equiv \left\{ j \,\middle|\, j \in P_t^k, ACCMA_{j,t} \geq \overline{\omega} \right\}, \ k = 1, 10. \quad (7) \end{aligned}$$

Here, $S_t^1\left(\overline{\omega}\right)$ and $S_t^{10}\left(\overline{\omega}\right)$ denote the set of filtered assets for the first and the tenth decile portfolios. $R_\tau\left(S_\tau\left(\overline{\omega}\right)\right)$ denotes the long-short portfolio returns with the set of assets $S_\tau\left(\overline{\omega}\right)$ at month τ. If the signal ratios change over time, the threshold level $\overline{\omega}_t$ would also 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

$$R_{Filtered,t} = R_t\left(S_t\left(\overline{\omega}_t\right)\right) = \begin{cases} R_t^{10}\left(S_t^{10}\left(\overline{\omega}_t\right)\right) - R_t^1\left(S_t^1\left(\overline{\omega}_t\right)\right), & \rho > 0 \\ R_t^1\left(S_t^1\left(\overline{\omega}_t\right)\right) - R_t^{10}\left(S_t^{10}\left(\overline{\omega}_t\right)\right), & \rho < 0 \end{cases}. \quad (8)$$

Note that the filtered-sorting strategy prescribes decisions to dynamically change the set of equities to form long-short portfolios. For comparison, $S_t(0)$ denotes the whole set of assets available for investment, and thus the unfiltered long-short portfolio at month t (Eq. (1)) can be rewritten as:

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

3 Empirical analysis

3.1 Market anomalies

For our empirical analysis, we choose six well-known market anomalies: 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 tend to earn higher average returns than is 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 ratio show higher average returns than firms with low BM ratio. 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) included the size and the value premium effects into 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 return. Aharoni, Grundy, and Zeng (2013) document evidences for a relationship between investment and average return.[5] The effects of profitability (OP) and investment (INV) on average return were incorporated into the Fama-French (2015) five-factor model. The momentum effect shows that past returns (during 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 has documented significantly posi-

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

[5] For anomalies related with investment and profitability, 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).

tive and pervasive momentum profits.[6] The long-term reversal effects was documented by DeBondt and Thaler (1985). It indicates that past returns (during 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

We will apply the unfiltered and filtered methods into the U.S. individual stocks. We use all common stocks (share codes 10 and 11) listed in the New York and American Stock Exchanges from the Center for Research in Security Prices (CRSP) monthly file. 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 sorted with NYSE breakpoints. Our data selection criterion is consistent with prior studies (e.g., Jegadeesh and Titman (1993) and Han, Zhou, and Zhu (2016)).[7]

3.3 Distribution of accuracy index

The filtered-sorting method relies on the hypothesis that the predictive power of market anomaly attribute variable to forecast future returns is differentiated across the cross section of stocks. We use the accuracy index to examine the hypothesis. Under the null hypothesis that the market anomaly attribute variable does not possess any forecasting power, the accuracy index would have the mean value of one tenth for decile portfolios. Figure 1 shows empirical distributions of individual accuracy index (ACC) averaged over the sample

[6] For example, Jegadeesh and Titman (1993) and Asness (1994) sorted firms on the basis of three- to 12-month past returns and showed momentum profits in U.S. common stock returns from 1965 to 1989. Jegadeesh and Titman (2001) also documented momentum profits in a later period from 1990 to 1998. Israel and Moskowitz (2013) extended the period from 1927 to 1965 and from 1990 to 2012. Momentum profits were 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 reported momentum profit evidences across multiple markets and asset classes.

[7] All of the conventional (unfiltered) anomaly profit data in our analysis are available at Kenneth French's Data library. We closely follow the method to generate anomaly portfolios.

period for each of the six market anomalies and for all (All), the first (P^1) or 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 shows a distribution which is quite different from that of all stocks. Specifically, the proportion of stocks with high accuracy in the extreme portfolios is higher than that in all stocks. These observations largely support our hypothesis that market anomaly attribute variables possess predictive powers only for some stocks but not for all. Therefore, it would be profitable to effectively exclude such low-accuracy stocks in the portfolio.

3.4 Aggregate accuracy index

To support the validity of the proposed accuracy index, we examine whether the accuracy index can explain market anomaly profits well. In other words, a high level accuracy should be translated into a high profit of an anomaly portfolio. We construct aggregate accuracy indexes by averaging the cross section of accuracy indexes at each time. We then perform the following explanatory regression:

$$R_t = \alpha + \beta_1 ACCAG_{long,t} + \beta_2 ACCAG_{short,t} + \epsilon_t, \tag{10}$$

where R_t denotes a chosen long-short market anomaly profit at time t, $ACCAG_{long,t}$ and $ACCAG_{short,t}$ indicate aggregate accuracy indexes by averaging the cross section of accuracy indexes belonging to the long- and the short-leg portfolios, respectively. As Table 1 shows, the regression results imply that an increase in accuracy in both the long and short legs is well translated into an increase in the anomaly profits with R-squares ranging from 35% to 59%.

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

$$R_t = \alpha + \beta_1 ACCAG_{long,t-1} + \beta_2 ACCAG_{short,t-1} + \epsilon_t. \tag{11}$$

Table 1 also shows the forecasting regression results. Noteworthily, current aggregate accuracy indexes are positively correlated with future anomaly 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 anomalies while the long-leg aggregate accuracy index possesses significant forecasting powers for the BM anomaly. For the MOM anomaly, the long- and short-leg accuracy indexes are positively but insignificantly correlated with future anomaly profits.

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 monthly market-anomaly returns for each of accuracy states. We also consider contemporaneous (explanatory) and one-month lagged (forecasting) state classifications. Table 2 provides the results that market-anomaly returns are monotonically aligned with accuracy state. Further, the market anomaly returns are significantly higher during high accuracy states than low accuracy states not only in the explanatory state classification but also in the forecasting state classification. The Internet Appendix (Table A1) also provides the results for two alternative state classifications: top 20% and bottom 20%, or top 40% and bottom 40%. The results with alternative thresholds qualitatively remain the same. In sum, the results from both the regressions and the accuracy state classification suggest that the aggregate accuracy indexes possess not only explanatory power but also predictive power for market anomaly profits.

3.5 Portfolio performance

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

Summary statistics. Figure 2 shows cumulative returns of the filtered and the unfiltered portfolios for each of six market anomalies over the sample period. Remarkably, the filtered-sorting method shows cumulative returns which have grown much faster that those of the unfiltered-sorting method in all cases. Table 3 presents summary statistics of the profits from both methods. The conventional market-anomaly strategy generates 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 market anomalies. Notably, the filtered method yields much higher mean returns (ranging from 0.77% to 1.99% per month) than the unfiltered method in all cases. Although the filtered method yields higher volatilities than the unfiltered method, the Sharpe ratios of the filtered method (ranging from 0.36 to 0.85) are higher than those of the unfiltered (ranging from 0.30 to 0.76) in all cases (except the MOM). Interestingly, the filtered profit tends to be less skewed and thinner tailed than the unfiltered profit in most cases. The filtered method uses only a small portion (ranging from 9.1% to 16.9%) of stocks to form anomaly portfolios. Table 4 shows correlation coefficients between filtered and unfiltered anomaly profits. As expected, the filtered profits are highly correlated with the unfiltered profits; however, correlation coefficients between filtered profits and the corresponding unfiltered profits range from 0.451 to 0.745, and thus they are far from perfect correlation.

Risk-adjusted returns. We examine whether higher profits of the filtered method simply reflect more loadings on economic risk factors. To account for the effect of risk-taking on the filtered anomaly profits, we compute risk-adjusted filtered anomaly profits based on popular asset pricing models: the CAPM, Fama-French (1992, 1993) 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF3+mom), Fama-French (2015) 5-factor model (FF5), and FF5 plus Carhart's (1997) momentum factor model (FF5+mom).

Table 5 presents the risk-adjusted filtered anomaly profits as well as the risk-adjusted anomaly profit differences between the filtered and the unfiltered profits. While the risk-adjusted returns of the filtered are significantly positive in most cases, the risk-adjusted returns of the filtered are much greater than those of the unfiltered method. The difference between the risk-adjusted returns of both methods is positive and highly significant in most cases. This result implies that higher returns of the filtered method (relative to the unfiltered method) remain robust to these risk-adjustments.

Investment horizon. One-period analysis holds true for multi-periods only under some restrictive assumptions.[8] With general (and realistic) situations, it would be desirable to measure performance over an appropriate horizon. In that sense, it would be legitimate to compare 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, one-month horizon seems too short, with which performances are measured and shown in Table 3. Although investment horizons are various, 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 methods. With a 10-year horizon, the filtered method delivers better performance than the unfiltered method in most periods and most cases.

Hypothesis tests. Figure 4 illustrates empirical densities of both anomaly profits with a 10-year horizon. The unfiltered method yields positive returns in most chances. While the filtered profits tend to be more dispersed than the unfiltered returns, they distribute 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 unduly penalizes high volatility even when it is associated with positive and high returns, which is not a risk, but rather a potential gain. To take into account this consideration, we not only use the SR but also other measures for formal hypothesis tests: the Sortino ratio (SO), the upside potential ratio (UP), and the omega ratio (OM). The SO penalizes only with downside risk. The UP penalizes upside gains (relative to a target return) with downside risk. The OM measures the ratio of upside gain to downside loss relative to a target return. The Internet Appendix provides detailed explanations about these measures.

Based on these measures, we formally test the null hypothesis that both methods equally perform against the alternative hypothesis that the filtered method performs better than the unfiltered method. The p-value is calculated using a bootstrapping method.[9] Table 6

[8] For example, if returns follow an identically and independently normal dirstibution, then a one-period analysis can also hold for multi-periods. However, as Table 3 suggests, one-period returns are not normally distributed with fat tails.

