Do Cross-Sectional Stock Return Predictors Pass the Test without Data-Snooping Bias?

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Abstract

This study examines the possible data-snooping bias as a competing explanation for the anomalies in the cross-section of stock returns. We posit that the exhaustive standalone searches for profitable strategies could lead to recommending spuriously predictive variables. In order to explore the severity of this problem, we use a multiple testing method to evaluate the profitability of portfolios constructed by these predictors. Our empirical analyses suggest that over half of the findings based on individual testing method are no longer statistically significant after we adjust for data-snooping bias. Excluding the micro-cap stocks before portfolios construction and applying the notion of economic significance in this study further weaken the evidence for predictability.

JEL classification: G11, G12, G14.

Keywords: anomalies, data-snooping bias, stock return predictability, portfolio strategies.

1 Introduction

This study aims at the documented pieces of evidence for cross-sectional stock return predictability in the past decades, for which the prior studies provide two major competing explanations. The first one suggests that the earned excess returns merely serve to compensate for investors' assuming risk. For example, Hou et al. (2015) and Fama and French (2016) employ rational risk-based factor models to explain the predictability phenomena. The second explanation follows the behavioral-based theory; for example, Jacobs (2015) argues that the abnormal returns associated with the anomalies are mostly driven by investor sentiment. These explanations reinforce the attempts by financial practitioners and academic researchers to identify outperforming stock selection rules or anomalies.

In contrast, this study posits and examines the extent to which data-snooping bias could account for a substantial proportion of the significant findings of anomalies. Researchers have been searching for predictors and testing their predictive ability time and again. However, without properly adjusting the statistical inference, the studies that conduct a seemingly promising set of standalone hypothesis tests may *probably* commit Type I errors because of the repeated trials. Therefore, the collective efforts in analyzing the cross-sectional stock return predictability may mislead researchers to endorse false anomalies due to the bias in statistical inference. To mitigate the data-snooping bias problem, we collect a set of stock return predictors and conduct a simultaneous inference under one family of hypotheses such that the overall error rate is controlled.

Our study is closely related to Harvey et al. (2016), who apply a multiple testing method to estimate the adjusted critical value for t-ratios of the factor risk premium, and recommends a new threshold rule for future studies to justify a statistically significant risk factor. Our study, however, differs from theirs in two aspects. First, we focus on the mean and risk-adjusted returns of portfolios formed based on firm characteristics, while a lot of the factors studied in Harvey et al. (2016) are macroeconomic variables. Second, we employ a different multiple testing algorithm and can thus assess economic significance as well as statistical significance. That is, our method could estimate the critical values not only for the t-ratios, but also for the risk-adjusted returns.

The empirical results show that many of the predictors generating statistically significant portfolio mean returns based on individual testing methodology are no longer accurate under the simultaneous inference. The findings based on our notion of economic significance also suggest that only 15 out of the collected 135 firm characteristics effectively help construct profitable long-short portfolios. Furthermore, if we exclude micro-cap stocks before the portfolio construction, then only annual growth in split-adjusted shares outstanding could deliver an economically significant return spread. However, its superior portfolio performance disappears if we incorporate a risk adjustment with Fama and French (2015)'s 5-Factor model or Hou et al. (2015)'s Q-Factor model. For a further perspective, we classify the predictors into multiple families of hypotheses and construct another simultaneous inference. With this research design, we are able to identify statistically and economically significant predictors from the value and momentum categories along with the net share issues for the universe without micro-cap stocks. Our subsample analyses also complement the studies by McLean and Pontiff (2016) and Jones and Pomorski (2016), whose findings imply that the profitability of anomalies is less pronounced in the out-of-sample.

The rest of this article proceeds as follows. In the next section, we briefly review how the data-snooping bias could affect the stock return predictability tests. Section 3 explains the multiple testing procedure and describes the data. We present the benchmark results based on annually rebalanced portfolios in Section 4. Section 5 discusses the results based on monthly rebalanced portfolios. Section 6 provides additional analyses to assess if our tests are unduly conservative. Section 7 presents the results over different sample periods. Section 8 concludes.

2 Data-Snooping Bias and Market Efficiency Tests

The concern for data-snooping bias in conducting market efficiency test is well-aware in the literature. For instances, Sullivan et al. (1999) and Bajgrowicz and Scaillet (2012) address the problem of data-snooping bias in testing technical trading strategies; Fama and French (2010) and Barras et al. (2010) analyze which mutual funds are outperforming simply because of data-snooping bias, or luck in their own terminology; Conrad et al. (2003) and Harvey et al. (2016) estimate the critical values for determining the significance of cross-sectional stock return premium without data-snooping bias.

To illustrate why data-snooping bias could arise, consider a hypothetical example with a large number of time-series of returns being tested against market efficiency. The returns could be of mutual funds, technical trading strategies, or portfolios of stocks. Suppose the market is efficient, i.e., all of the true expected returns are less than or equal to zero. If we test the null hypotheses of zero expected returns individually, then it will be quite likely that one of the hypotheses is rejected, even though market efficiency is not violated. To be specific, suppose the typical 5% significance level is used, then the probability of resulting in at least one false rejection, which is one minus the probability of all null hypotheses being simultaneously accepted ($1 - (1 - 0.05)^M$), would approach one as the number of tests M gets large enough. Such inferential bias due to conducting the statistical tests individually is usually referred as data-snooping bias (or luck in Fama and French (2010) and Barras et al. (2010)).

The above example highlights the needs to test market efficiency by a number of return series simultaneously. Conrad et al. (2003) and Fama and French (2010) use simulation approach to approximate the joint distribution of expected returns under the null hypotheses. They then compare the statistics generated from actual and simulated data to evaluate the expected returns. For example, Conrad et al. (2003) quantify how much of the value-growth premium that may be attributed to data-snooping bias by first constructing simulated portfolios through grouping the stocks with a large number of independent random noises. The mean returns of those highly ranked simulated portfolios are then used as the hurdle rate for the mean portfolio returns from actual data.

Although the simulation approach is appealing because of its intuitiveness, it is not based on a formal statistical method. In other words, the approach does not provide a certain confidence level when it identifies portfolios with superior returns above the threshold. A multiple testing framework could overcome this shortcoming by introducing a notion of error rate. Barras et al. (2010), Bajgrowicz and Scaillet (2012), and Harvey et al. (2016) control the false discovery rate (FDR), defined as the expected value of the ratio of the number of Type I errors to the total number of rejected hypotheses. Sullivan et al. (1999) apply the Reality-Check (RC) method by White (2000) that could control family-wise error rate (FWER(1)), defined as the probability of committing at least one Type I error.

In a series of studies by Hansen (2005), Romano and Wolf (2005, 2007), Hsu et al. (2010), and Hsu et al. (2014), the RC method is generalized and improved. We follow the k-Stepwise Superior Predictive Ability test (Step-SPA(k)) by Hsu et al. (2014)[1]. The Step-SPA(k) controls FWER(k), the probability of committing at least k Type I errors, and has been shown to have better finite-sample statistical power in various scenarios.

There are two main differences between the procedures that follow White (2000) and the FDR controlling method in Barras et al. (2010), Bajgrowicz and Scaillet (2012), or Harvey et al. (2016). First, the former uses bootstrap to approximate the joint distribution of the test statistics and the latter needs to assume a specific form of dependence structure among the test statistics[2]. Second, the input of FDR controlling procedure are p-values, therefore it can only obtain the critical value for the studentized test statistics (typically in the form

[1]The method is introduced in the next section.

[2]The most celebrated FDR controlling procedure by Benjamini and Hochberg (1995) (BH) has been proven to hold under the positive regression dependence assumption. Benjamini and Yekutieli (2001) (BY) propose another procedure that could control FDR under arbitrary dependence structure. The BY's critical value is greater than the BH's since it needs to ensure FDR is bounded under the most general case. The advantage of bootstrap-based procedure, as adopted in this paper, is that it captures the dependence structure information from the data, hence it should have greater statistical power.

of t-ratios). Meanwhile, the Step-SPA(k) could provide critical value for non-studentized test statistics, i.e., the mean or risk-adjusted return itself, so it allows us to make inference on economic significance similar to Conrad et al. (2003).

3 Empirical Procedure

This section describes the empirical procedure. We first illustrate the multiple testing methodology, and then discuss the data collection and portfolio construction.

3.1 Multiple testing methodology

Simulating a typical research design in empirical asset pricing or anomaly studies, we sort the stocks into groups of portfolios based on a firm characteristic x_i at the end of every year or month. We then form a long-short portfolio based on the extreme groups and examine the resulting monthly portfolio returns with a linear factor model:

$$R_{it} = \alpha_i + \mathbf{F_t}'\beta_i + \varepsilon_{it}. \tag{1}$$

The magnitude of $\hat{\alpha}_i$ and its t-ratio are interpreted as the measures of significance of the anomaly. Here $\mathbf{F}_t$ is one of the sets of factor portfolio returns described in Subsection 3.2.3. If $\mathbf{F}_t$ is an empty vector, then $\hat{\alpha}_i$ is simply the estimator for mean return. We perform multiple testing on the estimated alphas from different factor models separately. A particular attention will be given to the case of mean returns to see how the data-snooping bias effect could explain the anomalies without any risk-factor models.

We tackle the problem of data-snooping bias by specifying a family of hypotheses and conducting multiple testing on it. In this study, the null hypotheses of interests are

$$H_0^i : \alpha_i \leq 0,\ i = 1, \ldots, M, \tag{2}$$

where M is the total number of portfolios to be considered in the family-wise hypothesis. If each study tests its proposed predictor x_i individually while ignoring the fact that one logically related hypothesis, i.e., whether the cross-sectional stock returns are predictable, has been tested multiple times, then there could be a potential data-snooping bias in the statistical inference.

To simultaneously test the hypotheses, we adopt the Step-SPA(k) by Hsu et al. (2014), which asymptotically controls the FWER(k) and is a generalization over Step-SPA(1) of Hsu et al. (2010). The test based on FWER(k) control could be more powerful since it allows us to make more false rejections. In practice, such relaxation is useful, especially when the universe of hypotheses is large. However, we also do not tolerate too many Type I errors. To choose k below 3 is typically suggested; for example, see the simulation results in Romano and Wolf (2007) and Hsu et al. (2014).

The step-by-step implementations of Step-SPA(k) procedure are explained in Appendix A. There are two versions of test statistics, studentized and non-studentized, that could serve different purposes. To explain the procedure intuitively, we use the non-studentized test statistics as an example here. Let $\mathcal{H}_0$ denote the set of index where the portfolios have true $\alpha_i \leq 0$. The goal of multiple testing method is to derive a critical value to separate the significant strategies from the ones in $\mathcal{H}_0$ while also controls FWER(k) below the level δ. The definition of FWER(k) suggests a valid critical value $CV(k,\delta)$ should satisfy the following:

$$\begin{aligned}\text{FWER}(k) &= \mathbb{P}\left\{\text{Reject at least } k \text{ of hypotheses in } \mathcal{H}_0\right\} \\ &= \mathbb{P}\left\{\text{The } k\text{-th largest value of } \{\sqrt{T}(\hat{\alpha}_i - \alpha_i), i \in \mathcal{H}_0\} > CV(k,\delta)\right\} \\ &\leq \delta\,.\end{aligned}$$

In practice, we do not know $\mathcal{H}_0$. Therefore, the stepwise procedure starts with $\mathcal{H}_0 = \{1,\ldots,M\}$ to obtain the most conservative critical value and then refines the choice of $\mathcal{H}_0$ in the next steps until no further improvement. As for the probability distribution of joint high-dimensional order statistics, Step-SPA(k) adopts the bootstrap method as an approximation; see Step (S4)–(S9) in Appendix A for further details. Therefore, the dependence structure among the test statistics is implicitly taken into consideration from the data. The final output of the Step-SPA(k) algorithm is $CV(k,\delta)$ that serves as a cut-off point to distinguish between the significant and insignificant strategies.

The adjusted critical value for t-ratios is obtained by applying Step-SPA(k) algorithm on the studentized test statistics. That is, we use $\sqrt{T}(\hat{\alpha}_i - \alpha_i)/\hat{\sigma}_i$ as the test statistics, where $\hat{\sigma}_i$ is the consistent estimator for the standard deviation of $\sqrt{T}(\hat{\alpha}_i - \alpha_i)$. Due to the multiplicity of testing related hypotheses, the adjusted critical value would be greater than 1.96, the quantile of two-sided test with 5% significance level based on univariate Gaussian distribution. Taking the non-studentized test statistics as the input of Step-SPA(k) algorithm would produce the critical value for alphas. We interpret this hurdle rate as the magnitude of the mean or risk-adjusted portfolio returns that should attain to be economically significant in supporting predictability after one adjusts for data-snooping bias. It makes use of the fact that the k-th best portfolio in $\mathcal{H}_0$ could generate $\sqrt{T}\hat{\alpha}$ as high as $CV(k,\delta)$ with $100(1-\delta)\%$ confidence level, so that a truly superior predictor should earn an $\sqrt{T}\hat{\alpha}$ greater than $CV(k,\delta)$.

We also note that the multiple testing differs from a joint test of $H_0 : \alpha_i \leq 0, i =$

$1, \ldots, M$, in which the GRS or GMM test, is usually utilized. A joint test examines an individual hypothesis of multiple parameters. Therefore, a rejection of the joint test leads to the conclusion that at least one of the alphas is significant but the researcher is clueless as to which or how many of them are significant, while the objective of a multiple testing is to distinguish between significant and insignificant alphas.

3.2 Data and portfolio construction

We retrieve the monthly stock returns from CRSP and follow the procedure outlined in Beaver et al. (2007) to adjust the stock returns for delisting bias. Unless stated otherwise, the monthly portfolio returns sample begins from July 1968 and ends in December 2015 that constitutes 570 observations.

3.2.1 Predictors

We collect a total of 135 annual predictors. There are 101 predictors calculated using Compustat Annual, among which 48 financial ratios come from Ou and Penman (1989), and the rest of them are firm characteristics that have been studied in the asset pricing or anomalies literature, either published or working papers. The remaining 34 predictors are constructed by using the data from stock prices and trading volume in CRSP. We present the definitions and references of these predictors in Table B1. Whenever the Compustat Annual data serve to form portfolios, we include only the firms with December fiscal year end to avoid look-ahead bias and exclude the financial firms (two-digit SIC code 60–67). The stocks with negative book value of equity are also excluded. Some of the predictors here overlap with the 80 anomalies studied in Hou et al. (2015) and the 100 firm characteristics in Green et al. (2014). The 135 variables in this study should provide a broad enough coverage of the predictors.

3.2.2 The universe of portfolios

Our baseline empirical analyses use annually rebalanced portfolio strategies. We follow the convention in literature to group the stocks into decile portfolios at the end of June every year. We then form the value-weighted long-short portfolios of the extreme groups and rebalance annually. To construct the universe of long-short portfolio returns, we consider two strategies for each of the firm characteristics: the first one is to long the highest-ranked portfolio and to short the lowest-ranked portfolio; the second one is to long the lowest-ranked portfolio and to short the highest-ranked portfolio. Therefore, if we have N firm characteristics, the family of hypotheses comprises $M = 2 \times N$ alphas. By considering two directions of long-short portfolio strategies for one predictor, we assume no a priori knowledge regarding the sign of relation between this predictor and the stock returns. We use superscripts lh and hl to indicate that the long-short portfolios are low-minus-high and high-minus-low, respectively.

3.2.3 Factor portfolio returns

To calculate the risk-adjusted returns, we consider five linear factor asset pricing models. The first four models are: CAPM or single index model, Fama and French (1993) 3-Factor model, Carhart (1997) 4-Factor model, and Fama and French (2015) 5-Factor model. The data for these factors are downloaded from Professor Kenneth French's website. The fifth model is Hou et al. (2015) Q-factor model. We follow the factor construction method in Section 2.1 of Hou et al. (2015). Since the measurement of profitability factor requires the information of earnings announcement date (Compustat Quarterly item RDQ), which are available after 1972, the estimation of alpha based on Q-factor model would use only the portfolio returns from July 1972 to December 2015.

4 Empirical Results

This section presents the baseline results of our empirical investigation on cross-sectional stock return predictability. The first subsection discusses how the data-snooping bias alone could affect the conclusion on identifying anomalies in the cross-section of stock returns. We then simultaneously test if the predictors could generate significant risk-adjusted returns in the next subsection. In the final subsection, we provide summary for some of the selected anomalies.

4.1 Analysis without risk factor model

Tables 1 and 2 present the number of rejections for the universes of annually rebalanced portfolios based on the studentized and non-studentized statistics, respectively. Their corresponding critical values $CV(k, \delta)$ are shown in parentheses. We choose to control the FWER(k) below $\delta = 5\%$ for k = 1, 2, and 3. For the studentized test statistics, Newey-West standard error with lag parameter equaling 4 is used to estimate the standard deviation parameter. For comparisons, we also present the number of rejected hypotheses based on individual testing method in the column "t>1.96" of Table 1. In the non-studentized tests, there is no corresponding cut-off point, thus we do not report the number of rejections based on individual testing.

Panels A–D of Tables 1 and 2 report the results using different universes of portfolios. Since it is prevalent for academic researchers to use decile portfolios, the results in Panel A would serve as our base case. We also present the results in Panel B, where the stocks are grouped into quintiles. Next, we follow Lewellen (2015) to consider two universes of portfolios labeled as "all-but-tiny" and "large-cap" stocks, and report their corresponding results in Panels C and D, respectively. The all-but-tiny stocks universe is a subsample where micro-cap stocks, defined as firms with market capitalization smaller than the NYSE 20% quantile at the end of June each year, are excluded. Lewellen (2015) and Fama and French (2016) suggest that the all-but-tiny universe can be used to check if the profitability of a portfolio is mostly driven by micro-cap stocks. In the large-cap universe, we constrain our sample to the stocks with market capitalization greater than the NYSE median at the portfolio formation time. This large-cap stocks subsample helps us examine whether the anomalies still exist in the population of stocks where market efficiency is more likely to hold.

By examining the difference between the numbers of rejections under multiple testing and individual tests in Table 1, we could assess how severe the data-snooping bias is. Without using any factor models, our long-short decile portfolios sample contains 41 (out of 135) significant anomalies if we test them individually. Nevertheless, only 9 out of the 41 are still significant according to the test that controls FWER(1). If we choose less stringent error rate, FWER(3), there are still more than 50% of the rejections which may be spurious findings. When we construct the portfolios using quintile breakpoints, the overall mean return dispersions become less significant. Based on $CV(3, 5\%)$, the number of rejections is 13 compared to 16 in the decile long-short portfolios.

Panel C of Table 1 shows the number of rejections where the micro-cap stocks are excluded before the decile long-short portfolios construction. While the significant anomalies do not disappear entirely, the numbers of rejections decrease substantially. It suggests that many of the profitable long-short portfolios are not exploitable by most investors since they depend on the micro-cap stocks. For the large-cap stocks universe, the numbers of rejections further decrease. In Panel D of Table 1, only 4 of the portfolios are with mean return dispersion remaining to be significant based on $CV(3, 5\%)$. If the data-snooping bias remains being unadjusted for, there are still 24 statistically significant anomalies even when we focus on the relatively more efficient stock market universe.

For the non-studentized test, the overall numbers of rejections are much smaller than the ones based on the studentized test. The non-studentized $CV(3, 5\%)$ is 0.78% without any risk adjustment in all stocks universe. This implies that the mean return spread has to be at least 0.78% to be claimed economically significant while also maintaining the probability of getting at least 3 false rejections under 5%. Based on the most conservative error rate FWER(1), the number of portfolios with significant mean returns is only 5. For the "all-but-tiny" stocks universe, there is only 1 long-short portfolio that can produce economically significant return dispersion based on $CV(2, 5\%)$.

Table 2 also shows that the hurdle rates for the universes of all-but-tiny and large-cap stocks are less than the ones for all stocks universe. For example, $CV(2, 5\%)$ for all stocks universe is 0.845, while the corresponding value for all-but-tiny stocks is 0.805. The exclusion of micro-cap stocks appears to reduce portfolio returns. Accordingly, the distribution of k-th largest portfolio mean return in $\mathcal{H}_0$ would also shift to the left. In spite of the decrease in threshold for economic significance, the number of rejections does not increase. Our results seem to echo Goyal and Welch (2008), who suggest that the economic significance of a time-series equity premium prediction model is harder to attain than the statistical significance.

