Firm Characteristics and Chinese Stocks

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Abstract

This paper conducts a comprehensive study on predicting the cross section of Chinese stock market returns with a large panel of 75 individual firm characteristics. We use not only the traditional Fama-MacBeth regression, but also "big-data" econometric methods: principal component analysis (PCA), the partial least squares (PLS) and forecast combination to extract information from all of the 75 firm characteristics. We find the firm characteristics are important predictors, significant both statistically and economically. In addition, the recent developed PLS performs the best. Our empirical results further indicate that those firm characteristics that are related to trading frictions, momentum, and profitability are the most effective predictors for future stock returns in the Chinese stock market.

JEL Classification: G12, G14

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1. Introduction

One of the fundamental problems in finance is to explain why different assets have different returns. In the US, there are a large number of studies documenting dozens of firm characteristics that forecast the cross-section of stock returns (e.g., Goyal, 2012; Harvey, Liu, and Zhu 2016; Mclean and Pontiff 2016). For example, Green, Hand, and Zhang (2017) examine the predictive power of 94 firm characteristics and test whether they have independent information. Yan and Zheng (2017) use bootstrap approach to construct thousands of fundamental signals from financial statements to predict cross-sectional returns. John Cochrane, in his AFA 2011 Presidential Address, refers to the proposed anomalies as "a zoo of new variables" and argue that researchers should use novel econometric methods to synthesize the huge amount of return predictors documented in the previous studies.

The Chinese stock market grows rapidly over time and ranks now the second largest in the world, and hence it has become an increasingly important part of the global capital market. Carpenter, Lu, and Whitelaw (2015) find that the informativeness of Chinese market has increased significantly recently, which is even comparable with the U.S. stock market. Thus, it is important to understand the asset pricing regularities in the Chinese market, as it becomes more and more attractive to global investors. However, there are few cross section studies on the Chinese stock market. Jiang, Qi, and Tang (2018) is an exception, but they study the cross-sectional predictability of Chinese stock market with only *three* profitability variables.

In this paper, we take up the challenges raised by Cochrane in the Chinese stock market. First, we create a comprehensive large set of 75 firm characteristics and examine their individual economic relevance and predictive power. Second, we study the information contained in *all* of the 75 firm characteristics on predicting the cross-sectional Chinese stock market returns. Since it is impossible to know, *ex ante*, which firm characteristics will have the greatest predictive in the future, it is important to examine all of them collectively, so that the forecasting strategy is implementable in real time.

In aggregating the information of all the firm characteristics, we use not only the traditional Fama-

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MacBeth regression, but also “big-data” econometric methods: principal component analysis (PCA), the partial least squares (PLS) and the forecast combination method. The PCA is a widely used dimension reduction tool, but it explains best the variance of the characteristics and not necessarily the asset returns. In contrast, the PLS, developed recently by Light, Maslov and Rytchkov (2017) extracts information from the characteristics to have the greatest covariance with the returns. The forecast combination method is the simplest of all, replying only on univariate regressions on one of the characteristics. While the method has a long history in economics (Timmermann, 2006), it is used primarily in time series forecasting. Our paper is of the first to use it in the cross section. Based on these methods, we synthesize information from all firm characteristics, construct pricing factors and form decile portfolios accordingly. We calculate the long-short portfolios’ raw returns, Sharpe ratios, and abnormal returns to evaluate the effectiveness of the four estimation techniques

Empirically, we consider a panel of 75 individual firm characteristics that are known to be related to expected returns from the most recent anomalies literature. The univariate portfolio analysis shows that 18 out of 75 firm characteristics produce statistically significant long-short spread portfolio value weighted returns at 10% level, 15 of them are significant at 5% level, and 8 of them are significant at 1% level. Interestingly, unlike the US, size is the most important in China, having the highest value weighted monthly hedge return is 1.84% (t=3.39). However, the highest value weighted Fama-French five-factor (FF5) alpha is 1.46% (t=5.95) per month, and is generated by ROA-based spread portfolio.

All of the four aggregation methods except the PCA show joint predictive power of all firm characteristics, and the PLS performs best. Specifically, we form ten decile portfolios according to the latent factor estimated using the PLS method and find that the decile portfolio returns increase monotonically with the PLS factor, and the long-short spread portfolio on the PLS factor generates sizable monthly average returns of 2.60% and 1.95% with the t-statistics 5.98 and 4.07 for equal- and value weighting schemes, respectively. In addition, the spread portfolio return of the PLS factor model is greater than all the sorted portfolio returns by individual firm characteristics, indicating the economic gain of information aggregation.