[9] We employ a block bootstrapping method to account for potential serial dependence. We also conduct a bootstrapping method assuming serial independence for robustness check. We find that both results are

presents the hypothesis test results based on the four performance measures with a 10-year horizon. For performance comparison, we set the target return as the mean return of the unfiltered method, with which the SO is zero, and the OM is one for the unfiltered method. The SR of the filtered method is significantly higher than that of the unfiltered method 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 filtered method outperforms the unfiltered method by providing significant relative upside gains.

3.6 Additional analyses

In this subsection, we perform several complementary analyses.

Long-leg vs. short-leg. As anomaly long-short portfolios consist of long- and short-legs, we decompose the relative gains of the filtered profits over the unfiltered ones into the two legs. Table 7 shows the results for the decomposition. The profit differences between the filtered and the unfiltered portfolios are positive and statistically significant for all anomalies (except the Size). These profit gains mainly come from the short-leg. As Figure 1 shows, the accuracy index for stocks belonging to the first decile portfolios shows distributions which are different from those of stocks in the tenth decile portfolios. This difference in accuracy may be related with the relative gains from short-legs.

Controlling for correlation. As Table 4 shows, the filtered anomaly profits are highly correlated with the unfiltered anomaly profits. We investigate whether the outperformance of the filtered profits simply reflects a strong correlation between both profits. For that purpose, we regress the filtered profits on the long- and the short-leg of the unfiltered profits. Table 8 shows the regression results. In most cases, the filtered profits tend to more sensitively respond to changes in both of the long- and the short-leg of the unfiltered profits; however, the filtered profits show significantly positive profits even after controlling for this sensitive responsiveness.

Monotonicity. Table 9 shows monthly returns of decile portfolios for the unfiltered

qualitatively similar in our analysis.

and the filtered anomaly portfolios. The unfiltered anomaly portfolio returns are largely monotonically aligned. This monotonicity implies that the market anomaly attribute systematically affects portfolio returns. The return monotonicity is also largely maintained even after the filtering. For a complementary analysis, we also construct a fixed accuracy filtered portfolio by apply a fixed accuracy threshold to select stocks. We vary the accuracy threshold level 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] percentile. Table 10 shows the result that while applying a higher accuracy threshold for filtering stocks generates higher anomaly profits, decile portfolios exhibit largely monotonic profits.

Independence. For the Size as an example, if the filtering is strongly correlated with the market anomaly attribute (i.e., firm size) itself, then filtered stocks in the long (short) leg tend to be large (small) stocks. In such a case, the outperformance of the filtered portfolio mainly comes from a smaller set of more extreme stocks and thus may be spurious. To check this possibility, Figure 5 shows the rank distributions of anomaly attributes of stocks in the filtered long- or short-leg of anomaly portfolios relative to all stocks in the unfiltered long- or short-leg for each of six anomalies. Under the null hypothesis of no-correlation, the ranks of anomaly attributes of the filtered-in stocks should be uniformly distributed. As Figure 5 illustrates, the anomaly attribute rank of the selected stocks is largely uniformly distributed in both the long- and the short-leg and also for all cases. This fact implies that the relative outperformance of the filtered portfolio is not spurious.

Filtered no-anomaly portfolios. Contrary to the filtered anomaly portfolios, if we select stocks with low accuracy, then we obtain less anomalous portfolios. We select stocks of which accuracy belongs to bottom x-percentile. We vary the bottom x-percentile from bottom 90th to 10th, decreasing with 10 percentile points and see whether the long-short portfolio return becomes insignificant at 5% level. Table 11 shows the results of forming this no-anomaly portfolios. We use returns or risk-adjusted alphas of the long-short portfolios to judge the no-anomaly. For the Size as an example, while the Size long-short portfolio returns remain significant with only bottom 10% stocks, the corresponding alphas are significant with bottom 90% stocks. After risk-adjustment, more stocks tend to be included in the portfolio to generate significant anomalous portfolio returns. Noteworthily, a high proportion of stocks do not deliver anomalous returns in most cases (except for the MOM). This result suggests that market anomalies may not be prevalent among the cross section of stocks but rather driven by only a small subset of high-accuracy stocks.

Diversification benefits. We consider investors who already hold well-diversified portfolios and examine whether adding filtered anomaly portfolios into the diversified portfolios provides relative gains, compared to unfiltered anomaly portfolios. The market minus risk-free portfolio (RMRF), Fama-French 3-factors (FF3), or Fama-French-Carhart 4-factors are considered as background portfolios. We form equal-weight portfolios with background portfolios and filtered/unfiltered anomaly portfolios. In most cases, filtered anomaly portfolios render relative gains over unfiltered anomaly portfolios even in the presence of background risks.

4 Robustness

In this section, we provide several results for robustness checks.

4.1 Value-weighted portfolios

We form valued-weighted anomaly portfolios for the unfiltered and the filtered methods and investigate whether the filtered anomaly portfolios still outperform the corresponding unfiltered portfolios. Table 13 presents the summary statistics of portfolio performances for both methods and for each of six anomalies. The Internet Appendix also shows their cumulative returns (Figure A1) and 10-year rolling cumulative returns (Figure A2). These results confirm that the filtered-sorting method also works well for valued-weighted anomaly portfolios. Interestingly, compared to equal-weight portfolios, the outperformance of the filtered method is greater for valued-weighted portfolios in many cases.

4.2 Alternative specifications

Besides the benchmark specification for the filtered-sorting method, several variants are also conceivable. An alternative accuracy index (ACC2) is devised as follows:

$$ACC2_{j,t} = \frac{|k-l|}{\sum_{l=1}^{10}|k-l|}, \quad j \in P_t^k,\ j \in Q_t^l. \tag{12}$$

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

Table 14 presents profit differences between the filtered and the unfiltered methods for various specifications and for each anomaly. The Internet Appendix (Figures A3 to A8) shows cumulative profits of the filtered and the unfiltered methods for various specifications and for each anomaly. 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, recursive accuracy index (ACCRC) delivers inferior anomaly profits. Employing the alternative accuracy index (ACC2) improves performances in some cases but deteriorates in other cases. Despite theses changes in performances of the filtered method, however, the performance comparisons between two methods confirm that the relative outperformance of the filtered method over the unfiltered one largely holds for specification changes.

4.3 Accuracy-weighted portfolios

Instead of equal-weight portfolios, we form portfolios with normalized accuracy index as weight.[10] This accuracy-weight portfolios put weights proportional to accuracy. We investigate whether such accuracy-weight portfolios render superior performances, compared to equal-weight portfolios. Superior performances of the accuracy-weight portfolios would be consistent with the outperformance of the filtered portfolios. Table 15 (Panel A) shows summary statistics of the profit difference between the accuracy-weight portfolios and the equal-weight portfolios. The Internet Appendix (Figure A9) shows cumulative profits of the accuracy-weight portfolios for the filtered and the unfiltered methods and for each anomaly. The accuracy-weight portfolios show higher profits than the equal-weight portfolios in all cases, and the return differences are statistically significant in most cases. We also apply the accuracy-weighting into value-weight portfolios. As Table 15 (Panel B) shows, we obtain similar results for the accuracy-value-weight portfolios.

4.4 Quintile portfolios

Besides decile portfolios, we also form quintile portfolios and examine whether the filtered method can still render superior performances. Table 16 presents summary statistics of performances of quintile anomaly portfolios under both methods. The Internet Appendix (Figure A10) shows cumulative profits of quintile anomaly portfolios for the filtered and the unfiltered methods and for each anomaly. Consistent with the case for decile portfolios, the filtered method outperforms the unfiltered method with quintile portfolios for each of the anomalies. The Internet Appendix (Table A2) also shows returns of quintile portfolios for both methods. Quintile portfolio returns are largely monotonically aligned for both methods and in all anomaly cases. In sum, the outperformance of the filtered method is robust to changes in the number of sorted portfolios.

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

4.5 Subperiod Analysis

We investigate whether the outperformance of the filtered method exists persistently or only for specific subperiods. Figure 6 shows anomaly profits of both methods during a decade for each of the anomalies. The size of the outperformance of the filtered method over the unfiltered method varies with subperiods and anomalies; however, the outperformance of the filtered method largely exists persistently over decades.

4.6 Transaction costs

Table 17 shows turnover ratios in percentage for monthly portfolio rebalancing. Although the turnover ratio differs with anomaly, the filtered method consistently requires more trading than the unfiltered method. To investigate whether the outperformance of the filtered method still exists 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 ourperformance of the filtered method 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 filtered method even in the presence of transaction costs.

5 Conclusion

In this paper, we propose a new method to deepen existing market anomaly profits. The new method uses only prior information provided by the existing method to filter out stocks that are less conforming to market anomalies. This additional filtering process can successfully improve market anomaly profits for several well-known market anomalies. The additional profits from the new method are largely driven by market inefficiency. Our new method also 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 no-anomaly portfolios. The results imply that market anomalies may not be prevalent but rather 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 additional anomaly profits may be driven by market inefficiency related with short-sale restrictions.

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

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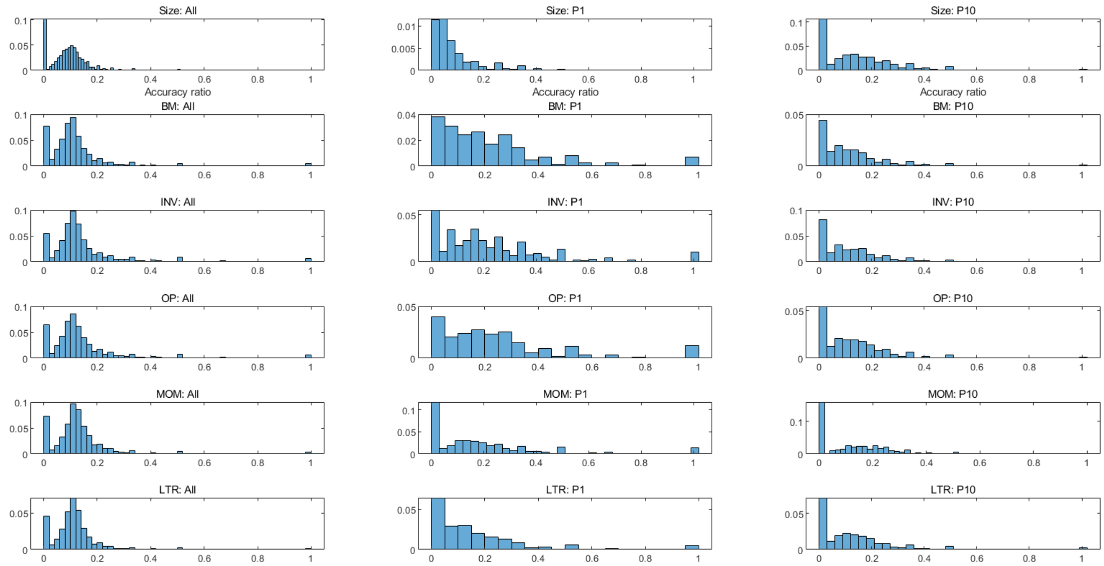

Figure 1. Distribution of accuracy index. This figure shows empirical distributions of individual accuracy index (ACC) averaged over the sample period for each of six market anomalies and for all (All), the first (P1) or the tenth (P10) decile portfolios.