4.2 Analysis with risk factor model

The multiple testing results for risk-adjusted returns suggest that some of the asset pricing models may be misspecified and thus fail to fully explain the cross-sectional stock return premium. Specifically, if a linear factor asset pricing model captures the return dispersions generated by the predictors, we should observe fewer rejections. However, this is not the case for all of the factor models. There are even more statistically significant alphas in the cases where we use CAPM, 3-Factor, and 5-Factor models.

In contrast, the 4-Factor and Q-Factor perform better. For the Q-factor model in Panel A of Table 1, there are 19 significant alphas after the risk adjustment under individual testing. If we control for FWER(3), there remain only 3 rejected anomalies. If we choose the most stringent error rate, FWER(1), then we would find no rejections at all. The pricing performance of 4-Factor model could be as well as that of Q-Factor model if we remove the tiny stocks. Panel C of Table 1 shows that there are only 2 rejections by the 4-Factor and Q-Factor models based on $CV(3, 5\%)$.

The critical values $CV(k, 5\%)$ may slightly vary with the choice of factor models, grouping methods, and universes of stocks. $CV(1, 5\%)$ ranges approximately between 3.35 and 3.54. When we relax the possible number of false rejections to 3, the critical value becomes as low as 2.75. The rule of thumb by Harvey et al. (2016), who state that the new critical value for t-ratio is 3.0, may correspond to $CV(2, 5\%)$ or $CV(3, 5\%)$. For instances, Panel A of Table 1 shows that the rule $t > 3.0$ effectively controls FWER(3), but not FWER(2), for Q-Factor alpha. Meanwhile, in the case of mean returns, $t > 3.0$ serves to control FWER(2).

For the evaluation based on economic significance in Table 2, the results in Panel C show that there are no more than 2 rejections by the 4-Factor and Q-Factor models. The significant predictors identified by different risk factor models appear to vary. For example, the only significant portfolios that are not explained by the 4-Factor model in the "all-but-tiny" stocks universe are net share issues, $\mathbf{issue}^{lh}$ and $\mathbf{issue5}^{lh}$. However, the net share issues premium are explained by the Q-Factor model, and the alpha that is not captured by the Q-Factor model turns out to be the result from firm characteristic $\mathbf{invest\_LWZ}^{hl}$.

4.3 Discussion of selected anomalies

This subsection discusses the results for some of the popular anomalies in detail. In each category, we report the $\hat{\alpha}$'s and t-ratios for the long-short decile portfolios based on several representative firm characteristics.

Value-growth premium. Panel A of Table 3 shows the mean returns and alphas for value-minus-growth portfolios across various factor models. The strategies $\mathbf{bm}^{hl}$ and $\mathbf{sp}^{hl}$ have the greatest return premium among the value-minus-growth portfolios in all stocks universe. After we remove the micro-cap stocks, the spreads for $\mathbf{bm}^{hl}$ and $\mathbf{sp}^{hl}$ decrease from 0.9% and 1.04% to 0.57% and 0.71%, respectively. Furthermore, while the t-ratios still exceed 2, they are no longer significant if we control FWER(3). The strategy $\mathbf{cfp}^{hl}$ is more profitable in the all-but-tiny stocks than the all stocks universe. It has 0.7% mean return spread, slightly below the non-studentized $CV(3, 5\%)$, and t-ratio above the corresponding $CV(3, 5\%)$.

The 3-Factor, 4-Factor, and 5-Factor models well explain the value-growth anomaly. Almost all of the alphas are indistinguishable from zero. The 3-Factor alpha of $\mathbf{cfp}^{hl}$ is 0.44% and has t-ratio 2.57 but it is no longer significant if we take into account of multiple testing. Meanwhile, its industry-adjusted version, $\mathbf{cfp\_ia}^{hl}$, has statistically significant 5-Factor alpha based on $CV(3, 5\%)$, but the profitability is mostly driven by micro-cap stocks. The Q-Factor model is also effective in capturing value-growth premium but seems to inflate the alphas of the portfolios with industry-adjusted firm characteristics. The portfolio mean return spreads of $\mathbf{bm\_ia}^{hl}$ and $\mathbf{cfp\_ia}^{hl}$ are insignificant in all types of stock universes, but their Q-Factor alphas turn significant in certain cases even after we adjust for data-snooping bias.

Momentum and volatility. The high-minus-low momentum and low-minus-high volatility portfolios are among the strategies that produce the greatest return spread in our sample of all stocks universe, Panels B and C of Table 3 summarize the results. The mean returns for long-short portfolios of $\mathbf{mom6}^{hl}$ (0.8%), $\mathbf{wh52}^{hl}$ (0.92%), $\mathbf{ma200}^{hl}$ (1.22%), $\mathbf{tvol\_d}^{lh}$ (0.82%), $\mathbf{tvol\_w}^{lh}$ (1%), and $\mathbf{ivolff\_w}^{lh}$ (0.91%) are all above the non-studentized $CV(3, 5\%)$. However, the return spreads are sharply reduced and are no longer significant if we restrict the stocks to the all-but-tiny subsample. Moreover, the Q-Factor model shrinks all of the return spreads, with the exception of $\mathbf{ma200}^{hl}$, into being insignificant in the all stock universe. The

Q-Factor alpha of $\mathbf{ma200}^{hl}$ becomes insignificant after we exclude the micro-cap stocks. The 4-Factor model works equally well in explaining momentum premium but fails to capture the return spreads in low volatility strategies.

Accrual, investment, and net share issues. Panel D of Table 3 summarizes the results for portfolios that are related to low growth anomaly. The t-ratios for mean returns of portfolios $\mathbf{issue}^{lh}$, $\mathbf{issue5}^{lh}$, and $\mathbf{grltnoa}^{lh}$ consistently surpass the $CV(2, 5\%)$ in the all and all-but-tiny stocks subsamples. However, only portfolio $\mathbf{issue}^{lh}$ generates economically significant alpha in both universes. Nonetheless, as shown by Fama and French (2016) or Hou et al. (2015), the low growth anomalies may be explained by the investment factor in either 5-Factor or Q-Factor model, which is why the economic significance of $\mathbf{issue}^{lh}$ disappears if we take risk-adjustment into consideration. For all types of risk-factor models, the portfolio alphas of $\mathbf{acc}^{lh}$ in all stocks universe exceed the 1.96 critical value but are insignificant under the multiple testing framework. The low investment portfolios, $\mathbf{invest\_TWX}^{lh}$, $\mathbf{invest\_AG}^{lh}$, and $\mathbf{invest\_LWZ}^{lh}$, earn positive premium, which is, however, insignificant with t-ratio below 1.96. The portfolio $\mathbf{invest\_LWZ}^{lh}$ has surprisingly significant negative alpha in the all-but-tiny subsample once the investment factor is included in the risk adjustment.

Profitability. Panel E of Table 3 presents the results of the portfolios sorted by profitability factors. We find that none of the mean returns in this category is significant by any criteria. Although the portfolios based on improved profitability measures, such as Novy-Marx (2013)'s $\mathbf{gpa}^{hl}$ and Ball et al. (2015)'s $\mathbf{opa}^{hl}$, have slightly greater mean returns than other profitability portfolios, they are still statistically and economically insignificant in our sample. The portfolio $\mathbf{opa}^{hl}$ has significant risk-adjusted returns in all stocks universe but only when the CAPM or 3-Factor model is used. The portfolio $\mathbf{opa}^{hl}$ generates 3-Factor alpha of 0.93% with t-ratio being 3.1, which exceed the corresponding studentized and non-studentized $CV(2, 5\%)$.

Illiquidity and trading activity. Panel F of Table 3 reports the results for portfolios that are constructed to earn the illiquidity premium. Our findings suggest that the best proxy for illiquidity premium is the portfolio $\mathbf{illiq}^{hl}$. Its studentized and non-studentized test statistics for mean returns are greater than the corresponding $CV(3, 5\%)$. The t-ratios of the alphas based on any risk factor models are also significant without data-snooping bias. However, the illiquidity premium in $\mathbf{illiq}^{hl}$ would sharply disappear once the micro-cap stocks are excluded before portfolio sorts. Two of the trading activity portfolios ($\mathbf{dvol}^{lh}$, and $\mathbf{std\_dvol}^{lh}$) by Chordia et al. (2001) generate modest mean returns and high t-ratios even in the case where we remove the micro-cap stocks, however they do not survive the test without multiple testing bias.

5 Monthly Rebalanced Portfolios

The profitability of some anomalies could be short-lived and may need rebalancing at monthly frequency. For example, one of the momentum strategies in Jegadeesh (1990) assumes one-month holding period. This subsection considers a universe where investors rebalance their portfolios at the end of every month. In this universe of monthly rebalanced portfolios, we use 45 predictors, where 34 of these are defined similarly to CRSP variables in the annual predictors. The additional 11 firm characteristics are computed with Compustat Quarterly. To ensure there is a large enough number of stocks to form portfolios in each decile group, the sample for monthly rebalanced portfolio returns starts from July 1978. We summarize the monthly predictors in Appendix B2.

Table 4 shows that the hurdle rates for t-ratios in the monthly rebalanced portfolios universe are lower than their annual counterpart. The cut-off points that control FWER(1), $CV(1, 5\%)$, to separate between superior and inferior portfolio strategies are approximately 2.93–3.19. The $CV(3, 5\%)$ ranges between 2.16 and 2.60. In contrast, the critical value for the non-studentized test statistics shown in Table 5 is generally greater than the annually rebalanced portfolio's. For instance, the $CV(3, 5\%)$ for mean return spread is 0.86% in the monthly rebalanced portfolios using all-but-tiny stocks, but the corresponding number in Table 2 shows 0.76%. This implies that the strategies under the null, i.e., the ones with less than zero actual mean returns, in the monthly rebalanced portfolios universe could produce greater portfolio returns. Intuitively, because there is a greater variation associated with higher turnover rate strategies, it should need a greater hurdle rate to justify the significance of the mean returns, and the resampling-based null distribution takes this effect into account. The critical values for the alphas of 5-Factor and Q-Factor model also increase. However, not all of the tests result in greater critical values, e.g., the multiple testing with CAPM and 3-Factor model.

Table 6 lists the portfolios with t-ratios of mean returns and Q-Factor's alphas exceeding their corresponding $CV(3, 5\%)$. After we exclude micro-cap stocks, 8 out of 44 anomalies are significant based on studentized test for the mean returns, and only 4 are with significant non-studentized test statistics. Similar to the annually rebalanced case, the high mean returns of low-minus-high volatility portfolios appear to be mostly attributed to micro-cap stocks. On the other hand, the momentum portfolios, such as $\mathbf{mom12}^{hl}$, $\mathbf{mom712}^{hl}$, and $\mathbf{mom12\_ia}^{hl}$, now perform better. The mean return spreads generated by $\mathbf{mom12}^{hl}$ (1.26%) and $\mathbf{mom712}^{hl}$ (1.24%) surpass the $CV(1, 5\%)$, but these are captured by the Q-Factor model. The only significant Q-Factor's alpha based on both studentized and non-studentized tests in all-but-tiny stocks universe is the short-term reversal strategy $\mathbf{ma20}^{lh}$. The momentum portfolio based on moving average $\mathbf{ma200}^{hl}$, which works well with annual rebalancing frequency, does not generate significant returns.

6 Is the Error Rate Unduly Conservative?

This section discusses whether the multiple testing that controls FWER(3) is unduly strict so that our empirical results identify too few superior predictors. We also consider a simultaneous inference scenario where anomalies are classified into multiple families to see if the test could uncover more significant findings.

6.1 Controlling the False Discovery Proportion

The generalization of FWER(1) to FWER(k) helps increase the statistical power of multiple testing when the number of hypotheses becomes too large. In our empirical analysis, we choose 3 as the maximum of k as suggested by the simulation results of Romano and Wolf (2007) and Hsu et al. (2014). Further increasing the k may induce too many Type I errors in the process of identifying anomalies. However, there is also a concern that $k = 3$ is still unduly stringent, thus reducing the statistical power to detect superior cross-sectional stock return predictors.

Romano and Wolf (2007) provide a "data-driven" procedure on how to choose k by controlling the probability of false discovery proportion (FDP), the ratio between the number of false rejections and the number of total rejections, exceeding γ below δ,

$$\text{FDX} \equiv \mathbb{P}\{\text{FDP} \geq \gamma\} \leq \delta. \tag{3}$$

Hsu et al. (2014) shows that the above inequality (3) is satisfied asymptotically by applying Step-SPA(k) algorithm until $k/(R_k+1) > \gamma$, where R_k is the number of total rejections based on Step-SPA(k) test.

Table 7 presents the implied choice of k so that the probability of FDP exceeding γ is bounded below $\delta = 0.05$. Genovese and Wasserman (2006) shows that controlling FDP at (γ, δ) level implies the FDR, the expected value of FDP, is bounded below $\gamma + (1-\gamma)\delta$. Therefore, FDR is also controlled at 0.0975 and 0.145 levels in the case of $\gamma = 0.05$ and $\gamma = 0.1$, respectively. To control FDR below 0.1 is widely accepted in the multiple testing literature and is also adopted by Harvey et al. (2016). In Table 7 the implied k never exceeds 3 except when testing the predictability using CAPM as the risk factor model. For the mean and Q-Factor alpha, the FDP controlling procedure implies that $k = 1$ is the appropriate error rate in both studentized and non-studentized tests. The overall results suggest that controlling FWER(3) is not too stringent.

6.2 Selective inference

This subsection aims at an algorithm of constructing hierarchical hypotheses by taking the insights from financial theories. Namely, it aims at an alternative algorithm in contrast with conducting the multiple testing in the previous discussion, where we formulate the family-wise hypothesis under one question: "Is the cross-sectional stock return predictable?" To illustrate how an alternative algorithm works. Consider, for instance, that we first examine the hypothesis "Does valuation ratio (or momentum, growth, etc.) predict stock returns?", and then perform multiple testing using the proxy variables for valuation ratio.

To accomplish this task, we adopt the selective inference procedure by Benjamini and Bogomolov (2014). Suppose the global family-wise hypothesis is classified into G multiple families. Let the mean exceedance FDP over the selected families be

$$\mathbb{E}^S[\text{FDX}] \equiv \mathbb{E}\left[\frac{1}{S_G}\sum_{g=1}^{S_G} \mathbb{1}\{\text{FDP}_g \geq \gamma\}\right] \leq \delta,$$

where S_G is the number of selected families and FDP_g is the FDP in group g. The Theorem 1 in Benjamini and Bogomolov (2014) proves that the following procedure controls $\mathbb{E}^S[\text{FDX}]$ at δ,

1. Select the family if the maximum of the t-ratio in the family exceed 1.96.
2. For each selected family g, identify the superior strategies by conducting the multiple testing which controls
$$\mathbb{P}\{\text{FDP}_g \geq \gamma\} \leq \frac{S_G}{G}\delta.$$

For studentized and non-studentized tests, we apply the same selection rule in Step 1[3]. In Step 2, we use the same algorithm as in controlling the FDP in the Equation (3), only now the test is performed within an isolated group and with a significance level that is adjusted for selection effect.

Table 8 shows the multiple testing results using $\gamma = 0.1$ and $\delta = 0.05$. We use the same classification of predictors listed in Table 3 and categorize the rest of the predictors into "Others". The total number of rejections may increase or decrease compared to the number

[3]The selection procedure in Step 1 could be based on Bonferroni procedure or other multiple testing procedure that satisfies the definition of simple selection procedure in Benjamini and Bogomolov (2014). Here we choose a less stringent criterion since one of our objectives in this subsection is to obtain a less conservative test.

of rejections by controlling FWER(3). For example, in the studentized test for all stocks universe the selective inference identifies 19 portfolios with significant mean returns, while the total number of rejections is 16 based on the test which controls FWER(3); however, the selective inference identifies fewer statistically significant predictors for the all-but-tiny stocks universe. We warn that the inference using multiple families does not guarantee the overall FWER(k) is still controlled. Nevertheless, the selective inference method is effective when we aim to label the predictors with certain types and conduct the multiple tests in two stages.

The selective inference procedure could lead to a different set of significant predictors. For example, the total number of significant Q-Factor alphas in the all stocks universe is 3 based on the studentized test statistics, which equals the number based on $CV(3, 5\%)$ (see Table 1). However, without separating the hypotheses into multiple families, **cfp_ia**^{hl}, **cashprod**^{hl}, and **illiq**^{hl} are the significant portfolios, while the selective inference identifies **cfp_ia**^{hl}, **ma200**^{hl}, and **illiq**^{hl} as the portfolios with significant Q-Factor alphas. Moreover, the selective inference procedure suggests that there are 6 economically significant portfolio mean returns from 3 different categories of firm characteristics in the all-but-tiny stocks universe. These portfolios are: **sp**^{hl}, **cfp**^{hl}, **mom6**^{hl}, **ma200**^{hl}, **issue**^{lh}, and **issue5**^{lh}. This is in contrast to the FWER(3) controlling procedure, which only identifies one economically significant portfolio (**issue**^{lh}). Another notable result is that none of the predictors in the "Others" category generate economically significant mean returns or Q-Factor alphas when tiny stocks are excluded before portfolio construction.

7 Data-Snooping Bias in the Pre-Fama and French (1993) Era

To distinguish between data-snooping bias and the post-publication effect documented by McLean and Pontiff (2016), we split the sample into pre- and post-1993 time periods. McLean and Pontiff (2016) show that many firm-characteristics lose their predictive power after the anomalies are made well-known by academic publications, and suggest that the role of arbitrage by sophisticated investors as the cause of disappearing anomalies. Since the publication of Fama and French (1993) should mark the beginning of active pieces of research work in cross-sectional stock return anomalies, we use the year 1993 as the approximate cut-off to investigate if the data-snooping bias is confounded by the post-publication effect.

Table 9 presents both pre- and post-1993 multiple testing results. In the pre-1993 sample period, studentized test shows a quite similar magnitude of data-snooping bias with the full sample analysis. For the all stocks universe, there are 44 portfolio mean returns with t-ratio above 1.96, but only 16 of those surpass $CV(3, 5\%)$. Compared to the results for the post-1993 period, the overall pieces of evidence for cross-sectional stock return predictability are more pervasive in the pre-1993. With adjustment for data-snooping bias and exclusion of micro-cap stocks, both studentized and non-studentized tests show none of the predictors could successfully construct a profitable long-short portfolio returns in the post-1993 sample period. The critical values for non-studentized test statistics are substantially greater in the post-1993 sample period. The result appears to reinforce the findings that it becomes much harder to find consistently outperforming stock selection rules in the post-Fama and French (1993) era[4].

Rolling subsample analysis. Instead of splitting the sample into two periods arbitrarily, we also examine how the predictive ability of the firm-characteristics evolves over time. As of the end of June each year, we use the data over the past 10 years to conduct the multiple testing. Figures 1 and 2 show the portfolios with studentized and non-studentized test statistics above $CV(3, 5\%)$ at the end of each vintage point, respectively. The results show that there remain fewer informative predictors in recent years. The findings are more pronounced using the all-but-tiny stocks universe[5].

Panels A and B of Figure 1 show that the portfolios $\mathbf{illiq}^{hl}$, $\mathbf{size}^{lh}$, $\mathbf{mom12\_ia}^{hl}$, $\mathbf{tvol\_w}^{hl}$, and $\mathbf{issue5}^{lh}$ are among the most statistically significant anomalies in the subsample before year 1990. After the year 2000, the cross-section of stock returns are mostly predictable by less "popular" firm characteristics (e.g., $\mathbf{cashprod}^{lh}$, $\mathbf{saleta}^{hl}$, and $\mathbf{chceq}^{lh}$). In the non-studentized test, the portfolio mean returns of $\mathbf{size}^{lh}$ and $\mathbf{bm}^{hl}$ are significant only for the periods before 1990. Between the vintage point from 1990 to 2000, low volatility and high momentum are the persistently profitable strategies. The evidence for cross-sectional stock return predictability barely exists in the most recent subsamples. Figure 2 also shows that the estimated $CV(3, 5\%)$ for non-studentized test using the sample period in the 2000's increases, which resemble the findings in the pre- versus post-1993 comparison study.