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We also test whether the PLS factor can be explained by the Fama-French five-factor (FF5) models (Fama and French, 2015), adding to the large recent literature on what anomalies in US stock market can be explained by the market, size, value, profitability or investment five factors. Our results indicate that PLS-based approach has significant FF5 alphas, implying that the PLS technique can extract a common factor with even more powerful forecasting information for the Chinese market than the FF5 model. Moreover, the Sharpe ratio of the PLS long-short portfolios are high, range from 1.48 to 1.66 for equal weighted portfolios, and 0.81 to 1.03 for value weighted portfolios.

In comparison with the PLS, we find that PCA generates insignificant spread portfolio return, suggesting that a large part of common variation in firm characteristics are common noises that are unrelated to expected stock returns. The Fama-MacBeth (FM) regression and the forecast combination (FC) methods are also less informative than the PLS. The value weighted monthly hedge return of FM factor portfolio is 1.01% (t=2.61), while the value weighted FC factor spread portfolio return is 0.74% (t=1.60) per month.

Moreover, we cluster and classify these 75 characteristics variables into six categories, such as the value-versus-growth, investment, profitability, momentum, trading frictions, and intangibles groups. By employing PLS approach, we find that variables belong to trading frictions, momentum, and profitability are more effective in forecasting the cross-sectional expected returns in Chinese stock market. For example, the trading friction based PLS actor spread portfolios generate 2.24% (t=5.47) and 1.86% (t=4.23) equal- and value- weighted monthly returns, respectively.

Our paper contributes to the growing asset pricing literature on Chinese stock market. Jiang et al. (2011) conduct a comprehensive investigation of the time-series return predictability of the Chinese stock market with many predictor variables. Jiang, Qi, and Tang (2018) test the cross-sectional predictability of Chinese stock market with three profitability variables. In contrast, we conduct by far the most comprehensive study of the cross-sectional return predictivity of Chinese stock market with 75 accounting and return related firm characteristics in the literature.

Our paper also contributes to the asset pricing literature on mega study of firm characteristics that

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forecast cross-section of stock returns. Stambaugh, Yu, and Yuan (2012) show that investor sentiment contributes to the predict power of 11 anomalies. Novy-Marx and Velikov (2015) investigate after-trading-cost performance of 23 anomalies. McLean and Pontiff (2016) examine the post-publication return predictability on 97 anomalies. Hou, Xue, and Zhang (2017) replicate 447 anomalies in finance and accounting literature. We extend these research to the Chinese stock market.

Our paper is also closely related to the growing works on applying machine learning and big data techniques in financial market. Light, Maslov, and Rytchkov (2017) propose the PLS approach for estimating expected returns on individual stocks from cross-sectional firm characteristics. Their econometric method is related to the time series PLS adopted by Kelly and Pruitt (2013, 2015), Huang et al. (2015), and Jiang et al. (2018). Based on the Goyal and Welch (2007) predictor dataset, Rapach, Strauss, and Zhou (2010) show that FC is a powerful forecasting method for the time-series of stock returns with a shrinkage interpretation, and Neely et al. (2014) propose the PCA approach to forecast the aggregate US stock returns. We conduct comparative analysis on different techniques in forecasting the cross-sectional expected stock returns.

The remainder of this paper is organized as follows. Section 2 discusses the data and calculation of 75 anomalies. Section 3 explores univariate portfolio analysis of firm individual characteristics. Section 4 employs portfolio tests to compare various information aggregation methods and investigate the return predictability for different categories of firm characteristics. Section 5 concludes the paper.

2. Data

We obtain data from the China Stock Market and Accounting Research (CSMAR) spanning from January 1998 to December 2016, including accounting data, monthly stock returns, Fama-French common factors (1993, 2015), Chinese risk-free rate, etc. Following Allen et al. (2015) and Carpenter, Lu, and Whitelaw (2015), our sample consisted of all of Chinese A-share stocks with accounting and returns data available. Stocks are traded on the Shanghai and Shenzhen main boards, SME Board, and ChiNext Board, to cover different levels of Chinese stock markets.

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To ensure the quality of data, we applied standard sample screening procedures. First, we excluded firm quarterly observations with "ST" (special treatment) and/or "PT" (particular transfer) status at the beginning of portfolio formation, which are stocks under financial distress and lack of market liquidity. Second, we excluded firms in the financial industry, according to the industry classification of the China Securities Regulatory Commission (CSRC).