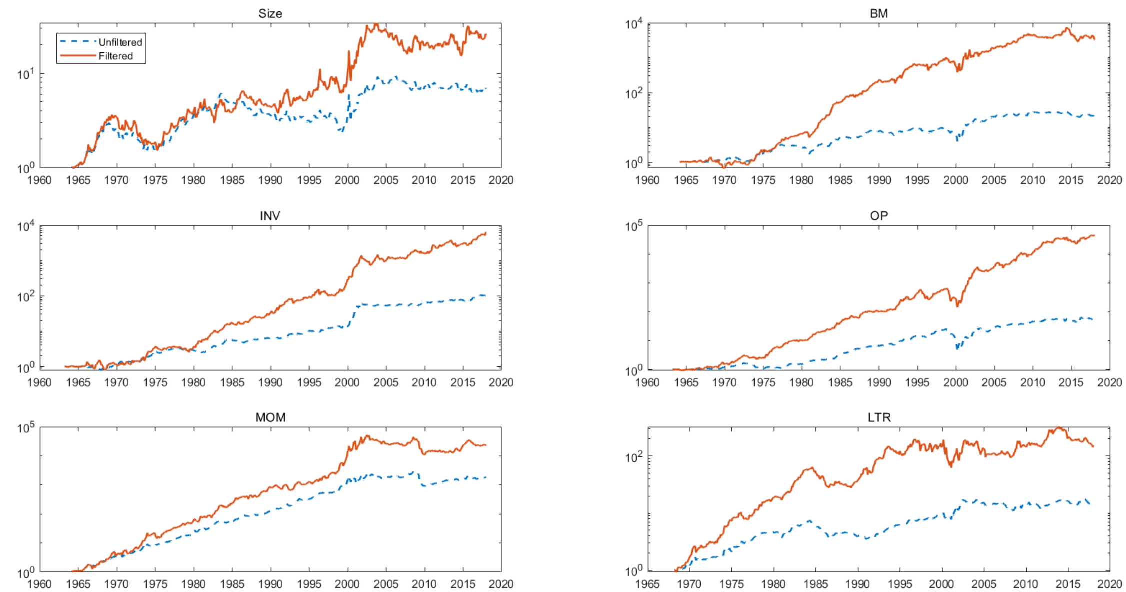

Figure 2. Cumulative market-anomaly profits. This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale.

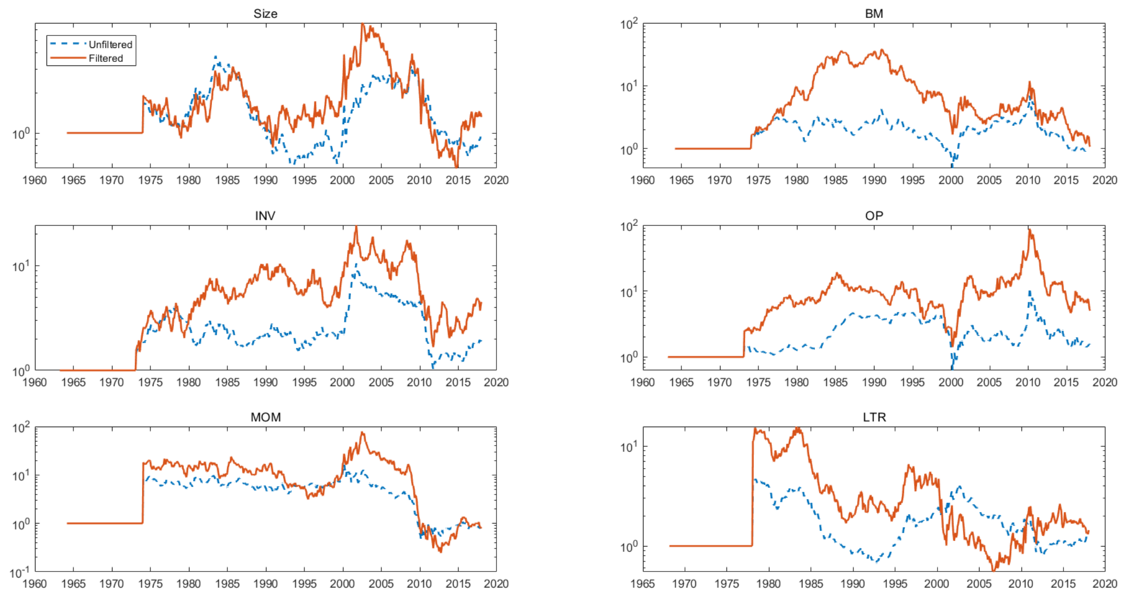

Figure 3. Rolling cumulative market-anomaly profits. This figure shows the time trends of 10-year rolling cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale.

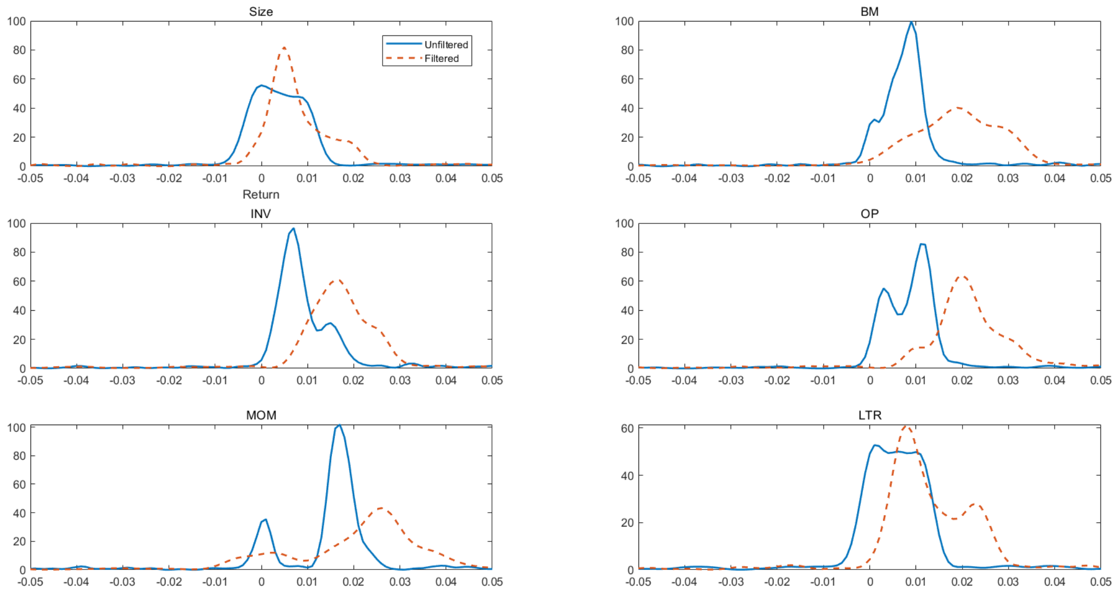

Figure 4. Empirical densities of rolling cumulative market-anomaly profits. This figure shows the empirical densities of 10-year rolling cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies.

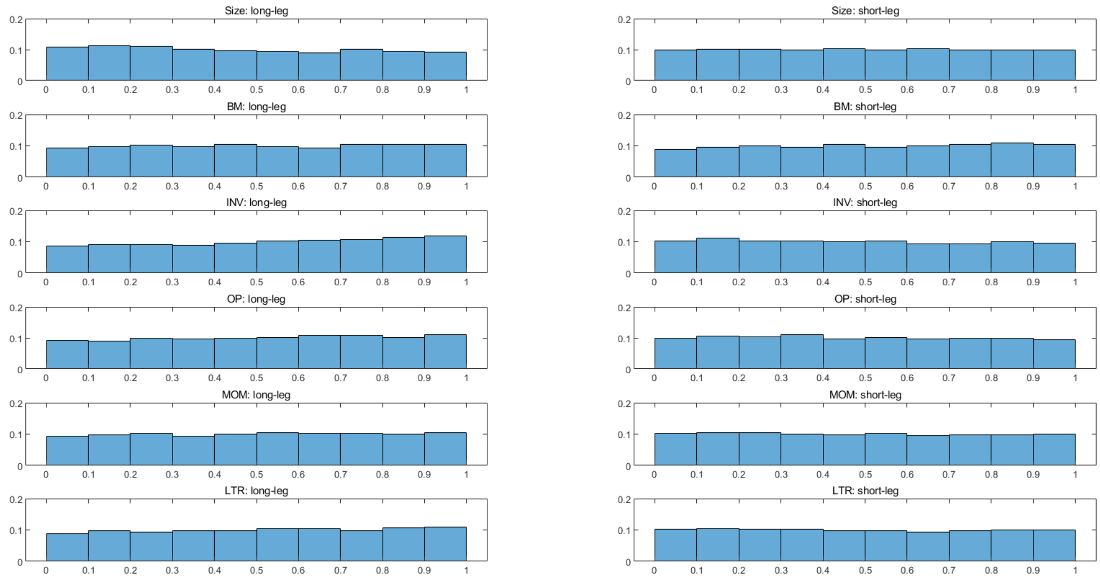

Figure 5. Rank distributions of market anomaly attributes in the filtered long- or short-leg portfolios. This figure shows the rank distributions of anomaly attributes of stocks in the filtered long- or short-leg of anomaly portfolios relative to all stocks in the unfiltered long- or short-leg for each of six anomalies.