8 Conclusion

This study investigates how the cross-sectional stock return predictors perform under the multiple testing method. We adopt firm characteristics from the empirical asset pricing literature and then form long-short portfolios to examine their profitability. The results show that most predictors lose their statistical significance once we adjust for data-snooping bias. Moreover, we find that the positive return spreads associated with some statistically significant anomalies are driven by micro-cap stocks. The pieces of evidence for economic significance are also

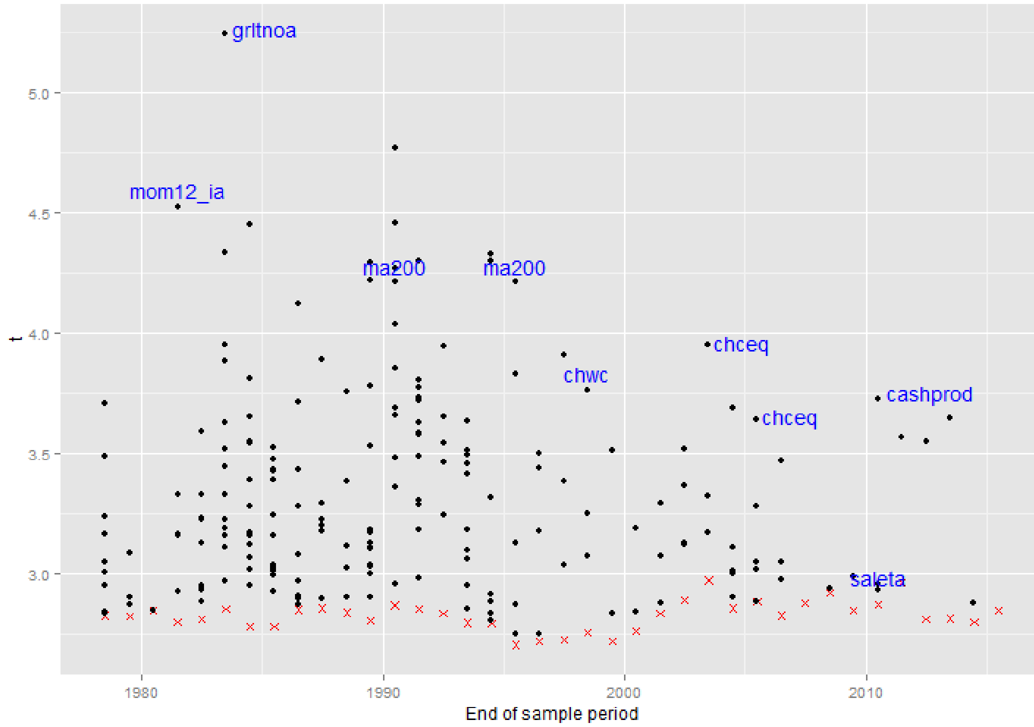
[4]The $CV(k, 5\%)$ is now greater due to the increasing variability of the k-th largest alpha.

[5]In the results not shown here, the analysis with Q-Factor model also confirms the pattern that the evidence for stock return predictability becomes weakened using the recent subsamples.

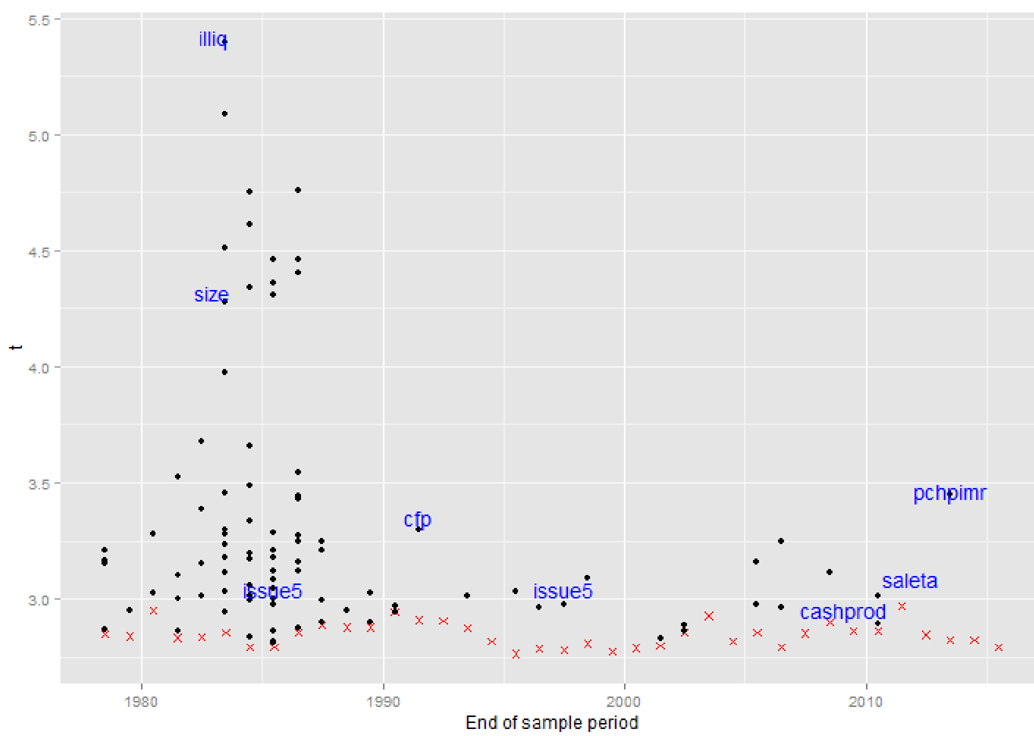
weak. For the annually rebalanced portfolios, the net share issues anomaly generates economically and statistically significant return premium, but it is well explained by 5-Factor or Q-Factor model. For the monthly rebalanced portfolios, only the short-term reversal strategy based on moving average delivers both economically and statistically significant mean return and Q-Factor alpha in the all-but-tiny stocks universe.

Under the selective inference with multiple families, we find more portfolios with economically significant mean returns than the multiple testing that controls the global error rate. Nevertheless, their risk-adjusted returns based on Q-Factor model do not surpass the corresponding critical values. Furthermore, our analyses with different subsamples suggest that the evidence for cross-sectional stock return predictability without data-snooping bias may be obtained mostly during the period before year 2000.

Figure 1: Studentized test with rolling subsamples.



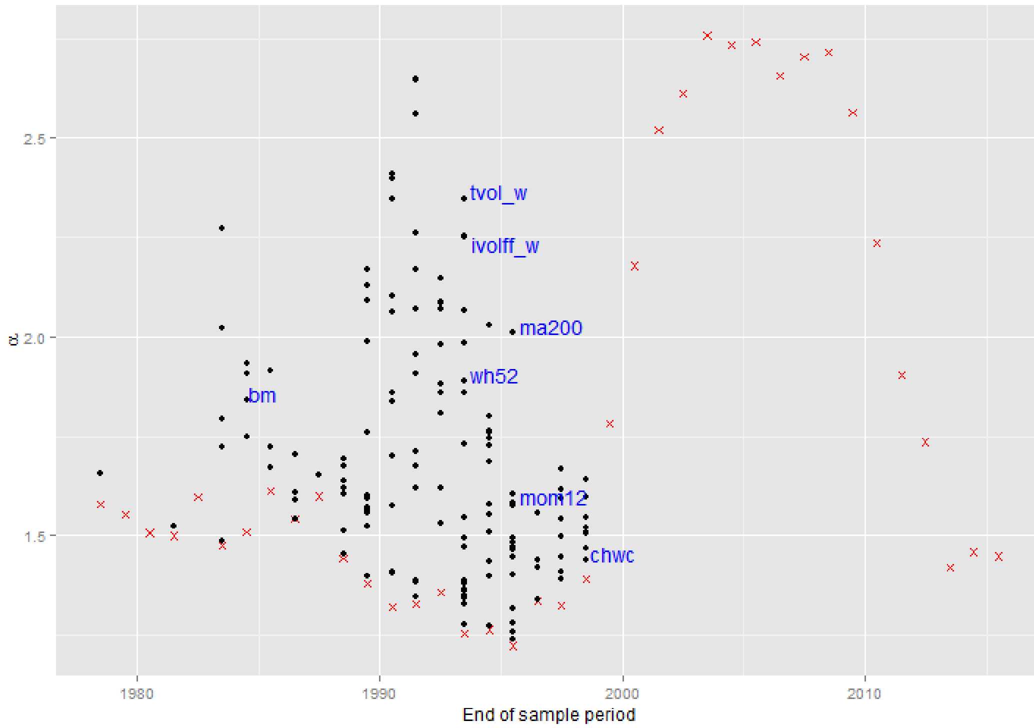
Panel A. All stocks universe



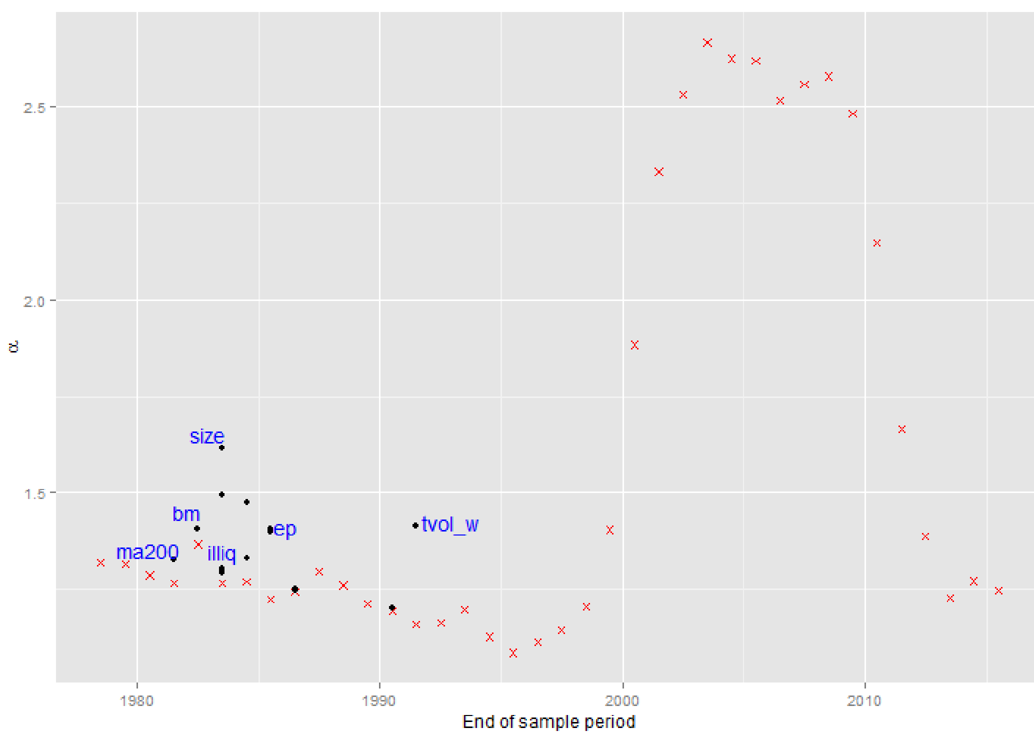
Panel B. All-but-tiny stocks universe

Note: The cross signs are the $CV(3, 5\%)$ for the t-ratios estimated with the past 10-year subsamples. The y-axis and x-axis denote the t-ratios for the mean returns and ending time points of the subsamples, respectively.

Figure 2: Non-studentized test with rolling subsamples.



Panel A. All stocks universe



Panel B. All-but-tiny stocks universe

Note: The cross signs are the $CV(3, 5\%)$ for the alphas estimated with the past 10-year subsamples. The y-axis and x-axis denote the mean returns and ending time points of the subsamples, respectively.

Table 1: The number of rejections based on t-ratios.

	FWER(1)	FWER(2)	FWER(3)	$t > 1.96$
Panel A. All stocks, long-short decile portfolios.				
Mean	9 (3.410)	15 (2.993)	16 (2.813)	41
CAPM	21 (3.423)	28 (2.995)	32 (2.747)	56
3-Factor	18 (3.456)	22 (3.012)	25 (2.782)	44
4-Factor	7 (3.452)	11 (3.017)	12 (2.799)	28
5-Factor	10 (3.472)	14 (3.022)	19 (2.800)	47
Q-Factor	0 (3.526)	3 (3.129)	3 (2.925)	19
Panel B. All stocks, long-short quintile portfolios.				
Mean	3 (3.378)	9 (3.016)	13 (2.839)	32
CAPM	18 (3.345)	23 (2.994)	29 (2.776)	57
3-Factor	14 (3.413)	18 (3.019)	22 (2.759)	49
4-Factor	3 (3.456)	6 (3.038)	9 (2.828)	21
5-Factor	15 (3.461)	18 (3.054)	21 (2.834)	47
Q-Factor	1 (3.448)	2 (3.127)	3 (2.912)	23
Panel C. All-but-tiny stocks, long-short decile portfolios.				
Mean	3 (3.490)	6 (3.102)	9 (2.879)	29
CAPM	10 (3.438)	16 (3.053)	19 (2.878)	49
3-Factor	6 (3.441)	10 (3.047)	13 (2.838)	38
4-Factor	1 (3.447)	1 (3.095)	2 (2.844)	12
5-Factor	10 (3.535)	16 (3.108)	20 (2.843)	39
Q-Factor	0 (3.516)	0 (3.103)	2 (2.898)	19
Panel D. Large-cap stocks, long-short decile portfolios.				
Mean	1 (3.464)	3 (3.127)	4 (2.908)	24
CAPM	3 (3.447)	6 (3.125)	8 (2.875)	36
3-Factor	5 (3.431)	7 (3.067)	8 (2.837)	24
4-Factor	1 (3.451)	1 (3.073)	2 (2.873)	9
5-Factor	9 (3.505)	14 (3.058)	18 (2.866)	38
Q-Factor	0 (3.456)	2 (3.103)	2 (2.942)	21

Note: The values in parentheses are the critical values $CV(k, 5\%)$ for the t-ratios, which are estimated so that FWER(k), $k = 1$, 2, and 3, is bounded below 5% level. To calculate the t-ratios, we use Newey-West standard error with lag parameter equaling 4. The row "Mean" reports the results for average portfolio returns without any risk adjustment. The "all-but-tiny" and "large-cap" stocks are those with market capitalization at the end of June greater than NYSE 20% and 50% quantiles, respectively.

Table 2: The number of rejections based on α's critical value.

	FWER(1)	FWER(2)	FWER(3)
Panel A. All stocks, long-short decile portfolios.			
Mean	5 (0.944)	9 (0.845)	15 (0.781)
CAPM	18 (0.856)	24 (0.743)	29 (0.674)
3-Factor	20 (0.731)	20 (0.643)	23 (0.590)
4-Factor	7 (0.769)	14 (0.654)	15 (0.597)
5-Factor	11 (0.725)	13 (0.625)	18 (0.574)
Q-Factor	0 (0.978)	0 (0.878)	1 (0.819)
Panel B. All stocks, long-short quintile portfolios.			
Mean	0 (0.789)	0 (0.725)	3 (0.695)
CAPM	13 (0.701)	17 (0.627)	20 (0.581)
3-Factor	13 (0.612)	17 (0.531)	18 (0.491)
4-Factor	3 (0.628)	6 (0.552)	8 (0.509)
5-Factor	13 (0.573)	17 (0.486)	22 (0.429)
Q-Factor	1 (0.747)	2 (0.669)	3 (0.624)
Panel C. All-but-tiny stocks, long-short decile portfolios.			
Mean	0 (0.862)	1 (0.805)	1 (0.755)
CAPM	9 (0.798)	12 (0.740)	13 (0.684)
3-Factor	9 (0.685)	14 (0.585)	16 (0.550)
4-Factor	0 (0.691)	1 (0.610)	2 (0.564)
5-Factor	11 (0.674)	16 (0.570)	20 (0.507)
Q-Factor	0 (0.920)	1 (0.805)	1 (0.758)
Panel D. Large-cap stocks, long-short decile portfolios.			
Mean	0 (0.826)	0 (0.755)	1 (0.709)
CAPM	2 (0.795)	7 (0.721)	7 (0.669)
3-Factor	4 (0.670)	8 (0.580)	11 (0.533)
4-Factor	0 (0.666)	0 (0.584)	2 (0.547)
5-Factor	11 (0.646)	15 (0.546)	21 (0.496)
Q-Factor	0 (0.887)	0 (0.781)	1 (0.733)

Note: The values in parentheses are the critical values $CV(k, 5\%)$ for $\hat{\alpha}$, which are estimated so that FWER(k), $k = 1$, 2, and 3, is controlled below 5% level. The mean and risk-adjusted returns are in percentage. The "all-but-tiny" and "large-cap" stocks are those with market capitalization at the end of June greater than NYSE 20% and 50% quantiles, respectively.

Table 3: Selected anomalies.

		Mean		CAPM		3-Factor		4-Factor		5-Factor		Q-factor	
		α	t	α	t	α	t	α	t	α	t	α	t
Panel A. Value-growth anomaly.													
bm^{hl}	all stocks	0.90	3.31	0.93	3.31	0.26	1.66	0.27	1.71	0.25	1.54	0.41	1.78
	all-but-tiny	0.57	2.33	0.66	2.55	0.01	0.09	-0.04	-0.30	-0.04	-0.28	0.04	0.16
bm_ia^{hl}	all stocks	0.26	1.32	0.18	0.82	0.07	0.35	0.14	0.71	0.38	2.03	0.60	2.70
	all-but-tiny	0.22	1.16	0.17	0.82	0.13	0.68	0.14	0.72	0.47	2.43	0.62	2.91
cfp^{hl}	all stocks	0.42	1.52	0.61	2.45	0.34	1.55	0.27	1.24	0.08	0.36	0.13	0.49
	all-but-tiny	0.70	3.09	0.89	4.08	0.44	2.57	0.34	2.10	0.13	0.83	0.21	1.02
cfp_ia^{hl}	all stocks	0.44	2.06	0.41	1.77	0.39	1.89	0.37	1.74	0.59	2.88	0.76	3.14
	all-but-tiny	0.28	1.48	0.23	1.15	0.15	0.84	0.21	1.06	0.30	1.68	0.54	2.63
em^{lh}	all stocks	0.02	0.10	-0.06	-0.24	-0.16	-0.61	-0.26	-1.08	0.29	1.09	0.25	0.78
	all-but-tiny	0.41	1.84	0.39	1.70	0.13	0.59	0.02	0.09	0.48	2.01	0.65	2.36
ep^{hl}	all stocks	0.25	0.80	0.49	1.78	0.22	0.87	0.08	0.31	0.06	0.27	0.21	0.72
	all-but-tiny	0.44	1.78	0.61	2.54	0.20	1.02	0.09	0.44	0.04	0.20	0.23	0.98
sp^{hl}	all stocks	1.04	3.14	1.04	2.88	0.26	1.21	0.25	1.15	-0.12	-0.56	0.02	0.06
	all-but-tiny	0.71	2.42	0.75	2.31	0.01	0.07	-0.01	-0.07	-0.37	-2.00	-0.19	-0.67
Panel B. Momentum strategy.													
mom6^{hl}	all stocks	0.80	3.17	0.81	3.27	0.85	3.41	0.13	0.48	0.81	2.74	0.43	1.30
	all-but-tiny	0.66	2.84	0.60	2.66	0.62	2.60	-0.08	-0.35	0.57	1.96	0.15	0.45
mom12^{hl}	all stocks	0.71	2.35	0.79	2.52	1.09	4.14	0.39	1.45	0.91	3.39	0.50	1.59
	all-but-tiny	0.41	1.60	0.43	1.57	0.72	3.27	0.08	0.36	0.69	3.07	0.20	0.73
mom712^{hl}	all stocks	-0.14	-0.45	-0.08	-0.23	0.30	1.17	-0.03	-0.12	0.29	1.12	0.12	0.38
	all-but-tiny	-0.08	-0.29	-0.09	-0.31	0.32	1.42	-0.02	-0.07	0.37	1.66	0.04	0.14
mom12_ia^{hl}	all stocks	0.59	2.48	0.62	2.57	0.90	4.28	0.40	1.79	0.86	3.69	0.61	2.14
	all-but-tiny	0.45	2.22	0.42	1.93	0.70	3.85	0.26	1.36	0.79	4.02	0.54	2.17
mom12_ind^{hl}	all stocks	-0.03	-0.10	-0.04	-0.15	0.19	0.71	-0.35	-1.36	0.12	0.47	-0.26	-0.82
	all-but-tiny	0.03	0.13	0.02	0.08	0.18	0.80	-0.36	-1.57	0.06	0.24	-0.43	-1.39
wh52^{hl}	all stocks	0.92	2.68	1.27	4.49	1.39	5.58	0.64	2.33	0.94	3.55	0.50	1.70
	all-but-tiny	0.52	2.17	0.83	4.37	0.91	4.81	0.28	1.47	0.57	2.93	0.15	0.75
ma50^{hl}	all stocks	0.66	2.55	0.75	2.84	1.07	4.22	0.55	2.04	1.26	5.02	0.72	2.36
	all-but-tiny	0.40	1.60	0.42	1.62	0.76	3.28	0.28	1.35	1.09	4.70	0.61	1.89
ma100^{hl}	all stocks	1.09	4.56	1.21	5.19	1.41	5.51	0.74	2.47	1.31	4.41	0.70	2.11
	all-but-tiny	0.62	2.53	0.66	2.73	0.90	3.51	0.26	0.94	0.99	3.20	0.46	1.17
ma200^{hl}	all stocks	1.22	4.50	1.31	5.04	1.53	5.79	0.68	2.32	1.42	4.65	0.84	2.53
	all-but-tiny	0.67	2.52	0.68	2.52	0.99	3.86	0.22	0.86	1.04	3.70	0.42	1.19
Panel C. Low volatility strategy.													
tvol_d^{lh}	all stocks	0.82	2.14	1.25	4.16	1.16	4.32	0.96	3.47	0.51	2.04	0.41	1.34
	all-but-tiny	0.33	1.01	0.79	3.20	0.54	2.70	0.37	1.84	0.00	0.02	-0.01	-0.06
tvol_w^{lh}	all stocks	1.00	2.28	1.50	4.44	1.33	4.85	1.16	4.21	0.62	2.78	0.67	2.07
	all-but-tiny	0.42	1.14	0.96	3.39	0.67	3.08	0.49	2.19	0.10	0.53	0.20	0.77
ivolff_d^{lh}	all stocks	0.72	2.19	1.07	3.88	1.03	4.73	0.83	3.40	0.39	1.96	0.25	1.05
	all-but-tiny	0.17	0.55	0.54	2.29	0.35	1.77	0.25	1.31	-0.11	-0.69	-0.14	-0.61
ivolff_w^{lh}	all stocks	0.91	2.27	1.31	4.02	1.22	4.56	1.06	3.89	0.55	2.35	0.58	1.88
	all-but-tiny	0.23	0.70	0.65	2.58	0.45	2.22	0.32	1.60	-0.07	-0.42	0.03	0.13

Table 3 (Continued): Selected anomalies.