We use the sample period from 2000 to 2016 in our main tests, after China's entry into the World Trade Organization (WTO). According to Carpenter, Lu, and Whitelaw (2015), a series of reforms and developments, like the initiation of securities laws and regulations, were introduced by CSRC authority during this period, to increase Chinese stock market transparency, audit quality, protection of minority shareholders, and general functioning and efficiency.

As fundamental signals about expected stock returns, we use 75 variables that are derived from recent famous asset pricing literature. These firm-level characteristics can be classified into six categories. The first category includes value-versus-growth-related variables, such as asset-to-market (AM), book-to-market equity (BM), cash flow-to-price (CFP), debt-to-equity ratio (DER), earnings-to-price (EP), and sales-to-price (SP). The second category contains investment-based characteristics such as accruals (ACC), capital expenditure growth (CAPXG), change in shareholders' equity (dBe), investment-to-assets (IA), inventory change (IVC), and net operating assets (NOA). The third group contains profitability-related variables such as asset turnover (ATO), cash productivity (CP), earnings before interests and taxes (EBIT), gross profitability (GP), return on assets (ROA), and return on equity (ROE). The fourth category includes momentum-related variables such as change in 6-month momentum (CHMOM), industry momentum (INMOM), 1-month momentum (MOM1M), 12-month momentum (MOM12M), volume momentum (VOLM), and volume trend (VOLT). The fifth group contains trading frictions-related characteristics such as market beta (BETA), idiosyncratic return volatility (IVOL), illiquidity (ILLIQ), price (PRC), firm size (SIZE), and share turnover (TURN). The last category includes intangibles-related variables such as firm age (AGE), cash flow-to-debt (CFD), current ratio (CR), quick ratio (QR), sales-to-cash (SC), and sales-to-inventory. The definition of each variable is described in Appendix B and it largely follows the original

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paper in which the variable is calculated and constructed as related to stock returns.

3. Univariate portfolio analysis on individual characteristics

We start our empirical study with investigating whether the firm individual characteristics can separately predict the cross-sectional stock returns. We sort all stocks with respect to each characteristic depending on the its data frequency. For most characteristics come from firm's fiscal year report, we form 10 decile portfolios at the end of June of year *t* according to the ranked values of each firm characteristic for the fiscal year ending in year *t*-1. Following Jiang, Qi, and Tang (2018), the portfolios based on gross profitability (GP), returns on assets (ROA), and return on equity (ROE) are using quarterly accounting data. These portfolios and other return-related portfolios, such as momentum, size, beta, volatility, are rebalanced at the end of each month by using the most recently available data. We then calculate monthly equal- and value-weighted returns on them. The return predictability of each characteristic is the difference between the realized return on top and bottom decile portfolios, which is referred to as the long-short portfolio returns. We invert the long and short portfolios if the characteristics are negatively related to the future returns. Table 1 reports monthly average raw returns (in percentage), abnormal returns (FF5 α, in percentage), and their *t*-statistics (in squared brackets) of long-short portfolios formed by the 75 firm characteristics. The spread portfolios are equal-weighted in Panel A and value-weighted in Panel B. The sample period of univariate analysis is from July 2000 to December 2016.

[Insert table 1]

Table 1 reports that a large amount of the 75 characteristics fail to predict future stock returns individually in Chinese stock market. Panel A shows that only 25 variables produce statistically significant hedge returns on equal-weighted portfolios at 90% level, whereas the absolute values of *t*-statistics of 11 variables exceed 3. Consistent with the literature, Panel B shows that the returns of long-short portfolios tend to be smaller when calculated for value-weighted portfolios. Only 18 variables significantly predict future returns, and 6 of them generate high hedge returns with *t*-statistics exceed 3. The variation in the *t*-statistics for equal-weighted spread portfolios across these significant characteristics is driven by the

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dispersion in expected hedge returns (they vary from 0.23% for payout yield to 2.18% for RMB trading volume), as well as in the FF5 alphas (they range from 0.09% for changes in gross property, plant, and equipment plus inventory-to-assets to 1.59% for standard deviation of RMB trading volume). Furthermore, the value-weighted Fama-French five-factor alphas of 38 characteristics are significant at 90% level, 34 of them are significant at 95% level, and 16 of them are significant at 99% level. In the considered sample, the most significant returns and FF5 alphas are produced by trading frictions-related variables.