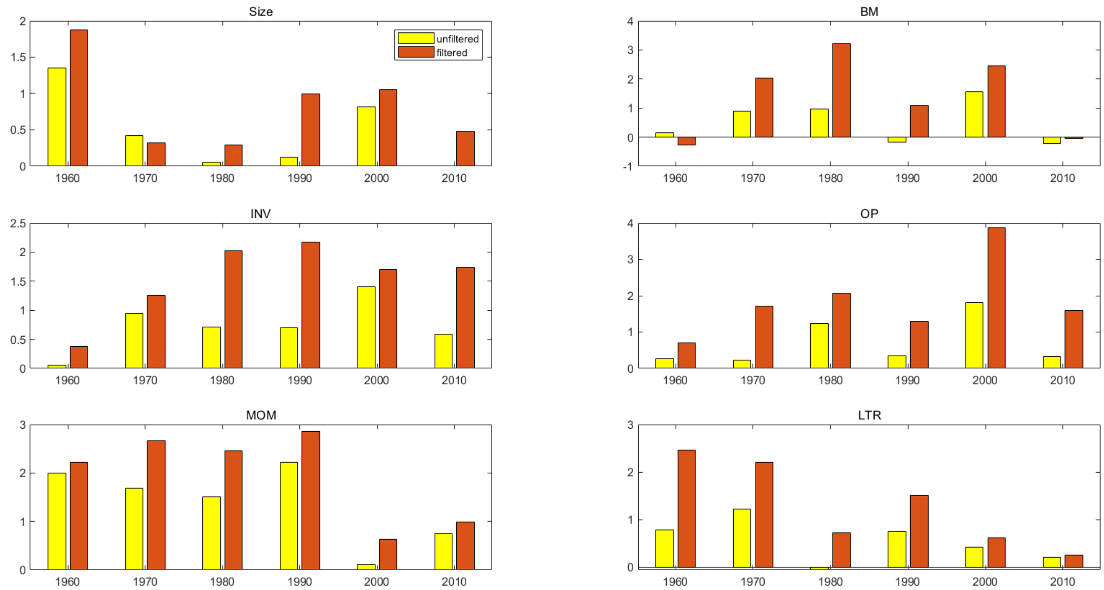

Figure 6. Anomaly profits during a decade. This figure shows anomaly profits of the filtered and the unfiltered methods during a decade for each of six anomalies.

Table 1. Regressions of market-anomaly profits on aggregate sorting accuracies

This table shows the results for the regressions of market-anomaly profits on aggregate sorting accuracies for each of six anomalies. Market-anomaly profits are regressed on contemporaneous ("Explanatory") or one-month lagged ("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.

		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**	

Table 2. Accuracy state and market-anomaly profits

This table shows monthly market anomaly returns (%) according to the contemporaneous ("Explanatory") or one-month lagged ("Forecast") accuracy state for each of six market anomalies. Based on the long or short leg 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 market anomaly portfolios between "high" and "low" states and their t-values are also provided. Bold-faced t-values indicate the 5% significance.

		Accuracy state				
		low	middle	high	h-l	(t-value)
		Explanatory				
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	**10.98**
	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**
		Forecast				
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	1.49	**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**

Table 3. Summary statistics

This table shows summary statistics of the unfiltered and the filtered market-anomaly profits for each of six market anomalies, 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 sorting method to available stocks (Proportion) is also provided.

	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

Table 4. Correlations

This table shows correlation coefficients between unfiltered and filtered market-anomaly profits.

		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	0.024	-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

Table 5. Risk-adjusted returns

This table shows the results about risk adjustment not only for market-anomaly profits of the filtered method but also for market-anomaly profit differences between the filtered and the unfiltered methods. The risk adjustment is based on CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF3+mom), Fama-French 5-factor model (FF5), FF5 plus Carhart's momentum factor model (FF5+mom). The risk-adjusted alpha indicates an annualized 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.

Model	Portfolios					
	Size	BM	INV	OP	MOM	LTR
	Filtered profits: alpha					
CAPM	8.21	22.45	20.46	24.39	24.59	14.65
FF3	6.94	16.65	18.13	23.20	27.60	13.08
FF3+mom	0.61	15.72	14.98	21.23	12.70	6.52
FF5	5.54	11.75	18.42	14.08	25.22	11.53
FF5+mom	0.36	11.50	15.79	13.42	12.89	6.47
	Filtered profits: t-value					
CAPM	**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					
CAPM	4.89	13.24	9.06	14.14	7.81	7.47
FF3	5.89	13.95	11.20	14.95	8.17	9.89
FF3+mom	2.41	10.21	7.74	13.08	7.23	4.79
FF5	4.03	11.29	13.64	13.52	7.08	9.39
FF5+mom	1.28	8.41	10.44	12.12	6.40	5.32
	Filtered profits - unfiltered profits: t-value					
CAPM	**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**	**3.46**	**3.75**	**2.00**	1.83

Table 6. Hypothesis testing

This table shows the results of hypothesis tests for the null hypothesis that both the filtered and the unfiltered methods equally perform and for the alternative hypothesis that the filtered method performs better than the unfiltered method based on 10-year rolling cumulative returns. For hypothesis testing, portfolio performances are measured with four indicators: Sharpe ratio (SR), Sortino ratio (SO), upside potential (UP), and omega ratio (OM). The p-value is calculated using a block bootstrapping method.

	SR			SO		
	filtered	unfiltered	p-value	filtered	unfiltered	p-value
Size	1.313	0.803	0.000	2.448	0.000	0.000
BM	2.596	1.953	0.000	28.282	0.000	0.000
INV	3.291	1.990	0.000	37.793	0.000	0.000
OP	3.316	1.949	0.000	1210.448	0.000	0.000
MOM	1.791	2.001	0.738	1.158	0.000	0.000
LTR	1.966	1.115	0.000	14.921	0.000	0.000
	UP			OM		
	filtered	unfiltered	p-value	filtered	unfiltered	p-value
Size	2.835	0.639	0.000	7.324	1.000	0.000
BM	28.482	0.531	0.000	142.683	1.000	0.000
INV	37.935	0.670	0.000	267.606	1.000	0.000
OP	1210.500	0.587	0.000	23445.567	1.000	0.000
MOM	1.574	0.446	0.000	3.779	1.000	0.000
LTR	15.156	0.629	0.000	64.547	1.000	0.000

Table 7. Decomposition of anomaly-profit differences

This table shows the decomposition of the anomaly profit differences between the filtered and the unfiltered methods into the long- and the short-leg of the long-short anomaly portfolios. The returns are annualized returns in percentage. Bold-faced t-values indicate the 5% significance.

	Portfolios					
	Size	BM	INV	OP	MOM	LTR
Difference	4.327	12.019	9.893	14.607	7.550	7.400
(t-value)	1.806	**4.168**	**3.200**	**4.976**	**2.617**	**2.347**
Long-leg	3.561	1.124	-0.933	5.647	1.104	0.099
(t-value)	1.628	0.674	-0.370	**2.933**	0.475	0.044
Short-leg	0.766	10.895	10.826	8.960	6.445	7.301
(t-value)	0.526	**3.949**	**4.921**	**3.548**	**3.064**	**3.275**

Table 8. Regression of filtered anomaly profits on unfiltered long- and short-leg anomaly profits

This table shows the results of the regressions of filtered anomaly profits on unfiltered long- and short-leg anomaly profits. The alphas are annualized returns in percentage. Bold-faced t-values indicate the 5% significance.

	Portfolios					
	Size	BM	INV	OP	MOM	LTR
alpha	5.266	14.581	8.843	14.233	5.775	6.719
(t-value)	**2.317**	**5.439**	**2.932**	**4.528**	1.785	**2.107**
Long-leg	1.161	0.908	1.038	1.017	1.114	1.150
(t-value)	**30.196**	**14.043**	**8.855**	**12.287**	**16.869**	**11.551**
Short-leg	-1.324	-1.113	-0.900	-0.984	-1.136	-1.181
(t-value)	**-19.421**	**-17.467**	**-9.308**	**-13.457**	**-19.702**	**-14.024**

Table 9. Decile portfolios

This table shows monthly returns of decile portfolios for the filtered and the unfiltered anomaly portfolios for each of six anomalies.

Decile	Portfolio					
	Size	BM	INV	OP	MOM	LTR
			Unfiltered			
1	1.29	0.77	1.20	0.57	0.35	1.28
2	1.06	0.87	1.21	0.81	0.79	1.25
3	1.16	0.86	1.19	0.95	0.93	1.19
4	1.04	0.99	1.20	1.09	1.00	1.11
5	1.12	1.02	1.18	1.09	1.09	1.19
6	1.14	1.09	1.18	1.16	1.10	1.19
7	1.03	1.16	1.13	1.19	1.24	1.09
8	1.06	1.21	1.07	1.23	1.27	1.07
9	1.01	1.28	0.87	1.29	1.47	1.00
10	0.88	1.38	0.42	1.31	1.71	0.75
			Filtered			
1	1.58	-0.17	1.12	-0.18	-0.18	1.28
2	1.13	0.71	1.39	0.52	0.97	1.30
3	1.26	0.98	1.45	0.83	0.76	1.10
4	0.91	0.99	1.24	1.18	1.01	0.98
5	1.15	1.11	1.10	1.18	1.07	1.09
6	1.20	1.22	1.30	1.16	0.79	1.22
7	1.10	1.25	1.12	1.23	1.21	1.06
8	1.01	1.24	0.70	1.16	1.01	0.87
9	1.04	1.20	0.60	1.43	1.42	0.80
10	0.81	1.49	-0.48	1.78	1.80	0.14

Table 10. Filtered anomaly returns with a fixed accuracy level

This table shows monthly returns of decile portfolios for the filtered and the unfiltered anomaly portfolios for each of six anomalies. The filtering is to select stocks of which accuracy index belongs to a range between a fixed percentile to the 100th percentile. We consider four fixed percentile levels: 0th, 30th, 60th, and 90th. Note that the case of the zeroth percentile corresponds to the unfiltered portfolios.