		Mean		CAPM		3-Factor		4-Factor		5-Factor		Q-factor	
		α	t	α	t	α	t	α	t	α	t	α	t
ivolcapm$_{\mathbf{d}}$^{lh}	all stocks	0.83	2.43	1.19	4.21	1.15	4.94	0.98	3.83	0.53	2.69	0.44	1.84
	all-but-tiny	0.13	0.45	0.51	2.16	0.31	1.58	0.24	1.21	-0.15	-0.88	-0.14	-0.60
ivolcapm$_{\mathbf{w}}$^{lh}	all stocks	0.81	2.00	1.22	3.74	1.13	4.20	1.01	3.83	0.45	1.97	0.50	1.63
	all-but-tiny	0.33	1.01	0.78	3.07	0.57	2.74	0.43	2.11	0.00	0.01	0.10	0.41
beta^{lh}	all stocks	0.15	0.49	0.65	2.64	0.39	1.69	0.11	0.44	-0.07	-0.30	-0.22	-0.79
	all-but-tiny	0.33	1.03	0.86	3.36	0.56	2.69	0.31	1.41	0.04	0.19	-0.01	-0.03
Panel D. Growth-related anomaly.													
invest_TWX^{lh}	all stocks	0.23	1.22	0.18	0.97	0.22	1.22	0.05	0.25	0.28	1.53	0.15	0.71
	all-but-tiny	0.26	1.49	0.27	1.48	0.33	1.92	0.13	0.74	0.31	1.82	0.09	0.44
invest_AG^{lh}	all stocks	0.29	1.44	0.41	2.13	0.23	1.15	0.19	0.91	0.01	0.05	-0.12	-0.45
	all-but-tiny	0.26	1.30	0.39	2.11	0.20	1.10	0.11	0.62	-0.14	-0.85	-0.34	-1.69
invest_LWZ^{lh}	all stocks	0.40	1.30	0.67	2.17	0.06	0.25	-0.12	-0.53	-0.61	-3.14	-0.69	-2.32
	all-but-tiny	0.38	1.19	0.65	2.07	0.05	0.22	-0.17	-0.79	-0.69	-3.49	-0.82	-2.75
agr^{lh}	all stocks	0.80	3.49	0.95	3.83	0.52	2.97	0.38	2.10	0.02	0.13	-0.08	-0.39
	all-but-tiny	0.63	2.74	0.81	3.34	0.40	2.42	0.32	2.04	-0.18	-1.29	-0.24	-1.32
issue^{lh}	all stocks	0.89	3.77	1.06	4.54	0.82	4.31	0.75	4.03	0.30	1.96	0.26	1.31
	all-but-tiny	0.83	3.61	0.95	3.98	0.73	4.13	0.66	3.82	0.23	1.65	0.16	0.87
issue5^{lh}	all stocks	0.71	3.48	0.83	4.39	0.81	4.02	0.71	3.33	0.37	2.22	0.33	1.51
	all-but-tiny	0.71	3.65	0.84	4.44	0.75	3.89	0.60	3.09	0.31	2.01	0.30	1.57
acc^{lh}	all stocks	0.43	2.19	0.52	2.60	0.51	2.62	0.46	2.13	0.51	2.58	0.52	2.34
	all-but-tiny	0.31	1.89	0.36	2.26	0.34	2.05	0.25	1.40	0.29	1.81	0.31	1.67
grltnoa^{lh}	all stocks	0.73	4.86	0.78	4.94	0.59	4.07	0.51	3.11	0.24	1.63	0.08	0.47
	all-but-tiny	0.52	3.30	0.59	3.51	0.45	2.94	0.39	2.39	0.08	0.56	-0.10	-0.59
Panel E. Profitability.													
gpa^{hl}	all stocks	0.25	0.99	0.41	1.61	0.41	1.72	0.28	1.21	-0.39	-2.33	-0.52	-2.33
	all-but-tiny	0.28	1.37	0.36	1.58	0.40	2.07	0.28	1.45	-0.31	-1.87	-0.44	-2.05
gpa_ia^{hl}	all stocks	0.23	0.97	0.44	1.92	0.47	2.24	0.39	1.92	0.02	0.14	-0.04	-0.20
	all-but-tiny	0.13	0.64	0.34	1.61	0.36	1.96	0.27	1.53	-0.05	-0.30	-0.12	-0.65
opa^{hl}	all stocks	0.59	1.73	0.87	2.86	0.93	3.10	0.78	2.61	0.14	0.47	0.01	0.02
	all-but-tiny	0.34	1.35	0.52	2.04	0.62	2.67	0.44	1.83	-0.12	-0.66	-0.35	-1.47
gmr^{hl}	all stocks	0.07	0.28	0.28	1.21	0.33	1.51	0.30	1.47	-0.07	-0.39	-0.04	-0.16
	all-but-tiny	0.14	0.71	0.30	1.67	0.44	2.57	0.42	2.61	0.15	1.01	0.20	1.14
roe^{hl}	all stocks	0.11	0.37	0.35	1.28	0.43	1.73	0.26	1.09	-0.21	-1.02	-0.28	-1.09
	all-but-tiny	-0.08	-0.31	0.11	0.41	0.15	0.60	0.07	0.30	-0.47	-2.28	-0.53	-1.91
roa^{hl}	all stocks	0.19	0.54	0.49	1.60	0.48	1.74	0.38	1.34	-0.26	-1.14	-0.25	-0.81
	all-but-tiny	-0.04	-0.16	0.19	0.75	0.23	0.95	0.13	0.55	-0.41	-2.07	-0.46	-1.79
roic^{hl}	all stocks	0.29	0.89	0.57	1.88	0.49	1.80	0.56	2.12	-0.12	-0.59	0.00	0.02
	all-but-tiny	0.04	0.16	0.25	0.99	0.29	1.23	0.17	0.73	-0.34	-1.76	-0.44	-1.86

Table 3 (Continued): Selected anomalies.

		Mean		CAPM		3-Factor		4-Factor		5-Factor		Q-factor	
		α	t	α	t	α	t	α	t	α	t	α	t
Panel F. Illiquidity and trading activity.													
illiq^{hl}	all stocks	0.81	3.82	0.82	3.88	0.62	4.52	0.54	3.86	0.65	4.36	0.57	3.44
	all-but-tiny	0.30	2.29	0.28	2.16	0.08	0.87	0.05	0.53	0.06	0.67	-0.06	-0.54
turn^{lh}	all stocks	0.20	0.68	0.59	2.32	0.20	1.00	0.13	0.67	-0.22	-1.07	-0.23	-0.80
	all-but-tiny	0.19	0.60	0.62	2.39	0.25	1.19	0.16	0.77	-0.26	-1.31	-0.25	-0.87
std_turn^{lh}	all stocks	0.15	0.52	0.55	2.31	0.30	1.53	0.18	0.96	-0.17	-0.93	-0.19	-0.76
	all-but-tiny	0.08	0.27	0.46	1.99	0.21	1.10	0.09	0.50	-0.29	-1.62	-0.25	-1.06
dvol^{lh}	all stocks	0.31	1.71	0.43	2.24	0.15	1.26	0.15	1.29	0.14	1.20	0.15	1.05
	all-but-tiny	0.34	2.55	0.40	2.98	0.14	1.79	0.13	1.64	0.07	0.96	0.03	0.23
std_dvol^{lh}	all stocks	0.39	2.43	0.54	3.24	0.29	2.70	0.24	2.26	0.24	2.22	0.23	1.61
	all-but-tiny	0.33	2.34	0.43	3.04	0.15	1.67	0.09	1.01	0.05	0.62	0.00	0.04
zerotrade^{hl}	all stocks	0.41	1.45	0.86	3.49	0.45	2.26	0.36	1.92	0.02	0.10	0.02	0.07
	all-but-tiny	0.21	0.71	0.61	2.37	0.23	1.05	0.11	0.52	-0.31	-1.62	-0.33	-1.22
to12^{hl}	all stocks	0.25	0.79	0.68	2.64	0.32	1.56	0.24	1.18	-0.12	-0.61	-0.07	-0.24
	all-but-tiny	0.12	0.37	0.57	2.11	0.19	0.89	0.09	0.40	-0.32	-1.56	-0.23	-0.78

Table 4: Studentized multiple testing with monthly rebalanced portfolios.

	FWER(1)	FWER(2)	FWER(3)	$t > 1.96$
Panel A. All stocks, long-short decile portfolios.				
Mean	10 (3.063)	15 (2.660)	19 (2.444)	24
CAPM	23 (2.929)	23 (2.523)	29 (2.185)	32
3-Factor	22 (3.004)	27 (2.501)	28 (2.193)	29
4-Factor	17 (3.029)	19 (2.592)	22 (2.294)	25
5-Factor	14 (3.148)	18 (2.700)	19 (2.428)	26
Q-Factor	2 (3.068)	4 (2.767)	12 (2.476)	14
Panel B. All-but-tiny stocks, long-short decile portfolios.				
Mean	4 (3.047)	7 (2.757)	8 (2.499)	17
CAPM	17 (3.080)	24 (2.624)	25 (2.340)	27
3-Factor	21 (3.012)	22 (2.596)	25 (2.311)	27
4-Factor	5 (3.128)	9 (2.679)	13 (2.365)	19
5-Factor	4 (3.191)	7 (2.823)	9 (2.580)	15
Q-Factor	1 (3.106)	3 (2.808)	3 (2.596)	4

Note: See Table 1's note.

Table 5: Non-studentized multiple testing with monthly rebalanced portfolios.

	FWER(1)	FWER(2)	FWER(3)
Panel A. All stocks, long-short decile portfolios.			
Mean	11 (1.098)	15 (0.876)	17 (0.767)
CAPM	19 (0.849)	23 (0.679)	29 (0.530)
3-Factor	18 (0.760)	20 (0.614)	28 (0.493)
4-Factor	16 (0.767)	17 (0.631)	17 (0.549)
5-Factor	6 (1.097)	10 (0.960)	13 (0.837)
Q-Factor	0 (1.264)	1 (1.113)	3 (1.019)
Panel B. All-but-tiny stocks, long-short decile portfolios.			
Mean	2 (0.988)	3 (0.896)	4 (0.857)
CAPM	16 (0.815)	19 (0.684)	20 (0.616)
3-Factor	17 (0.735)	20 (0.612)	20 (0.544)
4-Factor	3 (0.759)	11 (0.644)	15 (0.551)
5-Factor	3 (0.971)	4 (0.869)	5 (0.790)
Q-Factor	0 (1.135)	1 (1.025)	1 (0.954)

Note: See Table 2's note.

Table 6: Monthly rebalanced portfolios with t-ratios greater than $CV(3, 5\%)$.

Panel A. All stocks, mean return spread.

	abr^{hl}	**mom712**^{hl}	**ma20**^{lh}	**mom12**^{hl}	**mom12_ia**^{hl}	**mom6**^{hl}	**ivolff_d**^{lh}
α	1.187	1.615	0.993	1.915	1.290	1.361	1.469
t	6.747	5.237	4.664	4.432	3.632	3.553	3.527
	ivolcapm_d^{lh}	**sue**^{hl}	**illiq**^{hl}	**tvol_d**^{lh}	**roaq1**^{hl}	**roaq2**^{hl}	**roaq3**^{hl}
α	1.404	0.441	0.713	1.446	0.816	0.790	0.928
t	3.527	3.208	3.161	3.101	2.992	2.867	2.814
	tvol_w^{lh}	**ivolff_w**^{lh}	**taxmom**^{hl}	**maxret**^{lh}	**ivolcapm_w**^{lh}		
α	1.357	1.287	0.423	1.006	1.217		
t	2.680	2.648	2.623	2.594	2.516		

Panel B. All-but-tiny stocks, mean return spread.

	abr^{hl}	**ma20**^{lh}	**mom712**^{hl}	**mom12**^{hl}	**sue**^{hl}	**illiq**^{hl}	**mom12_ia**^{hl}
α	0.764	0.860	1.241	1.259	0.434	0.453	0.928
t	4.690	4.663	4.136	3.584	2.997	2.996	2.950
	mom6^{hl}						
α	0.842						
t	2.631						

Panel C. All stocks, Q-Factor alpha.

	abr^{hl}	**ma20**^{lh}	**tvol_w**^{lh}	**ivolff_d**^{lh}	**mom712**^{hl}	**illiq**^{hl}	**size**^{lh}
α	1.103	1.182	0.939	0.939	0.941	0.464	1.035
t	5.225	4.155	2.916	2.815	2.755	2.707	2.697
	ivolcapm_w^{lh}	**tvol_d**^{lh}	**ivolff_w**^{lh}	**accq**^{lh}	**season**^{hl}		
α	0.832	0.901	0.815	0.436	0.546		
t	2.670	2.654	2.559	2.515	2.508		

Panel D. All-but-tiny stocks, Q-Factor alpha.

	ma20^{lh}	**abr**^{lh}	**season**^{hl}
α	1.079	0.597	0.514
t	4.248	2.882	2.825

Table 7: The choice of k by controlling FDP.

		Mean	CAPM	3-Factor	4-Factor	5-Factor	Q-Factor
Panel A. Studentized test.							
All stocks	$\gamma = 0.05$	1	2	1	1	1	1
	$\gamma = 0.1$	2	4	3	1	2	1
All-but-tiny stocks	$\gamma = 0.05$	1	1	1	1	1	1
	$\gamma = 0.1$	1	2	1	1	2	1
Panel B. Non-studentized test.							
All stocks	$\gamma = 0.05$	1	1	2	1	1	1
	$\gamma = 0.1$	1	4	3	1	2	1
All-but-tiny stocks	$\gamma = 0.05$	1	1	1	1	1	1
	$\gamma = 0.1$	1	2	2	1	2	1

Note: This table reports the choice of k in FWER(k) by controlling the probability of FDP exceeding γ to be below 5%.

Table 8: Selective inference with multiple families.

	Studentized		Non-studentized	
	Mean	Q-Factor	Mean	Q-Factor
Panel A. All stocks.				
Value	2 (2.618)	1 (2.710)	2 (0.713)	0 (0.794)
Momentum	7 (2.104)	1 (2.472)	6 (0.626)	1 (0.774)
Volatility	3 (2.246)	0 (2.552)	6 (0.617)	0 (0.749)
Growth	4 (2.440)	0 (2.653)	4 (0.636)	1 (0.573)
Profitability	$\sharp$	0 (2.633)	$\sharp$	0 (0.759)
Trading	1 (2.619)	1 (2.549)	1 (0.707)	0 (0.647)
Others	2 (3.363)	0 (3.407)	1 (0.920)	0 (0.904)
Total	19	3	20	2
Panel B. All-but-tiny stocks.				
Value	1 (2.806)	1 (2.843)	2 (0.625)	0 (0.709)
Momentum	1 (2.570)	0 (2.730)	2 (0.639)	0 (0.895)
Volatility	$\sharp$	$\sharp$	$\sharp$	$\sharp$
Growth	4 (2.528)	0 (2.771)	2 (0.668)	1 (0.524)
Profitability	$\sharp$	0 (2.709)	$\sharp$	0 (0.652)
Trading	0 (2.602)	$\sharp$	0 (0.717)	$\sharp$
Others	0 (3.527)	0 (3.514)	0 (0.869)	0 (0.874)
Total	6	1	6	1

Note: This table reports the number of rejections and its critical value in parentheses when the average of exceedance FDP over the selected families is controlled at 5% significance level. We choose the exceedance level of FDP to be 0.1. The symbol $\sharp$ indicates that the family is not selected because its maximum t-ratio is below 1.96.

Table 9: Multiple testing using pre- and post-1993 sample periods.

		All stocks		All-but-tiny stocks	
		Mean	Q-Factor	Mean	Q-Factor
Panel A. Studentized test.					
Pre-1993	FWER(1)	7 (3.331)	7 (3.491)	2 (3.359)	3 (3.497)
	FWER(2)	13 (2.935)	8 (3.089)	7 (3.021)	3 (3.102)
	FWER(3)	16 (2.744)	9 (2.871)	12 (2.783)	7 (2.910)
	$t > 1.96$	44	25	36	29
Post-1993	FWER(1)	0 (3.381)	0 (3.458)	0 (3.372)	0 (3.444)
	FWER(2)	2 (3.073)	1 (3.026)	0 (3.041)	0 (3.041)
	FWER(3)	2 (2.861)	1 (2.843)	0 (2.880)	0 (2.855)
	$t > 1.96$	12	6	9	8
Panel B. Non-studentized test.					
Pre-1993	FWER(1)	8 (1.121)	8 (1.084)	0 (0.947)	1 (1.009)
	FWER(2)	13 (0.968)	10 (0.937)	1 (0.842)	1 (0.865)
	FWER(3)	16 (0.893)	11 (0.850)	2 (0.792)	6 (0.777)
Post-1993	FWER(1)	0 (1.592)	0 (1.398)	0 (1.451)	0 (1.356)
	FWER(2)	0 (1.440)	0 (1.259)	0 (1.355)	0 (1.212)
	FWER(3)	0 (1.381)	0 (1.185)	0 (1.293)	0 (1.138)

Note: The pre-1993 and post-1993 results correspond to the multiple testing using the sample periods before and after the end of June 1993, respectively.

A Step-SPA(k) algorithm

This appendix illustrates the Step-SPA(k) algorithm that controls the k-family-wise error rate (FWER(k)) asymptotically. The key assumptions made by Step-SPA(k) algorithm are: (i) the parameters vector $\{\hat{\alpha}_1, \ldots, \hat{\alpha}_M\}$ converges to multivariate normal distribution, and (ii) this asymptotic distribution can well be approximated by bootstrap simulation. We refer to Hsu et al. (2014) for further technical details and proofs.

Let $\hat{\alpha}_l$ denote the parameter of a portfolio $l \in \{1, \ldots, M\}$ estimated from a time-series sample of size T. The null hypotheses are $H_0^l : \alpha_l \leq 0,\ l = 1, \ldots, M$. We use the notation k-max$\{x_l; l \in A\}$ to denote k-th largest value of x in the subset $A \subseteq \{1, \ldots, M\}$. The following algorithm can be used to asymptotically control FWER(k) below a threshold level δ.

Step-SPA(k) algorithm

(S1) Run the regression

$$R_{lt} = \alpha_l + \mathbf{F_t}'\beta_l + \varepsilon_{lt},$$

where $\mathbf{F_t}$ is the vector of factor portfolio returns. To conduct multiple testing on the simple average returns, discard the $\mathbf{F_t}'\beta_l$.