[Insert figure 1]

Figure 1 shows that value weighted monthly average raw returns (in percentage) of long-short portfolios formed individually by the 75 firm characteristics. In contrast to the other firm characteristics, 1-month momentum, Dimson beta, illiquidity, RMB trading volume, and firm size appear to have larger absolute values of hedge returns on value-weighted portfolios. The highest spread portfolio return is generated by firm size, which is 1.84% (t=3.39) per month. In conclusion, only approximately one third of firm individual characteristics can significantly predict future stock returns in Chinese stock market, which indicates that exploring the characteristics-based factors is meaningful to find the commonality from these variables.

4. Empirical results

In this section, we compare several different methods to construct parsimonious factors to summarize forecasting information in many firm characteristics. These methods include Fama-MacBeth (FM) regression, principal component analysis (PCA), the partial least squares (PLS) approach, and forecast combination (FC).

4.1 Fama-MacBeth regression

We first adopt a common approach to extract expected returns, which is using fitted values of Fama-MacBeth (FM) regressions as proxies of future stock returns based on firm characteristics. We start with running the FM regressions of returns on lagged characteristics in each month. Then, we use the slopes of

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each individual variable to calculate fitted values as estimations of expected returns. Specifically, we consider three types of fitted values: the regression slopes are averaged over the past 12 months, the past 24 months, and the past 36 months. To examine the performance of FM regression approach empirically, we sort stocks into 10 decile portfolios on the proxies of expected returns and rebalance the portfolios monthly. Table 2 shows raw returns, Sharpe ratios, CAPM α, FF3 α, FF5 α, and their *t*-statistics of monthly equal- and value-weighted stock returns on decile portfolios.

[Insert table 2]

Our results demonstrate that the FM regression method provides effective estimates for expected returns. The raw returns of equal-weighted spread portfolios range from 0.92% (*t*=2.67) to 1.27% (*t*=3.75), and range from 0.39% (*t*=0.97) to 1.01% (*t*=2.61) for value weighted portfolios. The long-short strategy that based on averaging the fitted values over past 12 months generates highest Sharpe ratio compared to other averaging schemes, which has Sharpe ratios of 0.95 and 0.66 for equal- and value- weighted spread portfolios. Nevertheless, in section 4.3, we will find that the hedge returns and *t*-statistics are significantly lower than those on PLS factor in all specifications from Table 4. Thus, the FM regression does not produce better proxies of expected returns than does the PLS-based approach. Furthermore, this approach may suffer from the multicollinearity problem especially when firm-level variables are highly correlated.

4.2 Principal component analysis

We then use principal component analysis (PCA) to aggregate information from firm characteristics and investigate whether the first principal component of all these variables can predict future stock returns. The PCA based approach can be employed by the following two steps:

Step 1. Apply the PCA to the standardized firm characteristics X_{it}^{a} and compute the coefficients $\beta_{(pca)t}^{a}, a = 1, \dots, A$. of the first principal component.

Step 2. Calculate a potential predictor of returns as

$$\hat{r}_{(pca)it} = \sum_{a=1}^{A} (\sum_{s \in \mathrm{T}} \beta_{(pca)s}^{a}) X_{it}^{a}, \tag{4.2.1}$$

where the coefficients $\beta_{(pca)s}^{a}$ are averaged over the past 12 months, the past 24 months, and the past 36

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months. Then, at the beginning of each month, we sort stocks into 10 decile portfolios on the predictor $\hat{r}_{(pca)it}$, and rebalance at the next month. The monthly equal- and value-weighted portfolio raw returns, Sharpe ratios, CAPM α, FF3 α, FF5 α, and their *t*-statistics are reported in table 3 below.

[Insert table 3]

Table 3 implies that the first principal component of PCA is a poor predictor of future stock returns. Both equal- and value-weighted spread portfolios cannot produce significant raw returns when the averaging windows are 12 months, 24 months, and 36 months. Moreover, the Sharpe ratios of the above long-short strategies tend to be 0. The FF5 alphas vary from 0.29% (*t*=0.58) to 0.49% (*t*=1.01) for equal-weighted spread portfolios, and vary from 0.46% (*t*=0.85) to 0.56% (*t*=1.06) for value-weighted spread portfolios, which means none of them are statistically significant. Therefore, PCA approach indeed underperforms FM regression approach. These results indicate the firm-level variables that share returns-unrelated common variation will contaminate the first principal component and decrease its return predictability.

4.3 PLS approach

Compared to FM regression and PCA approach, we now apply the PLS-based estimation procedure to the 75 firm characteristics and construct a factor that aggregates information on expected returns from all of them.