Decile	Percentile				Percentile			
	0	30	60	90	0	30	60	90
	Size				BM			
1	1.29	1.25	1.28	1.44	0.77	0.62	0.30	-0.10
2	1.06	1.10	1.06	1.02	0.87	0.89	0.81	0.68
3	1.16	1.24	1.22	1.18	0.86	0.88	0.84	0.85
4	1.04	1.07	1.06	0.78	0.99	0.97	1.02	0.89
5	1.12	1.16	1.18	1.01	1.02	1.03	1.01	0.96
6	1.14	1.18	1.17	1.15	1.09	1.10	1.14	1.25
7	1.03	1.05	1.04	1.00	1.16	1.16	1.16	1.26
8	1.06	1.08	1.05	0.91	1.21	1.22	1.23	1.29
9	1.01	1.02	0.97	0.95	1.28	1.28	1.27	1.21
10	0.88	0.88	0.88	0.74	1.38	1.36	1.40	1.51
	INV				OP			
1	1.20	1.23	1.22	1.15	0.57	0.47	0.31	-0.14
2	1.21	1.21	1.19	1.29	0.81	0.80	0.77	0.49
3	1.19	1.20	1.22	1.31	0.95	0.94	0.93	0.85
4	1.20	1.22	1.21	1.21	1.09	1.10	1.07	1.16
5	1.18	1.17	1.15	1.13	1.09	1.08	1.07	1.26
6	1.18	1.19	1.20	1.31	1.16	1.14	1.13	1.19
7	1.13	1.13	1.12	1.15	1.19	1.14	1.14	1.27
8	1.07	1.05	1.03	0.86	1.23	1.19	1.18	1.18
9	0.87	0.80	0.70	0.55	1.29	1.30	1.37	1.43
10	0.42	0.25	-0.02	-0.27	1.31	1.35	1.44	1.75

Table 10. Continued.

Decile	Percentile				Percentile			
	0	30	60	90	0	30	60	90
	Size				BM			
1	0.35	0.42	0.28	-0.20	1.28	1.24	1.31	1.20
2	0.79	0.84	0.86	0.96	1.25	1.28	1.27	1.20
3	0.93	0.98	0.95	0.83	1.19	1.18	1.21	1.10
4	1.00	1.01	0.99	0.87	1.11	1.09	1.08	0.97
5	1.09	1.06	1.03	0.96	1.19	1.19	1.15	1.12
6	1.10	1.09	1.10	0.96	1.19	1.19	1.16	1.12
7	1.24	1.24	1.25	1.18	1.09	1.09	1.07	1.11
8	1.27	1.23	1.21	1.08	1.07	1.09	1.07	1.02
9	1.47	1.43	1.41	1.37	1.00	1.00	0.97	0.86
10	1.71	1.67	1.66	1.66	0.75	0.66	0.47	0.24

Table 11. No-anomaly portfolios.

This table shows the results of forming no-anomaly portfolios by selecting stocks of which accuracy belongs to bottom x-percentile. The bottom x-percentile varies from bottom 90th to 10th, decreasing with 10 percentile points. The no-anomaly is defined by the event that the long-short portfolio return becomes insignificant at 5% level. The bottom x-percentiles are provided in the table.

	Model	Portfolios					
		Size	BM	INV	OP	MOM	LTR
Return		10	60	30	<10	<10	50
Risk-adjusted alpha	CAPM	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

Table 12. Diversification benefits with background risks.

This table shows the results of equal-weight portfolios with adding filtered or unfiltered anomaly portfolios into background portfolios. The market minus risk-free portfolio (RMRF), Fama-French 3-factors (FF3), or Fama-French-Carhart 4-factors are considered as background portfolios. The mean, Sharpe ratio (SR), and Sortino ratio (SO) of the equal-weight portfolio returns are reported.

Background risks →		RMRF		FF3		FF4	
Anomaly portfolios →		Unfiltered	Filtered	Unfiltered	Filtered	Unfiltered	Filtered
Size	Mean	5.35	7.59	4.91	6.40	5.62	6.74
	(t-value)	3.04	3.46	4.28	4.51	5.65	5.38
	SR	0.42	0.48	0.59	0.63	0.78	0.75
	SO	0.63	0.76	0.91	1.01	1.24	1.23
BM	Mean	6.64	12.88	5.26	9.42	5.89	9.00
	(t-value)	5.07	6.64	5.16	7.08	7.87	8.35
	SR	0.70	0.92	0.72	0.98	1.09	1.16
	SO	1.20	1.57	1.22	1.75	1.88	2.07
INV	Mean	7.96	13.18	5.61	8.22	6.04	8.13
	(t-value)	6.95	6.60	6.78	7.16	8.78	8.12
	SR	0.97	0.92	0.94	0.99	1.22	1.13
	SO	1.72	1.72	1.69	1.87	2.16	2.11
OP	Mean	7.74	15.44	5.50	9.35	5.95	9.03
	(t-value)	5.24	7.13	6.37	8.06	8.13	9.12
	SR	0.73	0.99	0.88	1.12	1.13	1.27
	SO	1.13	1.67	1.44	1.97	1.91	2.25
MOM	Mean	11.13	15.06	7.19	9.15	7.19	9.15
	(t-value)	6.22	6.19	7.35	7.19	7.35	7.19
	SR	0.86	0.86	1.02	1.00	1.02	1.00
	SO	1.41	1.53	1.71	1.77	1.71	1.77
LTR	Mean	6.17	9.72	4.77	6.54	5.37	6.79
	(t-value)	4.65	4.69	5.08	5.49	6.63	6.27
	SR	0.65	0.65	0.70	0.76	0.92	0.87
	SO	1.04	1.06	1.20	1.31	1.55	1.46

Table 13. Summary statistics: Value-weighted portfolios

This table shows summary statistics of the unfiltered and the filtered market-anomaly value-weighted portfolio profits for each of six market anomalies, 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.

	Portfolios					
	Size	BM	INV	OP	MOM	LTR
	Unfiltered					
Mean	0.440	0.296	0.374	0.435	1.274	0.215
(t-value)	**2.108**	1.534	1.925	**1.972**	**4.600**	1.043
Median	0.263	0.104	0.114	0.344	1.670	0.005
SD	5.299	4.908	4.976	5.656	7.039	5.047
SR	0.287	0.209	0.260	0.267	0.627	0.148
Skew	1.320	0.523	0.512	0.163	-0.384	0.455
Kurtosis	17.605	7.886	9.327	10.298	7.607	4.951
	Filtered					
Mean	0.653	1.627	1.780	1.720	2.049	1.178
(t-value)	**2.129**	**4.298**	**4.856**	**4.616**	**4.674**	**3.110**
Median	0.431	1.416	1.418	1.604	1.740	0.943
SD	7.801	9.619	9.393	9.552	11.144	9.267
SR	0.290	0.586	0.656	0.624	0.637	0.441
Skew	0.720	-0.205	-0.323	-0.250	0.235	0.155
Kurtosis	7.757	7.492	6.235	6.226	5.091	5.111

Table 14. Summary statistics: Alternative specifications

This table shows the average monthly returns in percentage of the difference between the filtered and the unfiltered anomaly portfolios for various specifications and for each of six anomalies. Refer to the text for detailed explanations about specifications. Bold-faced t-values indicate the 5% significance.

Specifications		Portfolios					
		Size	BM	INV	OP	MOM	LTR
ACCMA, ma=1, SR=0	Mean	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**
ACCMA, ma=0, SR=0	Mean	0.198	0.733	0.780	0.992	0.456	0.504
	(t-value)	1.185	**3.368**	**3.042**	**5.460**	1.840	**2.071**
ACCMA, ma=1, SR=1	Mean	0.042	0.516	0.348	1.142	0.189	0.413
	(t-value)	0.332	**4.636**	**2.279**	**5.715**	1.200	**2.749**
ACCMA, ma=0, SR=1	Mean	0.067	0.603	0.868	0.992	0.079	0.608
	(t-value)	0.558	**5.565**	**3.563**	**5.460**	0.500	**2.985**
ACCRC, ma=1, SR=0	Mean	0.034	0.947	0.697	1.102	0.769	0.628
	(t-value)	0.157	**3.812**	**2.605**	**4.231**	**3.019**	**2.289**
ACC2RC, ma=1, SR=0	Mean	0.441	0.637	0.432	1.106	0.635	0.291
	(t-value)	**2.348**	**2.627**	1.778	**4.657**	**2.725**	1.053
ACC2MA, ma=1, SR=0	Mean	0.600	0.770	0.553	1.150	0.392	0.261
	(t-value)	**2.757**	**3.243**	**2.178**	**5.044**	1.736	0.945

Table 15. Summary statistics: Accuracy-weight portfolios

This table shows summary statistics of the market-anomaly profit differences for each of six market anomalies, including mean, median, standard deviation (SD), skewness, kurtosis, and the Sharpe ratio (SR) of the average monthly return over the sample period. Panel A shows the results for the anomaly profit differences between accuracy-weight portfolios and equal-weight portfolios, and Panel B shows the results for the differences between the accuracy-value-weight portfolios and the value-weight portfolios. Bold-faced t-values indicate the 5% significance.