(S2) Compute the studentized or non-studentized test statistics for each portfolio

$$\hat{d}_l = \sqrt{T}\frac{\hat{\alpha}_l}{\hat{\sigma}_l} \quad \text{or} \quad \sqrt{T}\hat{\alpha}_l\,,$$

where $\hat{\sigma}_l$ is the consistent estimator of $\hat{\alpha}_l$'s standard deviation.

(S3) Compute the re-centering estimators

$$\hat{\alpha}_l^- = \hat{\alpha}_l \cdot \mathbb{1}\left(\sqrt{T}\hat{\alpha}_l \leq -\hat{\sigma}_l\sqrt{2\log\log T}\right),$$

where $\mathbb{1}$ is an indicator function.

(S4) For each bootstrap sample $b = \{1, \ldots, B\}$, calculate the studentized or non-studentized booootstrap statistics

$$\hat{d}_l^b = \sqrt{T}\frac{\hat{\alpha}_l^b - \hat{\alpha}_l + \hat{\alpha}_l^-}{\hat{\sigma}_l} \quad \text{or} \quad \sqrt{T}(\hat{\alpha}_l^b - \hat{\alpha}_l + \hat{\alpha}_l^-)\,,$$

where $\hat{\alpha}_l^b$ is the estimator of α_l using bootstrap sample b.

(S5) In each bootstrap sample, find k-max$\{\hat{d}_l^b; l \in A_1\}$, where $A_1 = \{1, \ldots, M\}$.

(S6) Define $\hat{q}(1-\delta, k, A_1) = \max\{\tilde{q}(1-\delta, k, A_1), 0\}$, where $\tilde{q}(1-\delta, k, A_1)$ is the $(1-\delta)$ empirical quantile of the B values k-max$\{\hat{d}_l^1; l \in A_1\}$, …, k-max$\{\hat{d}_l^B; l \in A_1\}$.

(S7) (a) If $\max\{\hat{d}_l; l \in A_1\} \leq \hat{q}(1-\delta, k, A_1)$, then accept all null hypotheses and stop.

(b) If $\hat{d}_l > \hat{q}(1-\delta, k, A_1)$, then reject H_0^l.

(S8) Denote the collection of the index of the rejected hypotheses and the remaining hypotheses from the previous step by R_2 and A_2, respectively.

(a) If $|R_2| < k$, then stop.

(b) If $|R_2| \geq k$, then find the new critical value as follows

$$\hat{c}(1-\delta, k, A_2) = \max_{I \subset R_2, |I|=k-1} \left\{\hat{q}(1-\delta, k, J); J = A_2 \cup I\right\},$$

where $|A|$ denotes the number of elements in set A and $\hat{q}(1-\delta, k, J)$ is calculated as in the step (S5).

(S9) (a) If $\max\{\hat{d}_l; l \in A_2\} \leq \hat{c}(1-\delta, k, A_2)$, then there is no further rejection, stop.

(b) If $\hat{d}_l > \hat{c}(1-\delta, k, A_2)$ with $l \in A_2$, then reject H_0^l and go back to step (S7) by replacing R_2 and A_2 with R_j and A_j, $j \geq 3$.

For the studentized test, we use Newey-West standard error with lag parameter equaling 4 to estimate σ_l. To generate the bootstrap sample in Step (S4), we employ the stationary bootstrap procedure by Politis and Romano (1994), which re-samples the original data in blocks to capture the time-series dependence structure. Specifically, a bootstrap sample b is a set of random index obtained by the following algorithm.

Stationary bootstrap algorithm

(B1) Generate a random integer t_1^b which is uniformly distributed between 1 and T.

(B2) With probability Q, set $t_2^b = t_1^b + 1$, and with probability $1-Q$, t_2^b is obtained by generating random interger between 1 and T.

(B3) Repeat step (B2) until the b-th bootstrap sample has T observations.

Politis and Romano (1994) show that the block size from the above algorithm follows a geometric distribution with parameter Q. In our empirical analysis, we use $Q = 0.8$, so that the expected block size is 5. We set the number of bootstrap replications $B = 2,000$.

B Predictor Definition

B.1 Annual Predictors

Table B1: Annual predictor definition

Variable	Reference	Definition
absacc	Bandyopadhyay et al. (2010)	abs(**acc**)
acc	Sloan (1996)	(Δ\{(ACT − CHE) − (LCT − DLC − TXP)\} − DP) / avg2(AT)
agr	Cooper et al. (2008)	AT / lag1(AT) − 1
ato	Soliman (2008)	SALE/avg2(**noa**)
bas12	Liu (2006)	The average of daily (ASKHI − BIDLO) / (ASKHI + BIDLO)/2 over the past 12 months.
beta	Fama and MacBeth (1973)	The beta coefficient of CAPM using weekly returns data over the past 52 weeks.
bm	Stattman (1980)	(SEQ + TXDB + ITCB - pref) / (PRCC_F × CSHO) [a]
bm_ia	Asness et al. (2000)	**bm** − IndMean(**bm**)
cash	Palazzo (2012)	CHE / AT
cashprod	Chandrashekar and Rao (2009)	(PRCC_F × CSHO + DT − AT) / CHE
cfodebt	Ou and Penman (1989)	OANCF / avg2(DT) [b]
cfp	Desai et al. (2004)	OANCF / (PRCC_F × CSHO)
cfp_ia	Asness et al. (2000)	**cfp** − IndMean(**cfp**)
chato	Soliman (2008)	Δ\{SALE/avg2(**noa**)\}
chato_ia	Soliman (2004)	**chato** − IndMean(**chato**)
chceq	Richardson et al. (2005)	ΔCEQ / avg2(AT)
chdiv	Ou and Penman (1989)	ΔDVT
chemp	Belo et al. (2014)	ΔEMP / avg2(EMP)
chemp_ia	Asness et al. (2000)	**chemp** − IndMean(**chemp**)
chfin	Richardson et al. (2005)	Δ\{(IVST + IVAO) − (DLTT + DLC + PSTK)\} / avg2(AT)
chinv	Thomas and Zhang (2002)	ΔINVT / avg2(AT)
chmom	Gettleman and Marks (2006)	**mom1** × **mom6** − **mom712**
chnco	Richardson et al. (2005)	Δ\{(AT − ACT − IVAO) − (LT − LCT − DLTT)\} / avg2(AT)
chpm	Soliman (2008)	Δ\{OIADP/SALE\}
chpm_ia	Soliman (2004)	**chpm** − IndMean(**chpm**)
chrnoa	Soliman (2008)	Δ\{OIADP/avg2(**noa**)\}
chrnoa_ia	Soliman (2004)	**chrnoa** − IndMean(**chrnoa**)
chroe	Ou and Penman (1989)	Δ**roe**
chwc	Richardson et al. (2005)	Δ\{(ACT − CHE) − (LCT − DLC)\} / avg2(AT)
currat	Ou and Penman (1989)	ACT / LCT
debteq	Ou and Penman (1989)	LT / (AT − LT)
deprppe	Ou and Penman (1989)	DP / PPEGT
dvol	Chordia et al. (2001)	log(lag2(PRC×VOL))
dy	Ball (1978)	DVT / (PRCC_F × CSHO)
em	Loughran and Wellman (2011)	(PRCC_F × CSHO + DLC + DLTT − pref − CHE) / OIBDP
ep	Basu (1983)	IB / (PRCC_F × CSHO)
gmr	Ou and Penman (1989)	(SALE − COGS) / SALE
gpa	Novy-Marx (2013)	(SALE − COGS) / AT
gpa_ia	Novy-Marx (2013)	**gpa** − IndMean(**gpa**)
grltnoa	Fairfield et al. (2003)	Δ**noa**/avg2(AT) − **acc**
herf	Hou and Robinson (2006)	Herfindahl index, IndSum($\{\text{SALE/IndSum(SALE)}\}^2$)

Table B1 (Continued): Annual predictor definition

Variable	Reference	Definition
illiq	Amihud (2002)	The average of daily abs(RET)/(PRC×VOL) over the past 12 months.
invest_LWZ	Liu et al. (2009)	(CAPX − SPPE) / PPEGT
invest_TWX	Titman et al. (2004)	(CAPX/SALE) / lag1(avg3(CAPX/SALE)) − 1
invest_AG	Anderson and Garcia-Feijòo (2006)	(lag1(CAPX) − lag3(CAPX)) / lag3(CAPX)
invtgr	Belo and Lin (2011)	(INVT/cpi) / lag1(INVT/cpi) − 1
invturn	Ou and Penman (1989)	COGS / avg2(INVT)
issue	Fama and French (2008)	log((CSHO×AJEX) / lag1(CSHO×AJEX))
issue5	Daniel and Titman (2006)	log((CSHO×AJEX) / lag5(CSHO×AJEX))
ivolcapm_d	Ang et al. (2006)	The root mean square error of CAPM model using daily returns data over the past 1 month.
ivolcapm_w	Bali and Cakici (2008)	The root mean square error of CAPM using weekly returns data over the past 52 weeks.
ivolff_d	Ang et al. (2006)	The root mean square error of Fama-French 3-Factor model using daily returns data over the past 1 month.
ivolff_w	Bali and Cakici (2008)	The root mean square error of Fama-French 3-Factor model using weekly returns data over the past 52 weeks.
lev	Bhandari (1988)	LT / (PRCC_F × CSHO)
ma100	Han et al. (2013)	The end of month PRC / the past 100-day average of daily PRC
ma20	Han et al. (2013)	The end of month PRC / the past 20-day average of daily PRC
ma200	Han et al. (2013)	The end of month PRC / the past 200-day average of daily PRC
ma50	Han et al. (2013)	The end of month PRC / the past 50-day average of daily PRC
maxret	Bali et al. (2011)	The maximum of daily RET over the past 1 month
mom1	Jegadeesh (1990)	$1 + \text{RET}_t$
mom12	Jegadeesh (1990)	$\prod_{i=t-1}^{t-11}(1 + \text{RET}_i)$
mom12_ia	Asness et al. (2000)	**mom12** − IndMean(**mom12**)
mom12_ind	Moskowitz and Grinblatt (1998)	IndMean(**mom12**)
mom36	DeBondt and Thaler (1985)	$\prod_{i=t}^{t-35}(1 + \text{RET}_i)$
mom36_ia	Asness et al. (2000)	**mom36** − IndMean(**mom36**)
mom6	Jegadeesh and Titman (1993)	$\prod_{i=t-1}^{t-5}(1 + \text{RET}_i)$
mom36	DeBondt and Thaler (1985)	$\prod_{i=t}^{t-59}(1 + \text{RET}_i)$
mom712	Novy-Marx (2012)	$\prod_{i=t-6}^{t-11}(1 + \text{RET}_i)$
nicfo	Ou and Penman (1989)	NI / OANCF
nimr	Ou and Penman (1989)	NI / SALE
noa	Fairfield et al. (2003)	RECT + INVT + PPENT + ACO + INTAN + AO − AP − LCO − LO
oimr	Ou and Penman (1989)	OIBDP / SALE
oita	Ou and Penman (1989)	EBIT / avg2(AT)
opa	Ball et al. (2015)	(SALE − COGS − (XSGA − XRD)) / AT
orgcap	Eisfeldt and Papanikolaou (2013)	oc/AT [c]
orgcap_ia	Eisfeldt and Papanikolaou (2013)	**orgcap** − IndMean(**orgcap**)
pchcapx_ia	Lev and Thiagarajan (1993)	CAPX/lag1(CAPX) − IndMean(CAPX/lag1(CAPX))
pchcapxat	Ou and Penman (1989)	(CAPX / avg2(AT)) / lag1(CAPX / avg2(AT)) − 1
pchcurrat	Ou and Penman (1989)	**currat** / lag1(**currat**) − 1
pchdebteq	Ou and Penman (1989)	**debteq** / lag1(**debteq**) − 1
pchdepr	Ou and Penman (1989)	DP / lag1(DP) − 1
pchdeprppe	Ou and Penman (1989)	**deprppe** / lag1(**deprppe**) − 1
pchdltt	Ou and Penman (1989)	DLTT / lag1(DLTT) − 1

Table B1 (Continued): Annual predictor definition

Variable	Reference	Definition
pchgm_pchsale	Lev and Thiagarajan (1993)	(SALE−COGS)/lag1(SALE−COGS) − SALE/lag1(SALE)
pchgmr	Ou and Penman (1989)	**gmr** / lag1(**gmr**) − 1
pchinvta	Ou and Penman (1989)	(INVT/AT)/ lag1(INVT/AT) − 1
pchinvturn	Ou and Penman (1989)	**invturn** / lag1(**invturn**) − 1
pchnimr	Ou and Penman (1989)	**nimr** / lag1(**nimr**) − 1
pchoimr	Ou and Penman (1989)	**oimr** / lag1(**oimr**) − 1
pchoita	Ou and Penman (1989)	**oita** / lag1(**oita**) − 1
pchpimr	Ou and Penman (1989)	**pimr** / lag1(**pimr**) − 1
pchppeteq	Ou and Penman (1989)	**ppeteq** / lag1(**ppeteq**) − 1
pchquick	Ou and Penman (1989)	**quick** / lag1(**quick**) − 1
pchsale	Ou and Penman (1989)	SALE / lag1(SALE) − 1
pchsale_pchinvt	Lev and Thiagarajan (1993)	SALE/lag1(SALE) − INVT/lag1(INVT)
pchsale_pchrect	Lev and Thiagarajan (1993)	SALE/lag1(SALE) − RECT/lag1(RECT)
pchsale_pchxsga	Lev and Thiagarajan (1993)	SALE/lag1(SALE) − XSGA/lag1(XSGA)
pchsaleinv	Ou and Penman (1989)	**saleinv** / lag1(**saleinv**) − 1
pchsaleta	Ou and Penman (1989)	**saleta** / lag1(**saleta**) − 1
pchsalewc	Ou and Penman (1989)	**salewcap** / lag1(**salewcap**) − 1
pchtie	Ou and Penman (1989)	**tie** / lag1(**tie**) − 1
pchwcap	Ou and Penman (1989)	(ACT − LCT) / lag1(ACT − LCT) − 1
pchwcapta	Ou and Penman (1989)	**wcapta** / lag1(**wcapta**) − 1
pctacc	Hafzalla et al. (2011)	(Δ\{(ACT − CHE) − (LCT − DLC − TXP)\} − DP) / abs(IB)
pdelay1	Hou and Moskowitz (2005)[d]	$1 - R_r^2 \ / \ R_u^2$
pdelay2	Hou and Moskowitz (2005)	$\sum_{j=1}^{4}(j \times d_j) \ / \ (b + \sum_{j=1}^{4} d_j)$
pdelay3	Hou and Moskowitz (2005)	$\sum_{j=1}^{4}(j \times T(d_j)) \ / \ (T(b) + \sum_{j=1}^{4} T(d_j))$
pimr	Ou and Penman (1989)	PI / SALE
pm	Soliman (2008)	OIADP / SALE
ppeteq	Ou and Penman (1989)	PPEGT / TEQ
quick	Ou and Penman (1989)	(ACT − INVT) / LCT
rnoa	Soliman (2008)	OIADP / avg2(**noa**)
roa	Ou and Penman (1989)	NI / avg2(AT)
roe	Ou and Penman (1989)	NI / avg2(TEQ)
roic	Brown and Rowe (2007)	(EBIT − NOPI) / (CEQ + LT − CHE)
salecash	Ou and Penman (1989)	SALE / avg2(CHE)
saleinv	Ou and Penman (1989)	SALE / avg2(INVT)
saleppe	Ou and Penman (1989)	SALE / avg2(PPEGT)
salerec	Ou and Penman (1989)	SALE / avg2(RECT)
saleta	Ou and Penman (1989)	SALE / avg2(AT)
salewcap	Ou and Penman (1989)	SALE / avg2(ACT − LCT)
season	Keloharju et al. (2016)	The average of RET_{t-11}, RET_{t-23}, ..., RET_{t-239}
size	Banz (1981)	PRCC_F × CSHO
size_ia	Asness et al. (2000)	**size** − IndMean(**size**)
sp	Barbee et al. (1996)	SALE / (PRCC_F × CSHO)
std_dvol	Chordia et al. (2001)	log(lag2(s_dvol)), s_dvol is the standard deviation of PRC×VOL over the past 36 months.
std_turn	Chordia et al. (2001)	log(lag2(s_turn)), s_turn is the standard deviation of VOL/SHROUT over the past 36 months.
tie	Ou and Penman (1989)	EBIT / XINT
tangible	Hahn and Lee (2009)	(CHE + 0.715×RECT + 0.547×INVT + 0.535×PPENT) / AT

Table B1 (Continued): Annual predictor definition

Variable	Reference	Definition
to12	Liu (2006)	The average of daily VOL/SHROUT over the past 12 months.
turn	Chordia et al. (2001)	log(lag2(VOL/SHROUT))
tvol_d	Ang et al. (2006)	The standard deviation of daily RET over the past 1 month
tvol_w	Bali and Cakici (2008)	The standard deviation of weekly RET over the past 52 weeks
wcapta	Ou and Penman (1989)	(ACT − LCT) / AT
wh52	George and Hwang (2004)	The end of month PRC / the maximum of daily PRC over the past 12 months
zerotrade	Liu (2006)	(nzero12 + (1/turn12) / 11000) × 21 / ndays12 [e]

Note: The data sources are CRSP and Compustat. The variables with capitalized names are CRSP or Compustat raw variables. The notation abs(x) denotes the absolute value of x, lagN(x) denotes $\mathrm{x}_{t-\mathrm{N}}$, $\Delta\{x\}$ denotes $\mathrm{x}_t - \mathrm{x}_{t\text{-N}}$, and avgN(x) denotes the average value of $\mathrm{x}_t, \dots, \mathrm{x}_{t\text{-N}+1}$. The time series index $\{t, t\text{-}1, \dots\}$ indicates monthly frequency for CRSP variables unless explicitly stated otherwise, and t is the portfolio formation time (the end of June). Meanwhile, $\{t, t\text{-}1, \dots\}$ of Compustat variables means annual frequency, where t is the latest fiscal year end. Whenever Compustat variables are used, only firms with December fiscal year end are included in the portfolios. IndMean(x) and IndSum(x) are the industry mean and sum of x, respectively. We use 2-digit SIC code for the industry classification.

[a] For the preferred stock, we use pref = PSTKRV. We replace PSTKRV with PSTKL if the former is missing. If both PSTKRV and PSTKL are missing, then we use pref = PSTK.

[b] If OANCF is missing, we replace it with IB − (Δ{(ACT − CHE) − (LCT − DLC − TXP)} − DP).

[c] oc is calculated recursively: $\mathrm{oc}_t = 0.85 \times \mathrm{oc}_{t\text{-}1} + \mathrm{XSGA}_t/\mathrm{cpi}_t$, $\mathrm{oc}_0 = 4 \times \mathrm{XSGA}_0/\mathrm{cpi}_0$.

[d] We use the data from the past 52 weeks to estimate the following two regressions:

$$\text{r:} \quad (\mathrm{RET}_t - \mathrm{Rf}_t) = a^r + b^r(\mathrm{Rm}_t - \mathrm{Rf}_t) + \nu_t^r,$$

$$\text{u:} \quad \mathrm{RET}_t - \mathrm{Rf}_t = a + b(\mathrm{Rm}_t - \mathrm{Rf}_t) + \sum_{k=1}^{4} d_k(\mathrm{Rm}_{t\text{-}k} - \mathrm{Rf}_{t\text{-}k}) + \nu_t,$$

where Rm and Rf are value-weighted market portfolio returns and one-month Treasury bill rate, respectively. R_r^2 and R_u^2 are the R-squared's of model r and u, respectively. $T(c)$ denotes the ratio between the parameter c and its standard error.

[e] nzero12 is the total number of zero trading volume days over the past 12 months, turn12 is the sum of daily VOL/SHROUT over the past 12 months, and ndays12 is the total number of trading days over the past 12 months divided by 12.

B.2 Monthly Predictors

There are 34 monthly predictors defined identically in Table B1: **bas12**, **beta**, **chmom**, **dvol**, **illiq**, **ivolcapm_d**, **ivolcapm_w**, **ivolff_d**, **ivolff_w**, **ma100**, **ma20**, **ma200**, **ma50**, **maxret**, **mom1**, **mom12**, **mom12_ia**, **mom12_ind**, **mom36**, **mom6**, **mom60**, **mom712**, **pdelay1**, **pdelay2**, **pdelay3**, **season**, **std_dvol**, **std_turn**, **to12**, **turn**, **tvol_d**, **tvol_w**, **wh52**, and **zerotrade**.