Following Light, Maslov, and Rytchkov (2017), we assume there is a latent variable to represent all the firm characteristics which relates to future stock returns. Consider firm characteristics are observed in at least two periods and the stock market has N stocks. The expected return of stock *i* at time *t* is $r_{it} = E[R_{it+1}|\mathrm{I}_t]$, where I_t denotes all the information available at time *t*. Therefore, the realized return of stock *i* is

$$R_{it+1} = r_{it} + \varepsilon_{it+1}, \qquad i = 1, \dots, N, \tag{4.3.1}$$

where $E[\varepsilon_{it+1}|\mathrm{I}_t] = 0$ and unexpected return ε_{it+1} are assumed to be independent from all elements in the information set I_t, whereas ε_{it+1} and ε_{jt+1} can be correlated when $i \neq j$. In practice, the expected

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returns are difficult to estimate directly from the information set, but one can observe various firm characteristics $X_{it}^{a}, a = 1, \dots, A$. Then, we demean and standardize all the firm characteristics on each month. Therefore, these firm-level variables have zero cross-sectional means and unit variances. In the factor model, we further assume that the latent variable r_{it} is the only factor in the information set which relates to expected returns:

$$X_{it}^{a} = \eta_t^{a}(r_{it} - \bar{r}_t) + r_{it}^{a}, \tag{4.3.2}$$

where η_t^{a} represents the sensitivity of characteristic X^{a} to future stock returns, and $\bar{r}_t$ is the average of cross-sectional expected returns at time *t*. Therefore, the estimates of expected returns $\hat{r}_{it}$ are constructed in two steps:

Step 1. Run separate cross-sectional regressions of $\hat{R}_{it}, i = 1, \dots, N$ on each individual firm-level variable $X_{it-1}^{a}, a = 1, \dots, N$ for $a = 1, \dots, A$ and denote the obtained slopes as β_t^{a}.

Step 2. For each firm $i, i = 1, \dots, N$ run a regression of X_{it}^{a} on $\beta_t^{a}, a = 1, \dots, A$, and denote the obtained slopes as $\hat{r}_{it}$.

The expected returns can be estimated more precisely and less biased if we use information of characteristics and not only from data in periods *t* and *t*-1. Therefore, we calculate particular time series averages of $\beta_t^{s}, s \leq t$ in the first step and use them in the regression of second step instead of β_t^{a}. Specifically, we separately consider the different versions of PLS-based factor on the averages of β_s^{a} over the past 12 months, past 24 months, past 36 months.

To explore the relation between the PLS factor and expected stock returns, we employ the same approach as we use in univariate portfolio analysis for individual firm characteristics. At the beginning of each month, we sort firms into 10 decile portfolios according to PLS factor estimation of expected returns, hold for one month and calculate the monthly portfolio returns. Particularly, decile 1 refers to firms in the lowest decile and decile 10 to firms in the highest. The "(10-1)" spread portfolio is computed as long the highest decile and short the lowest decile. Table 4 shows time series averages and *t*-statistics of monthly equal- and value-weighted stock returns on decile portfolios formed by sorting firms on PLS based factor model. The time series averages include raw returns, Sharpe ratios (SR), CAPM α, FF3 α, FF5 α, and

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market adjusted returns (L-SMKT). The PLS factor is constructed with different averaging of β^a in the first step over the most recent 12 months (in Panel A), 24 months (in Panel B), and 36 months (in Panel C).

[Insert table 4]

In Panel A of Table 4, we find that PLS factor-based equal-weighted portfolios' monthly average raw returns increase from 0.36% to 2.96% for the lowest and highest deciles, respectively. The average return of the equal-weighted spread portfolio is 2.60% (*t*=5.98) per month, which indicates that the long-short trading strategy of buying the highest and selling the lowest deciles will earn annual returns of about 31.20% on average. Moreover, the Sharpe ratio of this strategy achieves 1.52, which means comparatively large and steady investment benefits. Our results also show strong and positive PLS-based premium. Specifically, the equal-weighted spread portfolio has a monthly CAPM alpha of 2.62% (*t*=6.00), a monthly FF3 alpha of 2.33% (*t*=5.26), and a monthly FF5 alpha of 2.12% (*t*=4.79). Since some practitioners argue that it is hard to short a stock in Chinese market because of the short sell restrictions. Hence, we propose a new strategy that buying the highest PLS factor-based portfolio and short the value-weighted aggregate market portfolio, and compute the spread portfolio return denoted as market adjusted return (L-SMKT). The monthly market adjusted return of equal-weighted portfolio is 1.42% (*t*=4.31), which is lower than the normal long-short portfolio but still statistically significant. Right-hand side of Panel A represents the results on PLS-based value weighted portfolios. The spread portfolio generates monthly raw return of 1.95% (*t*=4.07), the monthly market adjust return of 1.28% (*t*=3.03), and with Sharpe ratio of 1.03. The CAPM, FF3, and FF5 alphas of spread portfolio are 1.98% (*t*=4.13), 1.68% (*t*=3.45), and 1.44% (*t*=2.97), respectively.