	Portfolios					
	Size	BM	INV	OP	MOM	LTR
	A. Accuracy-weight minus equal-weight					
Mean	0.203	0.442	0.388	0.420	0.040	0.142
(t-value)	**1.996**	**5.472**	**4.750**	**5.732**	0.674	**1.961**
Median	0.100	0.499	0.448	0.414	0.050	0.181
SD	2.586	2.051	2.092	1.877	1.508	1.771
SR	0.272	0.746	0.642	0.775	0.092	0.278
Skew	2.584	-0.917	0.169	-0.358	-0.105	0.629
Kurtosis	32.705	8.424	10.533	9.070	7.012	13.831
	B. Accuracy-value-weight minus value-weight					
Mean	0.043	0.263	0.260	0.339	0.018	0.158
(t-value)	0.527	**3.818**	**3.746**	**4.343**	0.365	**2.243**
Median	-0.041	0.218	0.250	0.267	0.020	0.092
SD	2.055	1.750	1.781	2.003	1.221	1.717
SR	0.072	0.520	0.506	0.587	0.050	0.318
Skew	0.220	0.034	-0.064	0.932	-0.177	1.031
Kurtosis	4.568	5.515	14.323	9.685	4.894	12.068

Table 16. Summary statistics: Quintile portfolios

This table shows summary statistics of the unfiltered and the filtered market-anomaly profits from equal-weight quintile portfolios for each of six market anomalies, 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.

	Portfolios					
	Size	BM	INV	OP	MOM	LTR
	Unfiltered					
Mean	0.114	0.243	0.280	0.307	0.506	0.196
(t-value)	1.498	**2.851**	**4.239**	**3.630**	**5.000**	**3.210**
Median	0.030	0.120	0.173	0.255	0.628	0.152
SD	1.935	2.170	1.693	2.168	2.574	1.493
SR	0.204	0.389	0.573	0.491	0.682	0.455
Skew	0.826	-0.256	0.815	0.093	-0.049	0.516
Kurtosis	11.898	12.271	8.075	20.658	11.317	5.431
	Filtered					
Mean	0.483	0.626	0.597	0.769	0.793	0.459
(t-value)	**3.864**	**5.038**	**5.242**	**6.283**	**5.538**	**4.040**
Median	0.338	0.551	0.557	0.662	0.770	0.381
SD	3.179	3.159	2.917	3.136	3.641	2.777
SR	0.527	0.687	0.709	0.849	0.755	0.572
Skew	0.718	-0.413	-0.642	-0.049	0.293	0.066
Kurtosis	8.303	6.754	9.547	6.308	8.409	6.373

Table 17. Transaction costs

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

			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
	FF 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

Internet Appendix to

"Can prior information make market anomalies more anomalous? Evidence from common stocks"

November 2018

Abstract

This appendix presents supplementary results not included in the main body of the paper.

A1. Alternative performance measures

The downside risk (or downside deviation), DR, measures the risk that returns are less than a target return level T. Formally, the DR is defined as

$$DR = \left[\int_{-\infty}^{T} (T - r)^2 f(r) \, dr \right]^{1/2}, \tag{A-1}$$

where $f(r)$ denotes the density of the (F)MOM returns.

The Sortino ratio (SO), a variant of the SR, penalizes only with downside risk, unlike the SR.[1] Specifically, the SO is defined as

$$SO = \frac{R - T}{DR}, \tag{A-2}$$

where R indicates average (F)MOM returns.

The upside potential ratio (UP) penalizes upside gains (relative to a target return) with downside risk. The UP is computed as

$$UP = \frac{\int_{T}^{\infty} (r - T) f(r) \, dr}{DR}. \tag{A-3}$$

Lastly, the omega ratio (OM) measures the ratio of upside gain to downside loss relative to a target return and is formally defined as

$$OM = \frac{\int_{T}^{\infty} (r - T) f(r) \, dr}{\int_{-\infty}^{T} (T - r) f(r) \, dr}. \tag{A-4}$$

References

[1] Sortino, F.A., Price, L.N., 1994. Performance measurement in a downside risk framework. Journal of Investing. 3, 50–58.

[1] Refer to, for example, Sortino and Price (1994).

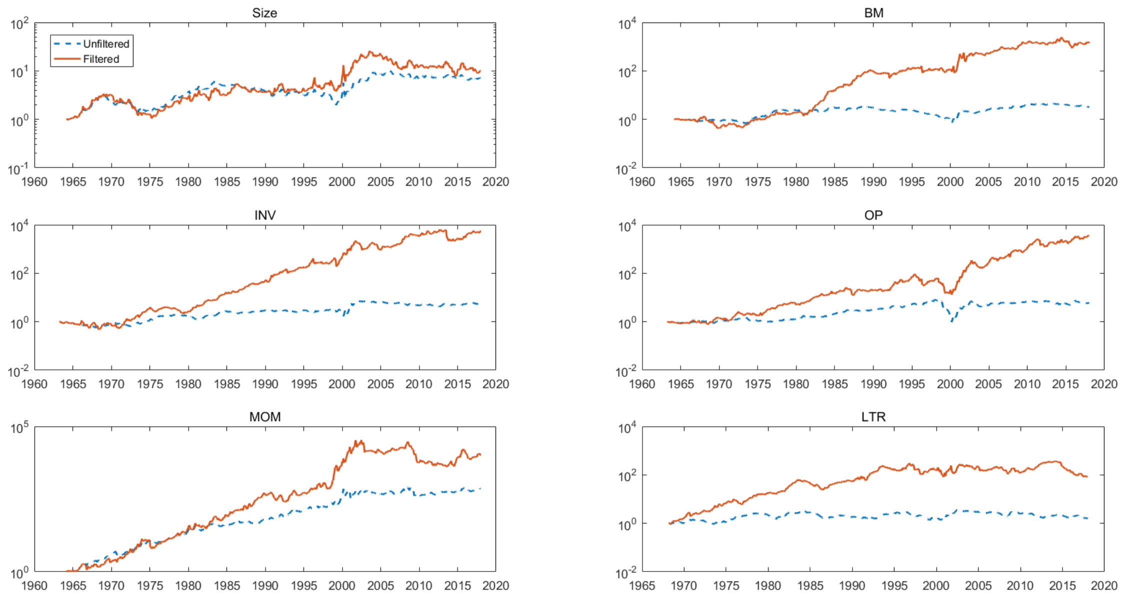

Figure A1. Cumulative market-anomaly profits of value-weighted portfolios. This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are value-weighted portfolios.

Figure A2. Rolling cumulative market-anomaly profits of value-weighted portfolios. This figure shows the time trends of 10-year rolling cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are value-weighted portfolios.

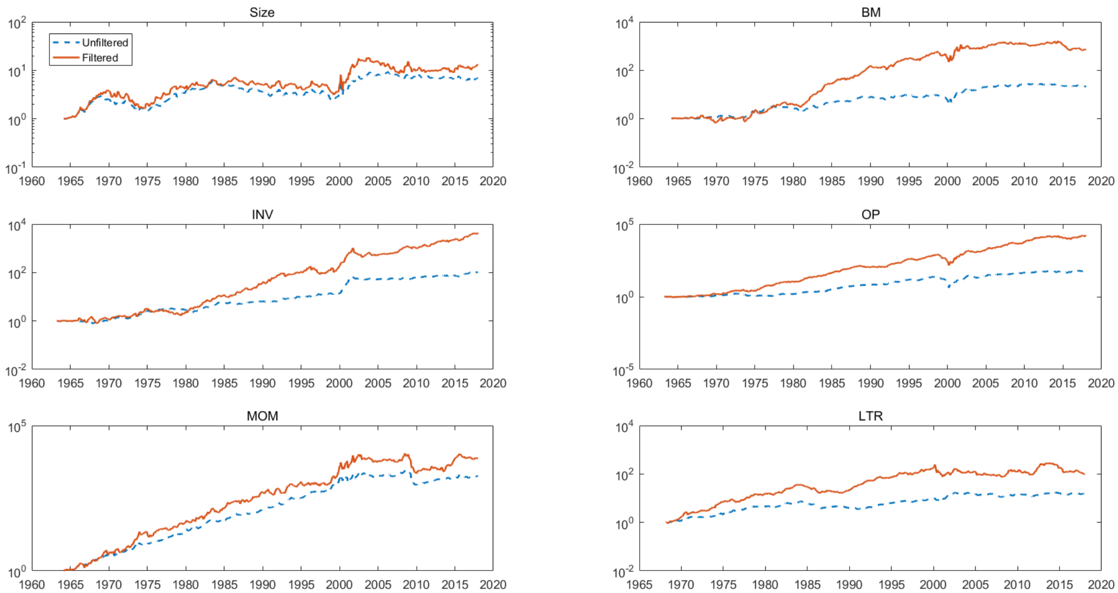

Figure A3. Cumulative market-anomaly profits with an alternative specification (ACCMA, ma=0, SR=0). This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are equal-weighted portfolios with an alternative specification (ACCMA, ma=0, SR=0).

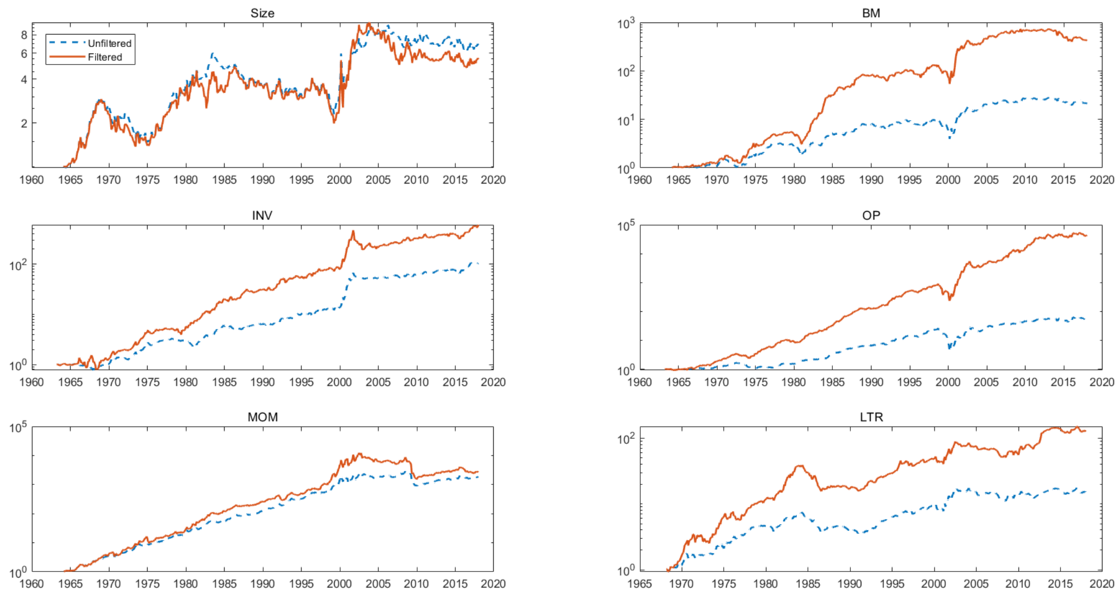

Figure A4. Cumulative market-anomaly profits with an alternative specification (ACCMA, ma=1, SR=1). This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are equal-weighted portfolios with an alternative specification (ACCMA, ma=1, SR=1).