The additional 11 predictors are summarized below. In each month, we use the earnings information from the most recent announcement date (Compustat Quarterly RDQ). We follow Hou et al. (2015) to assume that the balance sheet data are available with four-month lag after the end of fiscal quarter.

abr (Chan et al., 1996) is the cumulative abnormal returns from RDQ–2 to RDQ+1.

The abnormal return is the stock return minus the equal-weighted market portfolio return. The standardized unexpected earnings **sue** (Chan et al., 1996) is computed as annual change of EPSPXQ divided by its standard deviation computed with the most recent 8 quarterly observations.

dto (Garfinkel and Sokobin, 2006) is calculated as follows

$$\frac{1}{2}\sum_{t=\mathrm{RDQ}-1}^{\mathrm{RDQ}}(turn_t - turn_{mt}) - \frac{1}{50}\sum_{t=\mathrm{RDQ}-54}^{\mathrm{RDQ}-5}(turn_t - turn_{mt}),$$

where $turn$ = VOL/SHROUT and $turn_m$ is the average of all available $turn$ at time t. To obtain the standardized unexpected volume **suvol** (Garfinkel and Sokobin, 2006), we first run the following regression for each stock with 55 daily observations before RDQ,

$$VOL_t = a + b_1|RET|_t^+ + b_2|RET|_t^- + UV_t,$$

where the plus and minus superscripts indicate the positive and negative parts of the stock return, respectively. We then calculate $\sigma_t(UV)$ as the standard deviation of the residuals over the period [RDQ–54, RDQ–5]. The variable **suvol** is defined as $\sum_{t=\mathrm{RDQ}-1}^{\mathrm{RDQ}} UV_t$ scaled by $\sigma_t(UV)$.

revmom (Jegadeesh and Livnat, 2006) is annual change in revenue (REVT) divided by its standard deviation calculated with the most recent 8 quarterly observations. **accq** (Collins and Hribar, 2000) is the total accrual normalized by the mean total assets at the end of the two most recent quarters. The accrual is defined as quarterly change in ((ACTQ − CHEQ) − (LCTQ − DLCQ − TXPQ)) minus DPQ. **roaq1**, **roaq2**, and **roaq1** (Balakrishnan et al., 2010) are calculated as IBQ, NIQ, and (IBQ − SPIQ) scaled by one-quarter lag of ATQ, respectively. **taxmom** (Thomas and Zhang, 2011) is the annual change in tax expense (TXTQ) divided by four-quarter lag of total assets (ATQ). The variable **size** for monthly rebalancing portfolio is defined as PRC × SHROUT.

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Supplementary Materials
for
"Do Cross-Sectional Stock Return Predictors Pass the Test without Data-Snooping Bias?"

Contents

1 Lists of annually rebalanced portfolios with the t-ratios greater than 1.96

Annually rebalanced portfolios with the t-ratios greater than 1.96

	Mean (all stocks)				CAPM (all stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**grltnoa**^{lh}	4.861	0.732	1	**ma100**^{hl}	5.189	1.214
2	**ma100**^{hl}	4.561	1.092	2	**ma200**^{hl}	5.036	1.313
3	**ma200**^{hl}	4.504	1.220	3	**grltnoa**^{lh}	4.935	0.781
4	**chceq**^{lh}	4.290	0.989	4	**chceq**^{lh}	4.852	1.108
5	**illiq**^{hl}	3.817	0.807	5	**issue**^{lh}	4.543	1.055
6	**issue**^{lh}	3.774	0.888	6	**wh52**^{hl}	4.492	1.273
7	**chnco**^{lh}	3.551	0.579	7	**tvol_w**^{lh}	4.437	1.501
8	**agr**^{lh}	3.485	0.803	8	**issue5**^{lh}	4.390	0.832
9	**issue5**^{lh}	3.481	0.707	9	**ivolcapm_d**^{lh}	4.214	1.188
10	**bm**^{hl}	3.312	0.898	10	**tvol_d**^{lh}	4.164	1.247
11	**mom6**^{hl}	3.173	0.803	11	**ivolff_w**^{lh}	4.022	1.306
12	**invtgr**^{lh}	3.151	0.527	12	**ivolff_d**^{lh}	3.881	1.066
13	**sp**^{hl}	3.141	1.045	13	**illiq**^{hl}	3.876	0.816
14	**pchinv**^{lh}	3.112	0.520	14	**agr**^{lh}	3.834	0.949
15	**chinv**^{lh}	3.091	0.632	15	**chnco**^{lh}	3.762	0.638
16	**cashprod**^{lh}	2.817	0.476	16	**ivolcapm_w**^{lh}	3.736	1.221
17	**chemp**^{lh}	2.678	0.580	17	**invtgr**^{lh}	3.603	0.602
18	**wh52**^{hl}	2.676	0.916	18	**pchinv**^{lh}	3.573	0.596
19	**ma50**^{hl}	2.553	0.662	19	**zerotrade**^{hl}	3.493	0.859
20	**chmom**^{hl}	2.501	0.564	20	**chinv**^{lh}	3.459	0.735
21	**mom12_ia**^{hl}	2.477	0.591	21	**cashprod**^{lh}	3.425	0.571
22	**ivolcapm_d**^{lh}	2.434	0.828	22	**bm**^{hl}	3.310	0.927
23	**std_dvol**^{lh}	2.432	0.388	23	**mom6**^{hl}	3.271	0.806
24	**mom12**^{hl}	2.345	0.713	24	**std_dvol**^{lh}	3.235	0.540
25	**tvol_w**^{lh}	2.281	1.002	25	**chemp**^{lh}	3.215	0.732
26	**ivolff_w**^{lh}	2.268	0.913	26	**maxret**^{lh}	3.143	0.942
27	**size_ia**^{lh}	2.221	0.298	27	**salerec**^{hl}	3.110	0.520
28	**pchppeteq**^{hl}	2.211	0.380	28	**bas12**^{lh}	2.996	1.089
29	**acc**^{lh}	2.193	0.431	29	**cfodebt**^{hl}	2.941	0.709
30	**ivolff_d**^{lh}	2.186	0.720	30	**sp**^{hl}	2.882	1.042
31	**chfin**^{hl}	2.172	0.382	31	**opa**^{hl}	2.863	0.869
32	**pchgmr**^{hl}	2.156	0.328	32	**ma50**^{hl}	2.839	0.753
33	**saleta**^{hl}	2.150	0.534	33	**to12**^{lh}	2.644	0.684
34	**tvol_d**^{lh}	2.141	0.815	34	**beta**^{lh}	2.639	0.648
35	**salerec**^{hl}	2.126	0.378	35	**acc**^{lh}	2.596	0.516
36	**pchinvta**^{lh}	2.081	0.324	36	**pchdebteq**^{hl}	2.576	0.406
37	**pchwcap**^{lh}	2.073	0.239	37	**mom12_ia**^{hl}	2.566	0.621
38	**cfp_ia**^{hl}	2.056	0.441	38	**mom12**^{hl}	2.522	0.787
39	**ivolcapm_w**^{lh}	2.001	0.809	39	**pchwcap**^{lh}	2.510	0.297
40	**chwc**^{lh}	1.972	0.375	40	**cfp**^{hl}	2.453	0.610
41	**pctacc**^{lh}	1.964	0.292	41	**chwc**^{lh}	2.393	0.466
				42	**pm**^{hl}	2.380	0.715
				43	**chmom**^{hl}	2.363	0.556
				44	**turn**^{lh}	2.321	0.595
				45	**std_turn**^{lh}	2.315	0.548
				46	**pctacc**^{lh}	2.286	0.346
				47	**dvol**^{lh}	2.242	0.432
				48	**pchppeteq**^{hl}	2.220	0.394
				49	**ppeteq**^{hl}	2.206	0.591
				50	**pchinvta**^{lh}	2.183	0.338
				51	**invest_LWZ**^{lh}	2.171	0.666
				52	**invest_AG**^{lh}	2.125	0.410
				53	**chemp_ia**^{lh}	2.086	0.443
				54	**pchgmr**^{hl}	2.070	0.324
				55	**pimr**^{hl}	2.048	0.614
				56	**oimr**^{hl}	2.032	0.604

Annually rebalanced portfolios with the t-ratios greater than 1.96

	3-Factor (all stocks)				4-Factor (all stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**ma200**^{hl}	5.786	1.529	1	**tvol_w**^{lh}	4.214	1.162
2	**wh52**^{hl}	5.576	1.389	2	**issue**^{lh}	4.032	0.754
3	**ma100**^{hl}	5.511	1.415	3	**ivolff_w**^{lh}	3.894	1.061
4	**ivolcapm_d**^{lh}	4.936	1.152	4	**illiq**^{hl}	3.863	0.539
5	**tvol_w**^{lh}	4.849	1.335	5	**ivolcapm_d**^{lh}	3.832	0.976
6	**ivolff_d**^{lh}	4.732	1.026	6	**ivolcapm_w**^{lh}	3.827	1.013
7	**ivolff_w**^{lh}	4.564	1.221	7	**tvol_d**^{lh}	3.467	0.962
8	**illiq**^{hl}	4.523	0.623	8	**ivolff_d**^{lh}	3.402	0.834
9	**tvol_d**^{lh}	4.319	1.158	9	**issue5**^{lh}	3.327	0.707
10	**issue**^{lh}	4.314	0.818	10	**chceq**^{lh}	3.132	0.700
11	**mom12_ia**^{hl}	4.278	0.904	11	**grltnoa**^{lh}	3.108	0.511
12	**ma50**^{hl}	4.215	1.071	12	**chfin**^{hl}	2.967	0.545
13	**ivolcapm_w**^{lh}	4.202	1.128	13	**maxret**^{lh}	2.751	0.683
14	**mom12**^{hl}	4.141	1.089	14	**cfodebt**^{hl}	2.745	0.596
15	**grltnoa**^{lh}	4.073	0.595	15	**opa**^{hl}	2.607	0.782
16	**issue5**^{lh}	4.016	0.810	16	**ma100**^{hl}	2.466	0.741
17	**chceq**^{lh}	3.903	0.779	17	**wh52**^{hl}	2.327	0.641
18	**bas12**^{lh}	3.723	1.035	18	**chnco**^{lh}	2.325	0.392
19	**mom6**^{hl}	3.406	0.854	19	**ma200**^{hl}	2.325	0.682
20	**mom1**^{hl}	3.229	0.846	20	**std_dvol**^{lh}	2.260	0.245
21	**chfin**^{hl}	3.140	0.530	21	**bas12**^{lh}	2.222	0.689
22	**opa**^{hl}	3.100	0.925	22	**pm**^{hl}	2.208	0.492
23	**agr**^{lh}	2.967	0.524	23	**salerec**^{hl}	2.198	0.379
24	**maxret**^{lh}	2.862	0.739	24	**pchdeprppe**^{hl}	2.182	0.393
25	**cfodebt**^{hl}	2.839	0.612	25	**acc**^{lh}	2.125	0.464
26	**chnco**^{lh}	2.755	0.451	26	**roic**^{hl}	2.124	0.560
27	**std_dvol**^{lh}	2.701	0.294	27	**agr**^{lh}	2.098	0.378
28	**acc**^{lh}	2.618	0.514	28	**ma50**^{hl}	2.038	0.545
29	**pchgmr**^{hl}	2.588	0.391				
30	**chpm**^{hl}	2.586	0.572				
31	**ma20**^{hl}	2.566	0.571				
32	**salerec**^{hl}	2.557	0.449				
33	**chinv**^{lh}	2.526	0.497				
34	**invtgr**^{lh}	2.456	0.406				
35	**pm**^{hl}	2.454	0.569				
36	**pchinv**^{lh}	2.429	0.402				
37	**pimr**^{hl}	2.306	0.558				
38	**zerotrade**^{hl}	2.259	0.450				
39	**chemp**^{lh}	2.247	0.388				
40	**gpa_ia**^{hl}	2.238	0.468				
41	**chwc**^{lh}	2.215	0.423				
42	**mom60**^{hl}	2.171	0.441				
43	**pchdeprppe**^{hl}	2.102	0.360				
44	**pchdltt**^{lh}	1.999	0.318				

Annually rebalanced portfolios with the t-ratios greater than 1.96

	5-Factor (all stocks)				Q-Factor (all stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**ma50**^{hl}	5.017	1.259	1	**illiq**^{hl}	3.437	0.569
2	**ma200**^{hl}	4.646	1.420	2	**cashprod**^{lh}	3.397	0.490
3	**mom1**^{hl}	4.505	1.140	3	**cfp_ia**^{hl}	3.144	0.760
4	**ma100**^{hl}	4.415	1.314	4	**bm_ia**^{hl}	2.704	0.602
5	**illiq**^{hl}	4.359	0.654	5	**ma200**^{hl}	2.531	0.844
6	**noa**^{lh}	3.961	0.757	6	**pchdepr**^{hl}	2.440	0.577
7	**chfin**^{hl}	3.740	0.654	7	**noa**^{lh}	2.424	0.660
8	**mom12_ia**^{hl}	3.690	0.864	8	**ma50**^{hl}	2.356	0.719
9	**wh52**^{hl}	3.545	0.942	9	**acc**^{lh}	2.338	0.520
10	**ma20**^{hl}	3.526	0.840	10	**gpa**^{lh}	2.333	0.524
11	**mom12**^{hl}	3.391	0.912	11	**invest_LWZ**^{hl}	2.323	0.692
12	**quick**^{hl}	3.390	0.557	12	**mom36**^{hl}	2.321	0.599
13	**lev**^{lh}	3.239	0.531	13	**pchdeprppe**^{hl}	2.264	0.461
14	**invest_LWZ**^{hl}	3.140	0.612	14	**chwc**^{lh}	2.261	0.498
15	**chpm**^{hl}	2.917	0.761	15	**chfin**^{hl}	2.222	0.464
16	**cfp_ia**^{hl}	2.878	0.593	16	**mom12_ia**^{hl}	2.145	0.610
17	**cashprod**^{lh}	2.843	0.376	17	**ma100**^{hl}	2.112	0.697
18	**cash**^{hl}	2.815	0.596	18	**tvol_w**^{lh}	2.072	0.668
19	**tangible**^{hl}	2.814	0.584	19	**mom1**^{hl}	1.966	0.649
20	**tvol_w**^{lh}	2.780	0.617				
21	**salecash**^{lh}	2.777	0.559				
22	**mom6**^{hl}	2.742	0.805				
23	**debteq**^{lh}	2.704	0.467				
24	**ivolcapm_d**^{lh}	2.694	0.534				
25	**acc**^{lh}	2.579	0.509				
26	**currat**^{hl}	2.493	0.403				
27	**size**^{lh}	2.449	0.488				
28	**ivolff_w**^{lh}	2.350	0.551				
29	**gpa**^{lh}	2.330	0.386				
30	**chceq**^{lh}	2.293	0.431				
31	**pchdeprppe**^{hl}	2.271	0.396				
32	**issue5**^{lh}	2.220	0.373				
33	**std_dvol**^{lh}	2.216	0.242				
34	**pchsale**^{hl}	2.198	0.417				
35	**pchdepr**^{hl}	2.192	0.392				
36	**chwc**^{lh}	2.183	0.423				
37	**deprppe**^{hl}	2.149	0.468				
38	**mom36**^{hl}	2.147	0.460				
39	**size_ia**^{lh}	2.120	0.224				
40	**orgcap**^{hl}	2.094	0.434				
41	**tvol_d**^{lh}	2.039	0.507				
42	**bm_ia**^{hl}	2.033	0.384				
43	**salerec**^{hl}	1.983	0.338				
44	**pchwcapta**^{lh}	1.974	0.184				
45	**ivolcapm_w**^{lh}	1.965	0.445				
46	**issue**^{lh}	1.963	0.299				
47	**ivolff_d**^{lh}	1.962	0.389				

Annually rebalanced portfolios with the t-ratios greater than 1.96

	Mean (all-but-tiny stocks)				CAPM (all-but-tiny stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**issue5**^{lh}	3.647	0.713	1	**issue5**^{lh}	4.440	0.844
2	**issue**^{lh}	3.614	0.831	2	**wh52**^{hl}	4.367	0.834
3	**chinv**^{lh}	3.523	0.544	3	**cfp**^{hl}	4.079	0.889
4	**chnco**^{lh}	3.450	0.542	4	**chceq**^{lh}	3.999	0.945
5	**grltnoa**^{lh}	3.297	0.524	5	**issue**^{lh}	3.979	0.953
6	**chceq**^{lh}	3.152	0.753	6	**chinv**^{lh}	3.955	0.625
7	**cfp**^{hl}	3.091	0.701	7	**chnco**^{lh}	3.800	0.611
8	**pchinv**^{lh}	3.027	0.489	8	**pchinv**^{lh}	3.518	0.570
9	**invtgr**^{lh}	3.025	0.489	9	**invtgr**^{lh}	3.516	0.569
10	**mom6**^{hl}	2.843	0.662	10	**grltnoa**^{lh}	3.509	0.587
11	**agr**^{lh}	2.739	0.634	11	**tvol_w**^{lh}	3.386	0.960
12	**chwc**^{lh}	2.678	0.427	12	**beta**^{lh}	3.359	0.856
13	**dvol**^{lh}	2.546	0.338	13	**agr**^{lh}	3.336	0.814
14	**ma100**^{hl}	2.532	0.622	14	**tvol_d**^{lh}	3.201	0.790
15	**ma200**^{hl}	2.520	0.674	15	**chwc**^{lh}	3.093	0.502
16	**chmom**^{hl}	2.495	0.538	16	**ivolcapm$_{\mathbf{w}}$**^{lh}	3.065	0.778
17	**sp**^{hl}	2.417	0.711	17	**std_dvol**^{lh}	3.040	0.427
18	**size_ia**^{lh}	2.396	0.313	18	**dvol**^{lh}	2.978	0.404
19	**std_dvol**^{lh}	2.338	0.326	19	**bas12**^{lh}	2.969	0.929
20	**bm**^{hl}	2.332	0.568	20	**cashprod**^{lh}	2.833	0.508
21	**pchppeteq**^{hl}	2.319	0.369	21	**ma100**^{hl}	2.734	0.663
22	**illiq**^{hl}	2.291	0.298	22	**mom6**^{hl}	2.660	0.605
23	**pchwcap**^{lh}	2.284	0.284	23	**salerec**^{hl}	2.642	0.364
24	**cashprod**^{lh}	2.244	0.409	24	**pchwcap**^{lh}	2.590	0.332
25	**mom12_ia**^{hl}	2.219	0.454	25	**ivolff_w**^{lh}	2.580	0.652
26	**wh52**^{hl}	2.174	0.522	26	**chemp**^{lh}	2.552	0.572
27	**pchdebteq**^{hl}	2.134	0.353	27	**bm**^{hl}	2.546	0.659
28	**pchsalewc**^{hl}	2.065	0.224	28	**ep**^{hl}	2.542	0.614
29	**chemp**^{lh}	1.983	0.427	29	**pchdebteq**^{hl}	2.524	0.439
				30	**ma200**^{hl}	2.524	0.684
				31	**chmom**^{hl}	2.454	0.554
				32	**turn**^{lh}	2.394	0.616
				33	**zerotrade**^{hl}	2.374	0.611
				34	**sp**^{hl}	2.309	0.753
				35	**ivolff_d**^{lh}	2.286	0.543
				36	**ppeteq**^{hl}	2.276	0.595
				37	**pchppeteq**^{hl}	2.257	0.384
				38	**acc**^{lh}	2.257	0.365
				39	**maxret**^{lh}	2.235	0.593
				40	**illiq**^{hl}	2.157	0.279
				41	**chemp_ia**^{lh}	2.156	0.416
				42	**ivolcapm$_{\mathbf{d}}$**^{lh}	2.156	0.508
				43	**invest_AG**^{lh}	2.115	0.392
				44	**to12**^{lh}	2.111	0.566
				45	**pdelay1**^{hl}	2.108	0.332
				46	**invest_LWZ**^{lh}	2.067	0.647
				47	**opa**^{hl}	2.043	0.518
				48	**cfodebt**^{hl}	1.994	0.385
				49	**std_turn**^{lh}	1.986	0.458

Annually rebalanced portfolios with the t-ratios greater than 1.96

3-Factor (all-but-tiny stocks)