[Insert figure 2]

Figure 2 shows time-series average loadings of each individual characteristics when calculating the PLS-based factor in step 1. We find that the absolute values of estimated slopes of illiquidity, maximum daily returns, RMB trading volume, return volatility, and zero trading days are higher than the other firm characteristics. This result also indicates that trading frictions-based variables are more related to the

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future returns, which is consistent with the findings in univariate portfolio analysis.

Panel B and C of Table 4 report the similar findings when we obtain PLS factor by using averages of β_s^a over the past 24 months, past 36 months. For example, the equal-weighted spread portfolio monthly returns range from 2.82% (*t*=5.43) and 2.91% (*t*=6.10), and the FF5 alphas range from 2.40% (*t*=4.62) to 2.72% (*t*=6.13) per month. For value-weighted spread portfolios, the raw returns, adjusted market returns, and the abnormal returns are lower than those in Panel A, but still economically large and statistically significant. Thus, our results imply that all the 75 firm characteristics in Chinese stock market indeed share the same expected return-related latent factor, which can be viewed as a commonality in the cross-sectional anomalies associated with various firm-level signals. The PLS factor method outperforms FM regression and PCA approach.

4.4 Forecast combination

In this subsection, we employ another approach which is denoted as forecast combination (FC) to summarize the expected returns. The core idea of this approach is to compute equal weighted fitted values from individual regressions of realized returns on each lagged firm characteristic.

In the first step, we run the 75 regressions separately of returns on each lagged characteristic in each month. Then, we use the slope of each firm characteristic to calculate the fitted value from each regression, which is the standardized firm characteristic multiplied by its estimated coefficient from the regressions. Therefore, the expected return of each stock is the equal weighted mean of these fitted values of 75 firm characteristics. Similar to FM regression, we consider three types of fitted values: the regression slopes are averaged over the past 12 months, the past 24 months, and the past 36 months. We then sort stocks into 10 decile portfolios on the forecast combination of fitted values and rebalance the portfolios monthly. Table 5 shows raw returns, Sharpe ratios, CAPM α, FF3 α, FF5 α, and their *t*-statistics of monthly equal- and value-weighted stock returns on decile portfolios.

[Insert table 5]

In Table 5, we can find that the forecast combination is better than PCA approach, but inferior to FM

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regression method. For instance, the highest long-short portfolio return on equal-weighted portfolios is 1.08% (*t*=2.53) with the average of fitted values over the past 12 month, whereas it is 1.27% (*t*=3.75) for FM regression based spread portfolio. The Sharpe ratios are varying from 0.15 to 0.64 for all the hedge strategies. Moreover, only equal-weighted spread portfolio averaging over past 12 and 36 months generate significant FF5 alphas of 0.87% (*t*=1.99) and 0.75% (*t*=1.96) per month. In all, the FC approach also does not produce better estimates of expected returns than the PLS factor model.

4.5 Performance of different factor categories

In this subsection, we investigate the performance of anomalies based on their different categories. As mentioned in section 2, we classify all the firm individual characteristics into six categories, including value-versus-growth, investment, profitability, momentum, trading frictions, and intangibles. Table 6 shows time series averages (raw returns, Sharpe ratios, CAPM α, FF3 α, FF5 α) and *t*-statistics of monthly equal- and value-weighted stock returns on decile portfolios formed by sorting firms on PLS based factor model with the average of β^a over the past 12 months.

[Insert table 6]

Our results indicate that anomalies belong to trading frictions, momentum, and profitability are more effective to aggregate the cross-sectional expected returns in Chinese stock market. Specifically, trading frictions-based spread portfolios generate 2.24% (*t*=5.47) and 1.86% (*t*=4.23) equal- and value-weighted raw returns per month. Momentum-based spread portfolios produce 1.46% (*t*=4.33) and 1.10% (*t*=2.65) equal- and value-weighted monthly returns, while the profitability-based long-short portfolio equal- and value-weighted returns are 1.02% (*t*=2.64%) and 0.94 (*t*=2.29), respectively. The Sharpe ratios of trading frictions-based long-short strategies range from 1.07 to 1.39, which represents the highest Sharpe ratios among all the categories. On the contrary, neither equal-weighted nor value-weighted spread portfolios based on value-versus-growth, investment, and intangibles can generate significant raw returns.