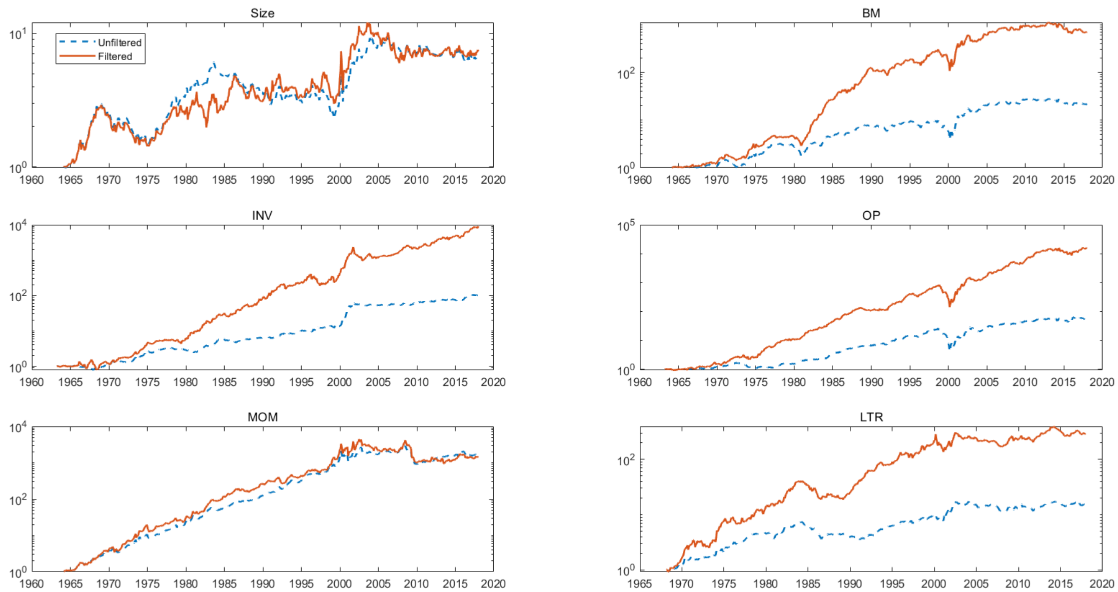

Figure A5. Cumulative market-anomaly profits with an alternative specification (ACCMA, ma=0, SR=1). This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are equal-weighted portfolios with an alternative specification (ACCMA, ma=0, SR=1).

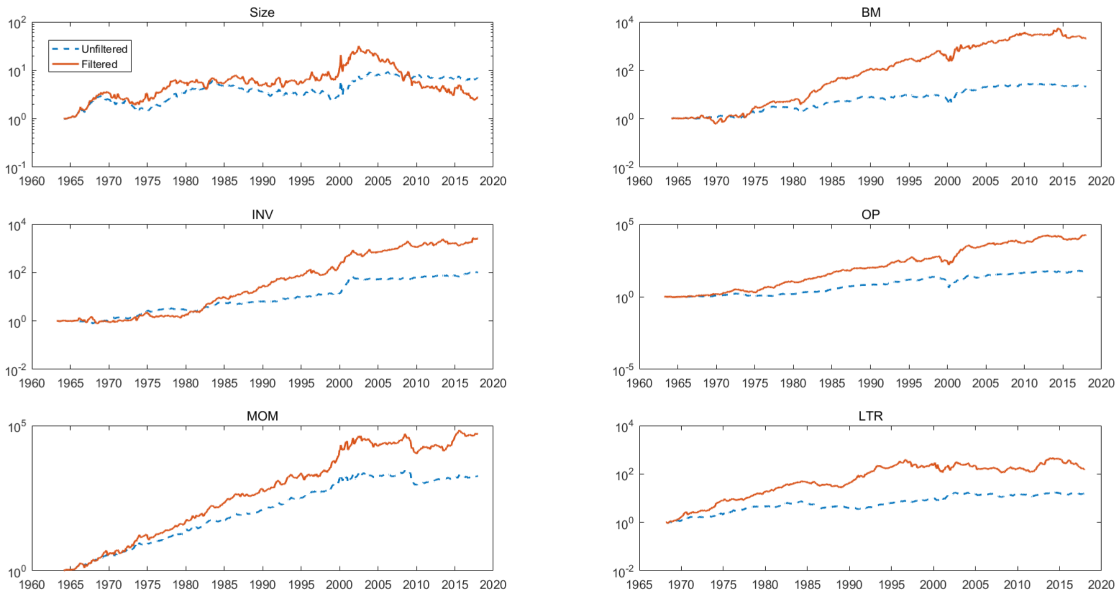

Figure A6. Cumulative market-anomaly profits with an alternative specification (ACCRC, ma=1, SR=0). This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are equal-weighted portfolios with an alternative specification (ACCRC, ma=1, SR=0).

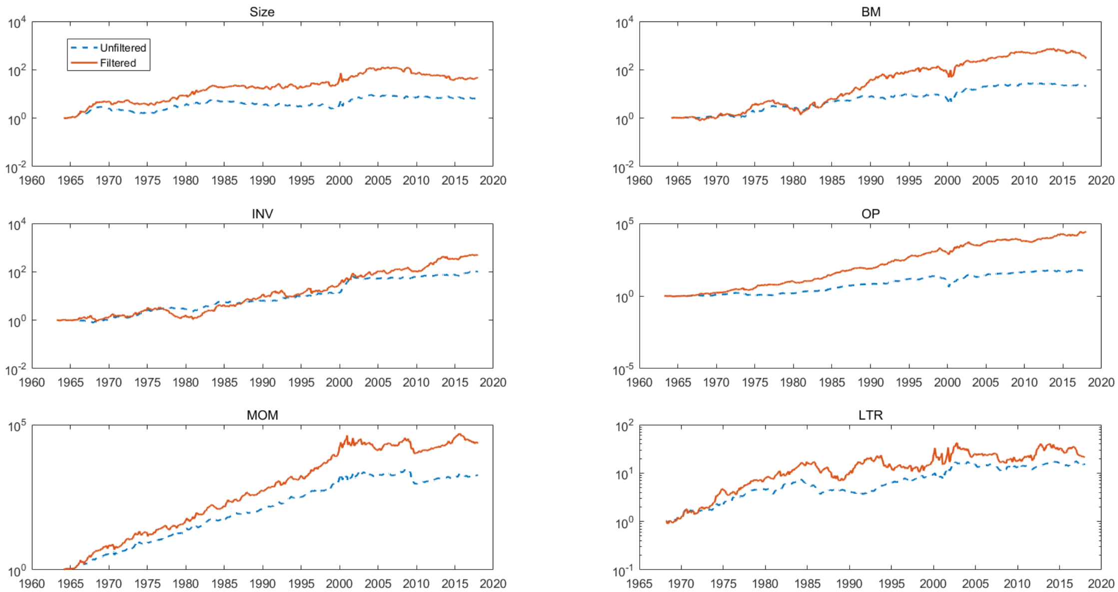

Figure A7. Cumulative market-anomaly profits with an alternative specification (ACC2RC, ma=1, SR=0). This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are equal-weighted portfolios with an alternative specification (ACC2RC, ma=1, SR=0).

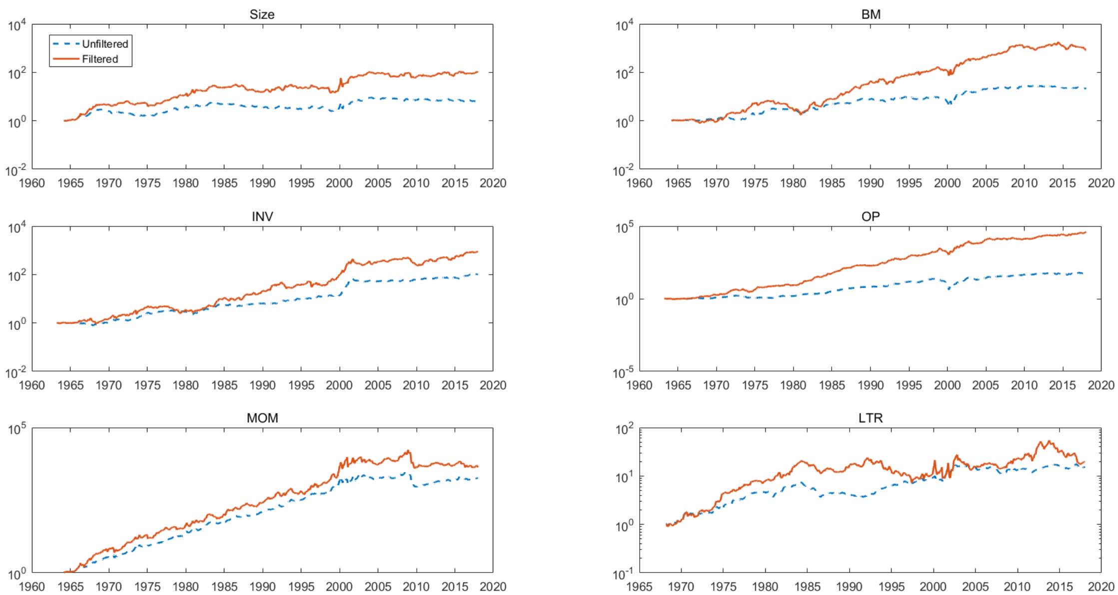

Figure A8. Cumulative market-anomaly profits with an alternative specification (ACC2MA, ma=1, SR=0). This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are equal-weighted portfolios with an alternative specification (ACC2MA, ma=1, SR=0).