	Portfolio	t	α
1	**wh52**^{hl}	4.811	0.915
2	**issue**^{lh}	4.128	0.731
3	**issue5**^{lh}	3.888	0.750
4	**ma200**^{hl}	3.861	0.988
5	**mom12_ia**^{hl}	3.852	0.702
6	**ma100**^{hl}	3.509	0.903
7	**ma50**^{hl}	3.277	0.764
8	**mom12**^{hl}	3.270	0.725
9	**chnco**^{lh}	3.112	0.474
10	**tvol_w**^{lh}	3.085	0.672
11	**chceq**^{lh}	2.984	0.524
12	**grltnoa**^{lh}	2.936	0.452
13	**chinv**^{lh}	2.934	0.436
14	**mom1**^{hl}	2.831	0.699
15	**ivolcapm_w**^{lh}	2.745	0.565
16	**tvol_d**^{lh}	2.696	0.539
17	**beta**^{lh}	2.686	0.560
18	**opa**^{hl}	2.674	0.616
19	**chwc**^{lh}	2.653	0.455
20	**mom6**^{hl}	2.597	0.620
21	**cfp**^{hl}	2.574	0.445
22	**gmr**^{hl}	2.571	0.437
23	**ma20**^{hl}	2.565	0.637
24	**bas12**^{lh}	2.472	0.638
25	**agr**^{lh}	2.422	0.396
26	**cfodebt**^{hl}	2.282	0.454
27	**chpm**^{hl}	2.266	0.446
28	**ato**^{hl}	2.250	0.381
29	**pchinv**^{lh}	2.234	0.355
30	**invtgr**^{lh}	2.231	0.354
31	**ivolff_w**^{lh}	2.218	0.450
32	**pchsalewc**^{hl}	2.176	0.242
33	**chfin**^{hl}	2.167	0.340
34	**pchoita**^{hl}	2.141	0.392
35	**gpa**^{hl}	2.067	0.403
36	**pchdebteq**^{hl}	2.064	0.312
37	**acc**^{lh}	2.052	0.337
38	**salerec**^{hl}	1.985	0.297

4-Factor (all-but-tiny stocks)

	Portfolio	t	α
1	**issue**^{lh}	3.824	0.662
2	**issue5**^{lh}	3.091	0.599
3	**gmr**^{hl}	2.611	0.424
4	**chnco**^{lh}	2.427	0.384
5	**grltnoa**^{lh}	2.395	0.395
6	**chceq**^{lh}	2.213	0.382
7	**tvol_w**^{lh}	2.192	0.491
8	**chfin**^{hl}	2.166	0.384
9	**cfodebt**^{hl}	2.165	0.446
10	**ivolcapm_w**^{lh}	2.112	0.433
11	**cfp**^{hl}	2.098	0.339
12	**agr**^{lh}	2.045	0.324

Annually rebalanced portfolios with the t-ratios greater than 1.96

	5-Factor (all-but-tiny stocks)				Q-Factor (all-but-tiny stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**noa**^{lh}	4.916	0.692	1	**cashprod**^{lh}	3.012	0.492
2	**ma50**^{hl}	4.700	1.091	2	**bm_ia**^{hl}	2.907	0.622
3	**mom1**^{hl}	4.458	1.063	3	**pchdepr**^{hl}	2.758	0.624
4	**quick**^{hl}	4.316	0.695	4	**invest_LWZ**^{hl}	2.751	0.825
5	**salecash**^{lh}	4.219	0.714	5	**pchsale**^{hl}	2.636	0.564
6	**mom12_ia**^{hl}	4.017	0.785	6	**cfp_ia**^{hl}	2.635	0.540
7	**ma20**^{hl}	3.863	0.995	7	**quick**^{hl}	2.438	0.587
8	**pchsale**^{hl}	3.817	0.600	8	**salecash**^{lh}	2.365	0.691
9	**debteq**^{lh}	3.708	0.574	9	**em**^{lh}	2.364	0.649
10	**ma200**^{hl}	3.697	1.038	10	**noa**^{lh}	2.225	0.520
11	**invest_LWZ**^{hl}	3.488	0.685	11	**mom12_ia**^{hl}	2.174	0.541
12	**lev**^{lh}	3.458	0.550	12	**rnoa**^{lh}	2.137	0.452
13	**tangible**^{hl}	3.442	0.656	13	**chemp**^{hl}	2.066	0.357
14	**cash**^{hl}	3.343	0.565	14	**oita**^{lh}	2.057	0.577
15	**ma100**^{hl}	3.195	0.990	15	**pchwcapta**^{lh}	2.056	0.230
16	**pchdepr**^{hl}	3.186	0.520	16	**gpa**^{lh}	2.053	0.443
17	**mom12**^{hl}	3.074	0.688	17	**debteq**^{lh}	2.004	0.478
18	**chpm**^{hl}	2.977	0.669	18	**mom1**^{hl}	1.986	0.636
19	**wh52**^{hl}	2.931	0.574	19	**saleta**^{lh}	1.981	0.399
20	**currat**^{hl}	2.920	0.454				
21	**wcapta**^{hl}	2.816	0.467				
22	**chfin**^{hl}	2.786	0.445				
23	**cashprod**^{lh}	2.627	0.349				
24	**oimr**^{lh}	2.511	0.465				
25	**bm_ia**^{hl}	2.429	0.468				
26	**mve**^{lh}	2.393	0.293				
27	**pm**^{lh}	2.364	0.486				
28	**size_ia**^{lh}	2.364	0.234				
29	**roe**^{lh}	2.284	0.468				
30	**pchsale_pchxsga**^{hl}	2.250	0.413				
31	**oita**^{lh}	2.245	0.475				
32	**pchwcapta**^{lh}	2.174	0.213				
33	**ppeteq**^{lh}	2.171	0.379				
34	**nimr**^{lh}	2.116	0.387				
35	**roa**^{lh}	2.067	0.409				
36	**em**^{lh}	2.012	0.484				
37	**issue5**^{lh}	2.010	0.306				
38	**sp**^{lh}	2.000	0.370				
39	**pchsaleinv**^{hl}	1.995	0.364				

2 Lists of monthly rebalanced portfolios with the t-ratios greater than 1.96

Monthly rebalanced portfolios with the t-ratios greater than 1.96

	Mean (all stocks)				CAPM (all stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**abr**^{hl}	6.747	1.187	1	**abr**^{hl}	7.053	1.215
2	**mom712**^{hl}	5.237	1.615	2	**tvol_d**^{lh}	5.621	2.146
3	**ma20**^{lh}	4.664	0.993	3	**mom12**^{hl}	5.553	2.159
4	**mom12**^{hl}	4.432	1.915	4	**ivolff_d**^{lh}	5.457	1.941
5	**mom12_ia**^{hl}	3.632	1.290	5	**tvol_w**^{lh}	5.317	2.078
6	**mom6**^{hl}	3.553	1.361	6	**mom712**^{hl}	5.238	1.643
7	**ivolff_d**^{lh}	3.527	1.469	7	**ivolcapm_d**^{lh}	5.100	1.889
8	**ivolcapm_d**^{lh}	3.208	1.404	8	**maxret**^{lh}	5.028	1.554
9	**sue**^{hl}	3.161	0.441	9	**ivolff_w**^{lh}	4.820	1.868
10	**illiq**^{hl}	3.101	0.713	10	**ivolcapm_w**^{lh}	4.645	1.792
11	**tvol_d**^{lh}	2.992	1.446	11	**mom6**^{hl}	4.603	1.611
12	**roaq1**^{hl}	2.867	0.816	12	**mom12_ia**^{hl}	4.360	1.424
13	**roaq2**^{hl}	2.814	0.790	13	**roaq3**^{hl}	4.302	1.265
14	**roaq3**^{hl}	2.794	0.928	14	**roaq2**^{hl}	4.074	1.055
15	**tvol_w**^{lh}	2.680	1.357	15	**roaq1**^{hl}	4.054	1.072
16	**ivolff_w**^{lh}	2.648	1.287	16	**sue**^{hl}	3.913	0.539
17	**taxmom**^{hl}	2.623	0.423	17	**wh52**^{hl}	3.801	1.433
18	**maxret**^{lh}	2.594	1.006	18	**ma20**^{lh}	3.638	0.771
19	**ivolcapm_w**^{lh}	2.516	1.217	19	**bas12**^{lh}	3.562	1.565
20	**accq**^{lh}	2.322	0.356	20	**zerotrade**^{hl}	3.436	0.955
21	**season**^{hl}	2.278	0.475	21	**illiq**^{hl}	3.361	0.804
22	**size**^{lh}	2.269	0.748	22	**std_dvol**^{lh}	3.191	0.628
23	**std_dvol**^{lh}	2.129	0.391	23	**revmom**^{hl}	3.077	0.437
24	**revmom**^{hl}	2.065	0.299	24	**taxmom**^{hl}	2.480	0.391
				25	**accq**^{lh}	2.436	0.371
				26	**size**^{lh}	2.336	0.774
				27	**ma200**^{hl}	2.330	0.906
				28	**to12**^{lh}	2.282	0.669
				29	**beta**^{lh}	2.214	0.724
				30	**dvol**^{lh}	2.034	0.435
				31	**turn**^{lh}	2.031	0.587
				32	**std_turn**^{lh}	2.029	0.572

Monthly rebalanced portfolios with the t-ratios greater than 1.96

	3-Factor (all stocks)				4-Factor (all stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**ivolff_d**^{lh}	7.219	1.962	1	**abr**^{hl}	6.124	1.071
2	**abr**^{hl}	7.183	1.289	2	**ivolff_d**^{lh}	4.995	1.547
3	**ivolcapm_d**^{lh}	6.695	1.913	3	**tvol_d**^{lh}	4.978	1.710
4	**mom712**^{hl}	6.625	1.879	4	**tvol_w**^{lh}	4.768	1.725
5	**tvol_d**^{lh}	6.523	2.102	5	**ivolff_w**^{lh}	4.604	1.563
6	**mom12**^{hl}	6.456	2.381	6	**ivolcapm_d**^{lh}	4.573	1.460
7	**ivolff_w**^{lh}	6.399	1.933	7	**ivolcapm_w**^{lh}	4.556	1.521
8	**ivolcapm_w**^{lh}	6.276	1.850	8	**maxret**^{lh}	4.490	1.231
9	**tvol_w**^{lh}	6.205	2.033	9	**ma20**^{lh}	4.386	1.013
10	**mom12_ia**^{hl}	6.020	1.711	10	**mom12**^{hl}	4.137	0.880
11	**maxret**^{lh}	5.990	1.531	11	**roaq2**^{hl}	3.953	0.950
12	**roaq2**^{hl}	5.076	1.202	12	**roaq3**^{hl}	3.812	1.051
13	**roaq1**^{hl}	4.947	1.198	13	**roaq1**^{hl}	3.720	0.934
14	**mom6**^{hl}	4.940	1.700	14	**mom712**^{hl}	3.672	0.940
15	**roaq3**^{hl}	4.923	1.328	15	**illiq**^{hl}	3.518	0.532
16	**wh52**^{hl}	4.726	1.569	16	**mom12_ia**^{hl}	3.450	0.731
17	**bas12**^{lh}	4.455	1.616	17	**size**^{lh}	3.185	0.881
18	**taxmom**^{hl}	3.864	0.557	18	**bas12**^{lh}	2.790	1.132
19	**illiq**^{hl}	3.689	0.532	19	**accq**^{lh}	2.628	0.381
20	**revmom**^{hl}	3.403	0.429	20	**taxmom**^{hl}	2.502	0.344
21	**sue**^{hl}	3.396	0.512	21	**zerotrade**^{hl}	2.499	0.521
22	**ma20**^{lh}	3.268	0.722	22	**std_dvol**^{lh}	2.367	0.319
23	**season**^{hl}	2.804	0.552	23	**revmom**^{hl}	2.225	0.302
24	**zerotrade**^{hl}	2.802	0.599	24	**sue**^{hl}	2.188	0.329
25	**ma200**^{hl}	2.767	1.031	25	**chmom**^{lh}	2.039	0.526
26	**std_dvol**^{lh}	2.699	0.360				
27	**accq**^{lh}	2.680	0.414				
28	**mom12_ind**^{hl}	2.325	0.714				
29	**size**^{lh}	2.150	0.514				

	5-Factor (all stocks)				Q-Factor (all stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**abr**^{hl}	7.005	1.342	1	**abr**^{hl}	5.225	1.103
2	**mom712**^{hl}	5.210	1.625	2	**ma20**^{lh}	4.155	1.182
3	**mom12_ia**^{hl}	4.258	1.495	3	**tvol_w**^{lh}	2.916	0.939
4	**ivolff_w**^{lh}	3.943	0.991	4	**ivolff_d**^{lh}	2.815	0.939
5	**tvol_w**^{lh}	3.942	1.026	5	**mom712**^{hl}	2.755	0.941
6	**ivolff_d**^{lh}	3.834	1.118	6	**illiq**^{hl}	2.707	0.464
7	**tvol_d**^{lh}	3.757	1.094	7	**size**^{lh}	2.697	1.035
8	**illiq**^{hl}	3.744	0.551	8	**ivolcapm_w**^{lh}	2.670	0.832
9	**ivolcapm_w**^{lh}	3.648	0.922	9	**tvol_d**^{lh}	2.654	0.901
10	**mom12**^{hl}	3.492	1.750	10	**ivolff_w**^{lh}	2.559	0.815
11	**ma20**^{lh}	3.399	0.866	11	**accq**^{lh}	2.515	0.436
12	**taxmom**^{hl}	3.259	0.507	12	**season**^{hl}	2.508	0.546
13	**season**^{hl}	3.244	0.643	13	**ivolcapm_d**^{lh}	2.129	0.745
14	**ivolcapm_d**^{lh}	3.224	1.009	14	**maxret**^{lh}	2.051	0.588
15	**size**^{lh}	3.086	0.911				
16	**maxret**^{lh}	3.025	0.719				
17	**accq**^{lh}	2.974	0.525				
18	**mom6**^{hl}	2.842	1.314				
19	**roaq2**^{hl}	2.458	0.467				
20	**roaq1**^{hl}	2.402	0.472				
21	**pdelay3**^{lh}	2.366	0.244				
22	**revmom**^{hl}	2.359	0.298				
23	**roaq3**^{hl}	2.320	0.515				
24	**std_dvol**^{lh}	2.138	0.288				
25	**sue**^{hl}	2.116	0.312				
26	**pdelay2**^{lh}	2.085	0.211				

Monthly rebalanced portfolios with the t-ratios greater than 1.96

	Mean (all-but-tiny stocks)				CAPM (all-but-tiny stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**abr**^{hl}	4.690	0.764	1	**abr**^{hl}	5.038	0.788
2	**ma20**^{lh}	4.663	0.860	2	**tvol_d**^{lh}	4.437	1.458
3	**mom712**^{hl}	4.136	1.241	3	**ivolcapm_d**^{lh}	4.266	1.246
4	**mom12**^{hl}	3.584	1.259	4	**mom12**^{hl}	3.965	1.327
5	**sue**^{hl}	2.997	0.434	5	**maxret**^{lh}	3.943	1.062
6	**illiq**^{hl}	2.996	0.453	6	**ivolff_d**^{lh}	3.940	1.145
7	**mom12_ia**^{hl}	2.950	0.928	7	**ma20**^{lh}	3.785	0.696
8	**mom6**^{hl}	2.631	0.842	8	**sue**^{hl}	3.682	0.528
9	**accq**^{lh}	2.410	0.339	9	**tvol_w**^{lh}	3.676	1.198
10	**roaq1**^{hl}	2.311	0.623	10	**mom712**^{hl}	3.624	1.146
11	**season**^{hl}	2.242	0.420	11	**ivolcapm_w**^{lh}	3.427	1.044
12	**taxmom**^{hl}	2.189	0.327	12	**roaq3**^{hl}	3.269	0.911
13	**chmom**^{lh}	2.165	0.547	13	**roaq1**^{hl}	3.238	0.845
14	**std_dvol**^{lh}	2.140	0.352	14	**bas12**^{lh}	3.232	1.157
15	**roaq2**^{hl}	2.130	0.548	15	**ivolff_w**^{lh}	3.160	0.939
16	**roaq3**^{hl}	2.088	0.627	16	**mom6**^{hl}	3.120	0.950
17	**dvol**^{lh}	2.033	0.301	17	**std_dvol**^{lh}	3.112	0.517
				18	**roaq2**^{hl}	3.020	0.755
				19	**wh52**^{hl}	2.956	0.903
				20	**revmom**^{hl}	2.937	0.427
				21	**mom12_ia**^{hl}	2.933	0.919
				22	**beta**^{lh}	2.852	0.860
				23	**illiq**^{hl}	2.817	0.453
				24	**dvol**^{lh}	2.772	0.420
				25	**accq**^{lh}	2.412	0.340
				26	**zerotrade**^{hl}	2.110	0.642
				27	**suvol**^{lh}	2.010	0.280

	3-Factor (all-but-tiny stocks)				4-Factor (all-but-tiny stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**abr**^{hl}	5.478	0.870	1	**abr**^{hl}	4.170	0.638
2	**mom712**^{hl}	5.240	1.403	2	**ma20**^{lh}	4.165	0.930
3	**mom12**^{hl}	5.110	1.560	3	**tvol_d**^{lh}	3.492	1.002
4	**ivolcapm_d**^{lh}	4.804	1.134	4	**ivolcapm_d**^{lh}	3.253	0.804
5	**ivolff_d**^{lh}	4.675	1.022	5	**ivolff_d**^{lh}	3.157	0.730
6	**tvol_d**^{lh}	4.665	1.264	6	**maxret**^{lh}	2.821	0.696
7	**mom12_ia**^{hl}	4.551	1.179	7	**roaq1**^{hl}	2.807	0.712
8	**roaq1**^{hl}	4.045	0.963	8	**chmom**^{lh}	2.741	0.734
9	**maxret**^{lh}	3.919	0.901	9	**roaq3**^{hl}	2.719	0.729
10	**roaq2**^{hl}	3.895	0.888	10	**roaq2**^{hl}	2.653	0.660
11	**roaq3**^{hl}	3.840	1.004	11	**tvol_w**^{lh}	2.481	0.706
12	**tvol_w**^{lh}	3.800	0.993	12	**mom712**^{hl}	2.418	0.587
13	**ivolcapm_w**^{lh}	3.423	0.905	13	**ivolcapm_w**^{lh}	2.400	0.679
14	**taxmom**^{hl}	3.365	0.445	14	**ma200**^{lh}	2.290	0.541
15	**ma20**^{lh}	3.347	0.665	15	**accq**^{lh}	2.179	0.322
16	**mom6**^{hl}	3.323	1.017	16	**ivolff_w**^{lh}	2.168	0.580
17	**wh52**^{hl}	3.277	0.940	17	**season**^{hl}	2.151	0.367
18	**revmom**^{hl}	3.264	0.426	18	**revmom**^{hl}	2.027	0.287
19	**ivolff_w**^{lh}	3.257	0.814	19	**sue**^{hl}	1.962	0.303
20	**sue**^{hl}	3.146	0.488				
21	**bas12**^{lh}	3.093	0.934				
22	**season**^{hl}	2.785	0.494				
23	**accq**^{lh}	2.430	0.350				
24	**beta**^{lh}	2.402	0.659				
25	**illiq**^{hl}	2.376	0.232				
26	**ma200**^{hl}	2.131	0.684				
27	**std_dvol**^{lh}	2.008	0.195				

Monthly rebalanced portfolios with the t-ratios greater than 1.96

	5-Factor (all-but-tiny stocks)				Q-Factor (all-but-tiny stocks)		
	Portfolio	t	α		Portfolio	t	α
1	**abr**^{hl}	5.091	0.903	1	**ma20**^{lh}	4.248	1.079
2	**mom712**^{hl}	4.419	1.282	2	**abr**^{hl}	2.882	0.597
3	**ma20**^{lh}	3.514	0.774	3	**season**^{hl}	2.825	0.514
4	**mom12_ia**^{hl}	3.349	1.092	4	**accq**^{lh}	2.410	0.430
5	**season**^{hl}	3.152	0.547				
6	**taxmom**^{hl}	2.989	0.432				
7	**accq**^{lh}	2.921	0.470				
8	**mom12**^{hl}	2.691	1.180				
9	**illiq**^{hl}	2.686	0.281				
10	**std_turn**^{hl}	2.390	0.427				
11	**turn**^{hl}	2.363	0.513				
12	**tvol_d**^{lh}	2.283	0.479				
13	**revmom**^{hl}	2.236	0.300				
14	**ivolcapm_d**^{lh}	2.045	0.418				
15	**mom6**^{hl}	2.022	0.840				