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5. Conclusion

In this paper, we create for the first time a large set 75 firm characteristics portfolios in the Chinese stock market, and apply the latest "big-data" methods to extract to aggregate forecasting information from the 75 firm characteristics for predicting the cross-section of expected Chinese stock returns. Empirically, we find firm characteristics have statistically and economically significant forecasting power. In comparing the "big-data" methods, we find that the PLS is the most efficient one in aggregating the information from all the characteristics. The long-short portfolio returns produced by using PLS are economically large and statistically significant, and perform better than all the firm characteristics individually even of one chooses them ex post. We also find that those firm characteristics that are relate to trading frictions, momentum, and profitability have stronger forecasting power for expected Chinese stock returns. While there are ample studies in the US to understand the role of firm characteristics in asset pricing, our paper provides the first empirical evidence on the value of a comprehensive set of characteristics in Chinese stock market, and highlights also the usefulness of novel techniques in machine learning to aggregate big-data information in the stock market. More future works could be done on the incremental predictive information of each characteristic variable to better understand the economic link and structure of the vast anomalies in Chinese stock market.

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Appendix A. List of Characteristics

The characteristics are grouped into six categories: (1) value-versus-growth; (2) investment; (3) profitability; (4) momentum; (5) trading frictions; (6) intangibles.

Acronym	Name	Reference
Panel A: Value-versus-growth		
AM	Assets-to-market	Fama and French (1992)
BM	Book-to-market equity	Rosenberg, Reid, and Lanstein (1985)
CFP	Cash flow-to-price	Lakonishok, Shleifer, and Vishny (1994)
DER	Debt-to-equity ratio	Bhandari (1988)
DLME	Long term debt-to-market equity	Bhandari (1988)
DP	Dividend-to-price ratio	Litzenberger and Ramaswamy (1982)
EP	Earnings-to-price	Basu (1983)
LG	Liability growth	Richardson, Sloan, Soliman, and Tuna (2005)
OCFP	Operating cash flow-to-price	Desai, Rajgopal, and Venkatachalam (2004)
PY	Payout yield	Boudoukh, Michaely, Richardson, and Roberts (2007)
Rev1	Reversal	De Bondt and Thaler (1985)
SG	Sustainable growth	Lockwood and Prombutr (2010)
SMI	Sales growth minus inventory growth	Abarbanell and Bushee (1998)
SP	Sales-to-price	Barbee, Mukherji, and Raines (1996)
TG	Tax growth	Thomas and Zhang (2011)
Panel B: Investment		
ACC	Accruals	Sloan (1996)
PACC	Percent accruals	Hafzalla, Lundhom, and Van Winkle (2011)
CAPXG	Capital expenditure growth	Mcconnell and Muscarella (1985)
dBe	Change in shareholders' equity	Richardson, Sloan, Soliman, and Tuna (2005)
dPIA	Changes in PPE and inventory-to-assets	Lyandres, Sun, and Zhang (2008)

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IA	Investment-to-assets	Cooper, Gulen, and Schill (2008)
IVC	Inventory change	Thomas and Zhang (2002)
IVG	Inventory growth	Belo and Lin (2011)
NOA	Net operating assets	Hirshleifer, Hou, Teoh, and Zhang (2004)
Panel C: Profitability		
ATO	Asset turnover	Soliman (2008)
CFOA	Cash flow over assets	Asness, Frazzini, and Pedersen (2017)
CP	Cash productivity	Chandrashekai and Rao (2009)
CTA	Cash-to-assets	Palazzo (2012)
CTO	Capital turnover	Haugen and Baker (1996)
EBIT	Earnings before interests and taxes	Greenblatt (2006)
EY	Earnings yield	Greenblatt (2006)
GM	Gross margins	Novy-Marx (2013)
GP	Gross profitability	Novy-Marx (2013); Jiang, Qi, and Tang (2018)
NPOP	Net payout over profits	Asness, Frazzini, and Pedersen (2017)
RNA	Return on net operating assets	Soliman (2008)
ROA	Return on assets	Balakrishnan, Bartov, and Faurel (2010); Jiang, Qi, and Tang (2018)
ROE	Return on equity	Hou, Xue, and Zhang (2015); Jiang, Qi, and Tang (2018)
ROIC	Return on invested capital	Greenblatt (2006)
TBI	Taxable income-to-book income	Green, Hand, and Zhang (2013)
Z	Z-score	Dichev (1998)
Panel D: Momentum		
CHMOM	Change in 6-month momentum	Gettleman and Marks (2006)
INDMOM	Industry momentum	Moskowitz and Grinblatt (1999)
MOM1M	1-month momentum	Jegadeesh (1990)
MOM6M	6-month momentum	Jegadeesh and Titman (1993)