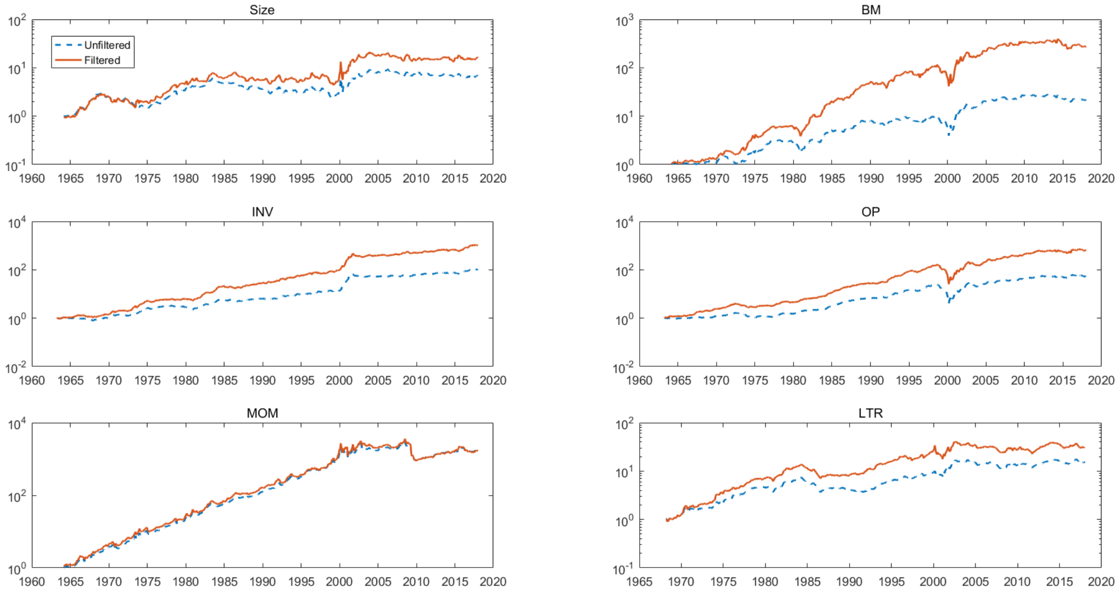

Figure A9. Cumulative market-anomaly profits of accuracy-weighted portfolios. This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are accuracy-weighted portfolios.

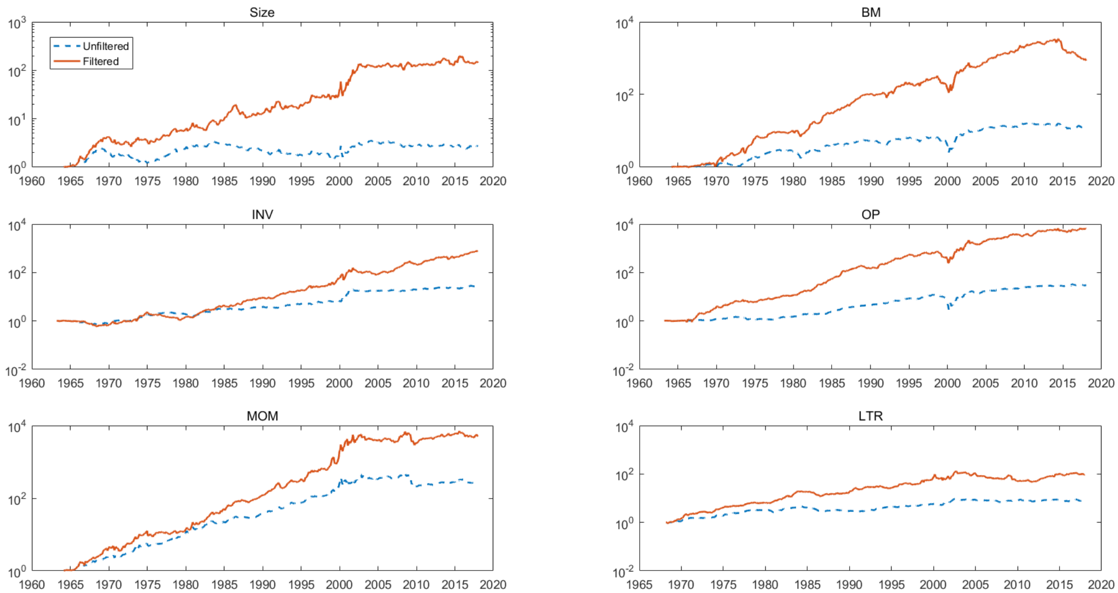

Figure A10. Cumulative market-anomaly profits of quintile portfolios. This figure shows the time trends of cumulative returns of the filtered and the unfiltered sorting methods for each of six market anomalies with a log scale. The market-anomaly portfolios are quintile portfolios.

Table A1. Accuracy state and market-anomaly profits: Alternative thresholds

This table shows market anomaly monthly returns (%) according to the contemporaneous ("Explanatory") or one-month lagged ("Forecast") accuracy state for each of six market anomalies. Based on the long or short leg aggregate accuracy index level, the accuracy state is classified into two alternative state classifications: high (top 20%), middle (middle 60%), and low (bottom 20%) in Panel A or high (top 40%), middle (middle 20%), and low (bottom 40%) in Panel B. The return differences ("h-l") of a market anomaly portfolio between "high" and "low" states and their t-values are also provided. Bold-faced t-values indicate the 5% significance.

		Explanatory					Forecast				
		Accuracy					Accuracy				
		low	middle	high	h-l	t-value	low	middle	high	h-l	t-value
A. (20, 80)											
Size	long	-3.11	0.36	4.19	7.30	**8.55**	0.13	0.28	1.06	0.93	1.47
	short	-3.69	0.14	4.83	8.52	**13.06**	-0.45	0.34	1.38	1.84	**3.03**
BM	long	-2.64	0.24	5.11	7.76	**8.26**	0.00	0.32	1.94	1.94	**3.08**
	short	-1.92	-0.04	4.76	6.68	**8.89**	-0.17	0.49	1.60	1.77	**2.72**
INV	long	-0.84	0.60	2.80	3.64	**7.05**	0.45	0.66	1.40	0.95	1.87
	short	-1.71	0.37	4.57	6.28	**9.34**	0.26	0.50	2.14	1.88	**2.98**
OP	long	-2.27	0.81	3.40	5.68	**3.99**	-0.08	0.78	1.42	1.50	**2.21**
	short	-0.85	-0.09	4.76	5.60	**6.15**	0.32	0.57	1.67	1.35	1.79
MOM	long	-3.80	1.21	6.36	10.16	**10.35**	0.53	1.65	1.29	0.76	0.74
	short	-3.13	1.56	5.21	8.34	**8.24**	1.21	1.27	1.75	0.54	0.68
LTR	long	-1.85	-0.10	3.54	5.38	**8.59**	1.02	0.30	0.92	-0.09	0.30
	short	-2.22	-0.03	3.38	5.59	**11.83**	0.42	0.19	1.42	1.00	**2.35**
B. (40, 60)											
Size	long	-2.01	0.46	2.63	4.64	**11.91**	0.20	0.70	0.48	0.28	0.66
	short	-2.32	0.32	3.27	5.59	**15.07**	-0.26	0.22	1.17	1.44	**3.31**
BM	long	-2.06	0.11	3.37	5.43	**9.19**	0.07	0.20	1.28	1.21	**2.82**
	short	-1.54	-0.59	3.06	4.59	**8.12**	0.13	0.11	1.19	1.05	**2.43**
INV	long	-0.68	0.74	2.23	2.90	**7.31**	0.59	0.28	1.16	0.57	1.45
	short	-1.15	0.35	2.83	3.98	**10.16**	0.29	0.23	1.46	1.17	**3.18**
OP	long	-1.00	0.58	2.58	3.58	**4.89**	0.37	-0.23	1.38	1.02	**2.35**
	short	-0.85	-0.07	2.74	3.59	**7.09**	0.23	0.55	1.35	1.12	**2.51**
MOM	long	-2.01	0.80	4.60	6.61	**10.03**	0.95	1.66	1.64	0.69	1.21
	short	-1.88	2.25	4.34	6.22	**8.91**	0.92	1.48	1.76	0.83	1.57
LTR	long	-1.51	-0.15	2.26	3.76	**10.82**	0.45	0.35	0.65	0.20	0.61
	short	-1.42	0.06	2.24	3.66	**11.38**	0.03	0.32	1.01	0.98	**2.84**

Table A2. Quintile portfolios

This table shows monthly returns of quintile portfolios for the filtered and the unfiltered anomaly portfolios for each of six anomalies.

Decile	Portfolio					
	Size	BM	INV	OP	MOM	LTR
			unfiltered			
1	1.17	0.83	1.21	0.69	0.57	1.26
2	1.10	0.94	1.19	1.02	0.97	1.15
3	1.13	1.06	1.18	1.12	1.10	1.19
4	1.04	1.16	1.10	1.21	1.25	1.08
5	0.94	1.32	0.65	1.30	1.59	0.87
			filtered			
1	1.68	-0.05	1.18	0.23	0.21	1.35
2	1.07	0.97	1.26	0.97	0.78	1.04
3	1.09	1.17	1.26	1.17	1.07	1.28
4	0.87	1.13	1.09	1.25	1.05	0.99
5	0.72	1.21	-0.01	1.77	1.80	0.43