3 Selective inference with multiple families

Selective inference (Mean)

	Studentized		Non-studentized	
	CV	Significant portfolios	CV	Significant portfolios
All stocks.				
Value	2.618	**bm**^{hl} (3.312), **sp**^{hl} (3.141).	0.713	**sp**^{hl} (1.045), **bm**^{hl} (0.898).
Momentum	2.104	**ma100**^{hl} (4.561), **ma200**^{hl} (4.504), **mom6**^{hl} (3.173), **wh52**^{hl} (2.676), **ma50**^{hl} (2.553), **mom12_ia**^{hl} (2.477), **mom12**^{hl} (2.345).	0.626	**ma200**^{hl} (1.220), **ma100**^{hl} (1.092), **wh52**^{hl} (0.916), **mom6**^{hl} (0.803), **mom12**^{hl} (0.713), **ma50**^{hl} (0.662).
Volatility	2.246	**ivolcapm_d**^{lh} (2.434), **tvol_w**^{lh} (2.281), **ivolff_w**^{lh} (2.268).	0.617	**tvol_w**^{lh} (1.002), **ivolff_w**^{lh} (0.913), **ivolcapm_d**^{lh} (0.828), **tvol_d**^{lh} (0.815), **ivolcapm_w**^{lh} (0.809),**ivolff_d**^{lh} (0.720).
Growth	2.440	**grltnoa**^{lh} (4.861), **issue**^{lh} (3.774), **agr**^{lh} (3.485), **issue5**^{lh} (3.481).	0.636	**issue**^{lh} (0.888), **agr**^{lh} (0.803), **grltnoa**^{lh} (0.732), **issue5**^{lh} (0.707).
Profitability	♯			
Trading	2.619	**illiq**^{hl} (3.817).	0.707	**illiq**^{hl} (0.807).
Others	3.363	**chceq**^{lh} (4.290), **chnco**^{lh} (3.551).	0.920	**chceq**^{lh} (4.290).
All-but-tiny stocks.				
Value	2.806	**cfp**^{hl} (3.091)	0.625	**sp**^{hl} (0.711), **cfp**^{hl} (0.701).
Momentum	2.57	**mom6**^{hl} (2.843)	0.639	**ma200**^{hl} (0.674), **mom6**^{hl} (0.662).
Volatility	♯			
Growth	2.528	**issue5**^{lh} (3.647), **issue**^{lh} (3.614), **grltnoa**^{lh} (3.297), **agr**^{lh} (2.739).	0.668	**issue**^{lh} (0.831), **issue5**^{lh} (0.713).
Profitability	♯			
Trading	2.602	–	0.717	–
Others	3.527	–	0.869	–

Selective inference (CAPM)

	Studentized		Non-studentized	
	CV	Significant portfolios	CV	Significant portfolios
All stocks.				
Value	2.544	**bm**^{hl} (3.310), **sp**^{hl} (2.882).	0.630	**sp**^{hl} (1.042), **bm**^{hl} (0.927).
Momentum	2.044	**ma100**^{hl} (5.189), **ma200**^{hl} (5.036), **wh52**^{hl} (4.492), **mom6**^{hl} (3.271), **ma50**^{hl} (2.839), **mom12_ia**^{hl} (2.566), **mom12**^{hl} (2.522)	0.647	**ma200**^{hl} (1.313), **wh52**^{hl} (1.273), **ma100**^{hl} (1.214), **mom6**^{hl} (0.806), **mom12**^{hl} (0.787), **ma50**^{hl} (0.753).
Volatility	0	**tvol_w**^{lh} (4.437), **ivolcapm_d**^{lh} (4.214), **tvol_d**^{lh} (4.164), **ivolff_w**^{lh} (4.022), **ivolff_d**^{lh} (3.881), **ivolcapm_w**^{lh} (3.736), **beta**^{lh} (2.639).	0	**tvol_w**^{lh} (1.501), **ivolff_w**^{lh} (1.306), **tvol_d**^{lh} (1.247), **ivolcapm_w**^{lh} (1.221), **ivolcapm_d**^{lh} (1.188), **ivolff_d**^{lh} (1.066),**beta**^{lh} (0.648).
Growth	2.203	**grltnoa**^{lh} (4.935), **issue**^{lh} (4.543), **issue5**^{lh} (4.390), **agr**^{lh} (3.834), **acc**^{lh} (2.596).	0.368	**issue**^{lh} (1.055), **agr**^{lh} (0.949), **issue5**^{lh} (0.832), **grltnoa**^{lh} (0.781), **invest_LWZ**^{lh} (0.666), **acc**^{lh} (0.516), **invest_AG**^{lh} (0.410).
Profitability	2.445	**opa**^{hl} (2.863)	0.666	**opa**^{hl} (0.869)
Trading	0	**illiq**^{hl} (3.876), **zerotrade**^{hl} (3.493), **std_dvol**^{lh} (3.235), **to12**^{lh} (2.644), **turn**^{lh} (2.321), **std_turn**^{lh} (2.315), **dvol**^{lh} (2.242).	0	**zerotrade**^{hl} (0.859), **illiq**^{hl} (0.816), **to12**^{lh} (0.684), **turn**^{lh} (0.595), **std$_{\mathbf{t}}$urn**^{lh} (0.548), **std$_{\mathbf{d}}$vol**^{lh} (0.540), **dvol**^{lh} (0.432).
Others	3.378	**chceq**^{lh} (4.852), **chnco**^{lh} (3.762), **invtgr**^{lh} (3.603), **pchinv**^{lh} (3.573), **chinv**^{lh} (3.459), **cashprod**^{lh} (3.425).	0.813	**chceq**^{lh} (1.108), **bas12**^{lh} (1.089), **maxret**^{lh} (0.942).
All-but-tiny stocks.				
Value	2.570	**cfp**^{hl} (4.079)	0.531	**cfp**^{hl} (0.889), **sp**^{hl} (0.753), **bm**^{hl} (0.659), **ep**^{hl} (0.614).
Momentum	2.339	**wh52**^{hl} (4.367), **ma100**^{hl} (2.734), **mom6**^{hl} (2.660), **ma200**^{hl} (2.524).	0.617	**wh52**^{hl} (0.834), **ma200**^{hl} (0.684), **ma100**^{hl} (0.663).
Volatility	0	**tvol_w**^{lh} (3.386), **beta**^{lh} (3.359), **tvol_d**^{lh} (3.201), **ivolcapm_w**^{lh} (3.065), **ivolff_w**^{lh} (2.580), **ivolff_d**^{lh} (2.286), **ivolcapm_d**^{lh} (2.156).	0	**tvol_w**^{lh} (0.960), **beta**^{lh} (0.856), **tvol_d**^{lh} (0.790), **ivolcapm_w**^{lh} (0.778), **ivolff_w**^{lh} (0.652), **ivolff_d**^{lh} (0.543), **ivolcapm_d**^{lh} (0.508).
Growth	2.338	**issue5**^{lh} (4.440), **issue**^{lh} (3.979), **grltnoa**^{lh} (3.509), **agr**^{lh} (3.336).	0.368	**issue**^{lh} (0.953), **issue5**^{lh} (0.844), **agr**^{lh} (0.814), **invest_LWZ**^{lh} (0.647), **grltnoa**^{lh} (0.587), **invest_AG**^{lh} (0.392).
Profitability	2.587	–	0.587	–
Trading	2.200	**std_dvol**^{lh} (3.040), **dvol**^{lh} (2.978), **turn**^{lh} (2.394), **zerotrade**^{hl} (2.374).	0.002	**turn**^{lh} (0.616), **zerotrade**^{hl} (0.611), **to12**^{lh} (0.566), **std_turn**^{lh} (0.458), **std_dvol**^{lh} (0.427), **dvol**^{lh} (0.404), **illiq**^{hl} (0.279).
Others	3.355	**chceq**^{lh} (3.999), **chinv**^{lh} (3.955), **chnco**^{lh} (3.800), **pchinv**^{lh} (3.518), **invtgr**^{lh} (3.516).	0.763	**chceq**^{lh} (0.945), **bas12**^{lh} (0.929)

Selective inference (3-Factor)

	Studentized		Non-studentized	
	CV	Significant portfolios	CV	Significant portfolios
All stocks.				
Value	♯			
Momentum	2.159	**ma200**^{hl} (5.786), **wh52**^{hl} (5.576), **ma100**^{hl} (5.511), **mom12_ia**^{hl} (4.278), **ma50**^{hl} (4.215), **mom12**^{hl} (4.141), **mom6**^{hl} (3.406).	0.563	**ma200**^{hl} (1.529), **ma100**^{hl} (1.415), **wh52**^{hl} (1.389), **mom12**^{hl} (1.089), **ma50**^{hl} (1.071), **mom12_ia**^{hl} (0.904), **mom6**^{hl} (0.854).
Volatility	2.046	**ivolcapm_d**^{lh} (4.936), **tvol_w**^{lh} (4.849), **ivolff_d**^{lh} (4.732), **ivolff_w**^{lh} (4.564), **tvol_d**^{lh} (4.319), **ivolcapm_w**^{lh} (4.202).	0.471	**tvol_w**^{lh} (1.335), **ivolff_w**^{lh} (1.221), **tvol_d**^{lh} (1.158), **ivolcapm_d**^{lh} (1.152), **ivolcapm_w**^{lh} (1.128), **ivolff_d**^{lh} (1.026).
Growth	2.383	**issue**^{lh} (4.314), **grltnoa**^{lh} (4.073), **issue5**^{lh} (4.016), **agr**^{lh} (2.967), **acc**^{lh} (2.618).	0.488	**issue**^{lh} (0.818), **issue5**^{lh} (0.810), **grltnoa**^{lh} (0.595), **agr**^{lh} (0.524), **acc**^{lh} (0.514).
Profitability	2.464	**opa**^{hl} (3.100)	0.623	**opa**^{hl} (0.925)
Trading	2.523	**illiq**^{hl} (4.523), **std_dvol**^{lh} (2.701).	0.481	**illiq**^{hl} (0.623).
Others	3.380	**chceq**^{lh} (3.903), **bas12**^{lh} (3.723).	0.702	**bas12**^{lh} (1.035), **mom1**^{hl} (0.846), **chceq**^{lh} (0.779), **maxret**^{lh} (0.739).
All-but-tiny stocks.				
Value	2.77	–	0.588	–
Momentum	2.186	**wh52**^{hl} (4.811), **ma200**^{hl} (3.861), **mom12ia**^{hl} (3.852). **ma100**^{hl} (3.509), **ma50**^{hl} (3.277), **mom12**^{hl} (3.270), **mom6**^{hl} (2.597).	0.490	**ma200**^{hl} (0.988), **wh52**^{hl} (0.915), **ma100**^{hl} (0.903), **ma50**^{hl} (0.764), **mom12**^{hl} (0.725), **mom12_ia**^{hl} (0.702), **mom6**^{hl} (0.620).
Volatility	2.488	**tvol_w**^{lh} (3.085), **ivolcapm_w**^{lh} (2.745), **tvol_d**^{lh} (2.696), **beta**^{lh} (2.686), **ivolff_w**^{lh} (2.218).	0.414	**tvol_w**^{lh} (0.672), **ivolcapm_w**^{lh} (0.565), **beta**^{lh} (0.560), **tvol_d**^{lh} (0.539), **ivolff_w**^{lh} (0.450).
Growth	2.488	**issue**^{lh} (4.128), **issue5**^{lh} (3.888), **grltnoa**^{lh} (2.936).	0.502	**issue5**^{lh} (0.750), **issue**^{lh} (0.731).
Profitability	2.388	**opa**^{hl} (2.607), **gmr**^{hl} (2.571).	0.559	**opa**^{hl} (0.616)
Trading	♯			
Others	3.396	–	0.655	**mom1**^{hl} (0.699)

Selective inference (4-Factor)

	Studentized		Non-studentized	
	CV	Significant portfolios	CV	Significant portfolios
All stocks.				
Value	♯			
Momentum	2.544	–	0.615	**ma100**^{hl} (0.741), **ma200**^{hl} (0.682), **wh52**^{hl} (0.641).
Volatility	1.995	**tvol_w**^{lh} (4.214), **ivolff_w**^{lh} (3.894), **ivolcapm_d**^{lh} (3.832), **ivolcapm_w**^{lh} (3.827), **tvol_d**^{lh} (3.467), **ivolff_d**^{lh} (3.402).	0.495	**tvol_w**^{lh} (1.162), **ivolff_w**^{lh} (1.061), **ivolcapm_w**^{lh} (1.013), **ivolcapm_d**^{lh} (0.976), **tvol_d**^{lh} (0.962), **ivolff_d**^{lh} (0.834).
Growth	2.492	**issue**^{lh} (4.032), **issue5**^{lh} (3.327), **grltnoa**^{lh} (3.108).	0.503	**issue**^{lh} (0.754), **issue5**^{lh} (0.707), **grltnoa**^{lh} (0.511).
Profitability	2.437	**opa**^{hl} (2.607)	0.603	**opa**^{hl} (0.782)
Trading	2.540	**illiq**^{hl} (3.863)	0.455	**illiq**^{hl} (0.539)
Others	3.399	–	0.718	–
All-but-tiny stocks.				
Value	2.751	–	0.551	–
Momentum	♯			
Volatility	2.446	–	0.516	–
Growth	2.612	**issue**^{lh} (3.824), **issue5**^{lh} (3.091).	0.493	**issue**^{lh} (0.662), **issue5**^{lh} (0.599).
Profitability	2.490	**gmr**^{hl} (2.611)	0.565	–
Trading	♯			
Others	3.463	–	0.674	–

Selective inference (5-Factor)

	Studentized		Non-studentized	
	CV	Significant portfolios	CV	Significant portfolios
All stocks.				
Value	2.709	**cfp_ia**^{hl} (2.878)	0.624	–
Momentum	2.617	**ma50**^{hl} (5.017), **ma200**^{hl} (4.646), **ma100**^{hl} (4.415), **mom12¡a**^{hl} (3.690), **wh52**^{hl} (3.545), **mom12**^{hl} (3.391), **mom6**^{hl} (2.742).	0.567	**ma200**^{hl} (1.420), **ma100**^{hl} (1.314), **ma50**^{hl} (1.259), **wh52**^{hl} (0.942), **mom12**^{hl} (0.912), **mom12¡a**^{hl} (0.864), **mom6**^{hl} (0.805).
Volatility	2.294	**tvol_w**^{lh} (2.780), **ivolcapm_d**^{lh} (2.694), **ivolff_w**^{lh} (2.350).	0.518	**tvol_w**^{lh} (0.617), **ivolff_w**^{lh} (0.551), **ivolcapm_d**^{lh} (0.534).
Growth	2.605	**invest_LWZ**^{hl} (3.140)	0.449	**invest_LWZ**^{hl} (0.612) **acc**^{lh} (0.509)
Profitability	2.616	–	0.600	–
Trading	2.610	**illiq**^{hl} (4.359)	0.484	**illiq**^{hl} (4.359)
Others	3.394	**mom1**^{hl} (4.505), **noa**^{lh} (3.961), **chfin**^{hl} (3.740), **ma20**^{hl} (3.526).	0.674	**mom1**^{hl} (1.140), **ma20**^{hl} (0.840), **chpm**^{hl} (0.761), **noa**^{lh} (0.757).
All-but-tiny stocks.				
Value	2.769	–	0.533	–
Momentum	2.393	**ma50**^{hl} (4.700), **mom12_ia**^{hl} (4.017), **ma200**^{hl} (3.697), **ma100**^{hl} (3.195), **mom12**^{hl} (3.074), **wh52**^{hl} (2.931).	0.606	**ma50**^{hl} (1.091), **ma200**^{hl} (1.038), **ma100**^{hl} (0.990), **mom12_ia**^{hl} (0.785), **mom12**^{hl} (0.688).
Volatility	♯			
Growth	2.870	**invest_LWZ**^{hl} (3.488)	0.432	**invest_LWZ**^{hl} (0.685)
Profitability	2.860	–	0.494	–
Trading	♯			
Others	3.493	**noa**^{lh} (4.916), **mom1**^{hl} (4.458), **quick**^{hl} (4.316), **salecash**^{lh} (4.219), **ma20**^{hl} (3.863), **pchsale**^{hl} (3.817), **debteq**^{lh} (3.708).	0.646	**mom1**^{hl} (1.063), **ma20**^{hl} (0.995), **salecash**^{lh} (0.714), **quick**^{hl} (0.695), **noa**^{lh} (0.692), **chpm**^{hl} (0.669), **tangible**^{hl} (0.656).

Selective inference (Q-Factor)

	Studentized		Non-studentized	
	CV	Significant portfolios	CV	Significant portfolios
All stocks.				
Value	2.710	**cfp_ia**^{hl} (3.144)	0.794	–
Momentum	2.472	**ma200**^{hl} (2.531)	0.774	**ma200**^{hl} (0.844).
Volatility	2.552	–	0.749	–
Growth	2.653	–	0.573	**invest_LWZ**^{hl} (0.692).
Profitability	2.633	–	0.759	–
Trading	2.549	**illiq**^{hl} (3.437)	0.647	–
Others	3.407	–	0.904	–
All-but-tiny stocks.				
Value	2.843	**bm_ia**^{hl} (2.907)	0.709	–
Momentum	2.730	–	0.895	–
Volatility	♯			
Growth	2.771	–	0.524	**invest_LWZ**^{hl} (0.825)
Profitability	2.709	–	0.652	–
Trading	♯			
Others	3.514	–	0.874	–

4 Pre- versus post-1993 period comparison

Pre- versus post-1993 comparison (all stocks)

		CAPM	3-Factor	4-Factor	5-Factor
Studentized test.					
Pre-1993	FWER(1)	15 (3.345)	18 (3.390)	9 (3.359)	7 (3.514)
	FWER(2)	24 (2.976)	22 (2.975)	14 (3.021)	12 (3.094)
	FWER(3)	31 (2.756)	29 (2.747)	17 (2.783)	13 (2.857)
	$t > 1.96$	53	49	37	29
Post-1993	FWER(1)	2 (3.382)	8 (3.431)	1 (3.443)	1 (3.503)
	FWER(2)	4 (3.033)	13 (3.032)	3 (3.050)	4 (3.111)
	FWER(3)	10 (2.800)	16 (2.814)	9 (2.834)	7 (2.888)
	$t > 1.96$	31	41	27	13
Non-studentized test.					
Pre-1993	FWER(1)	11 (1.043)	15 (0.896)	10 (0.919)	1 (1.009)
	FWER(2)	20 (0.892)	24 (0.721)	12 (0.761)	4 (0.865)
	FWER(3)	21 (0.819)	27 (0.659)	16 (0.688)	7 (0.777)
Post-1993	FWER(1)	3 (1.447)	9 (1.112)	3 (1.133)	3 (1.152)
	FWER(2)	4 (1.317)	14 (0.950)	4 (0.992)	4 (0.995)
	FWER(3)	6 (1.233)	15 (0.874)	6 (0.903)	6 (0.911)

Pre- versus post-1993 comparison (all-but-tiny stocks)

		CAPM	3-Factor	4-Factor	5-Factor
Studentized test.					
Pre-1993	FWER(1)	7 (3.380)	6 (3.432)	0 (3.493)	1 (3.473)
	FWER(2)	18 (2.995)	16 (3.035)	4 (3.050)	1 (3.093)
	FWER(3)	23 (2.774)	19 (2.806)	6 (2.869)	3 (2.900)
	$t > 1.96$	50	37	24	17
Post-1993	FWER(1)	0 (3.389)	2 (3.464)	1 (3.445)	0 (3.561)
	FWER(2)	2 (3.047)	4 (3.083)	2 (3.043)	1 (3.166)
	FWER(3)	4 (2.872)	9 (2.898)	4 (2.856)	1 (2.942)
	$t > 1.96$	22	26	16	18
Non-studentized test.					
Pre-1993	FWER(1)	3 (0.900)	5 (0.843)	0 (0.857)	0 (0.975)
	FWER(2)	10 (0.768)	8 (0.688)	2 (0.700)	0 (0.817)
	FWER(3)	15 (0.712)	14 (0.621)	4 (0.632)	0 (0.725)
Post-1993	FWER(1)	0 (1.398)	3 (1.022)	1 (1.004)	2 (1.003)
	FWER(2)	1 (1.287)	5 (0.915)	2 (0.892)	5 (0.857)
	FWER(3)	2 (1.215)	7 (0.842)	3 (0.831)	5 (0.780)