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MOM12M	12-month momentum	Jegadeesh and Titman (1993)
MOM36M	36-month momentum	Jegadeesh and Titman (1993)
VOLM	Volume momentum	Lee and Swaminathan (2000)
VOLT	Volume trend	Haugen and Baker (1996)
Panel E: Trading Frictions		
B_DIM	The Dimson beta	Dimson (1979)
B_DN	Downside beta	Ang, Chen, and Xing (2006)
BETA	Market beta	Fama and MacBeth (1973)
BETASQ	Beta squared	Fama and MacBeth (1973)
B_FF	Fama and French (1992) beta	Fama and French (1992)
B_FP	Frazzini and Pedersen (2014) beta	Frazzini and Pedersen (2014)
B_HS	Hong and Sraer (2015) beta	Hong and Sraer (2016)
IVOL	Idiosyncratic return volatility	Ali, Hwang, and Trombley (2003)
ILLIQ	Illiquidity	Amihud (2002)
MAXRET	Maximum daily returns	Bali, Cakici, and Whitelaw (2011)
PRC	Price	Blume and Husic (1973)
PRCDEL	Price delay	Hou and Moskowitz (2005)
RVOL	RMB trading volume	Chordia, Subrahmanyam, and Anshuman (2001)
SIZE	Frim size	Banz (1981)
STD_RVOL	Volatility of RMB trading volume	Chordia, Subrahmanyam, and Anshuman (2001)
STD_TURN	Volatility of turnover	Chordia, Subrahmanyam, and Anshuman (2001)
RETVOL	Return volatility	Ang, Hodrick, Xing, and Zhang (2006)
TURN	Share turnover	Datar, Naik, and Radcliffe (1998)
ZEROTRADE	Zero trading days	Liu (2006)
Panel F: Intangibles		
AGE	Firm age	Jiang, Lee, and Zhang (2005)

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CFD	Cash flow-to-debt	Ou and Penman (1989)
CR	Current ratio	Ou and Penman (1989)
CRG	Current ratio growth	Ou and Penman (1989)
QR	Quick ratio	Ou and Penman (1989)
QRG	Quick ratio growth	Ou and Penman (1989)
SC	Sales-to-cash	Ou and Penman (1989)
SI	Sales-to-inventory	Ou and Penman (1989)

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Appendix B. Definitions of Characteristics

This section provides the detailed definitions of variables employed in this paper. All the accounting variables are constructed from the CSMAR database. The annual statements are assumed to be publicly available by the end of June in the calendar year t+1 for the fiscal year t, while data from quarterly statements are updated monthly using the most recently announced quarterly accounting information.

AM: Assets-to-market, which is total assets for the fiscal year divided by fiscal-year-end market capitalization.

BM: Book-to-market equity, which is the book value of equity for fiscal year divided by fiscal-year-end market capitalization.

CFP: Cash flow-to-price, which is operating cash flows divided by fiscal-year-end market capitalization.

DER: Debt-to-equity ratio, which is total liabilities divided by fiscal-year-end market capitalization.

DLME: Long term debt-to-market equity, which is long term liabilities divided by fiscal-year-end market capitalization.

DP: Dividend-to-price ratio, which is annual total dividends payouts divided by fiscal-year-end market capitalization.

EP: Earnings-to-price, which is annual income before extraordinary items divided by fiscal-year-end market capitalization.

LG: Liability growth, which is the annual change in total liabilities divided by 1-year-lagged total liabilities.

OCFP: Operating cash flow-to-price, which is operating cash flow divided by fiscal-year-end market capitalization.

PY: Payout yield, which is annual income before extraordinary items minus the change of book equity

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divided by fiscal year end market capitalization.

Rev1: Reversal, which is cumulative returns from months t-60 to t-13.

SG: Sustainable growth, which is annual growth in book value of equity.

SMI: Sales growth minus inventory growth, which is annual growth in sales minus annual growth in inventory.

SP: Sales-to-price, which is the annual operating revenue divided by fiscal-year-end market capitalization.

TG: Tax growth, which is annual change in taxes payable divided by 1-year-lagged taxes payable.

ACC: Accruals, which is annual income before extraordinary items minus operating cash flows divided by average total assets.

PACC: Percent accruals, which is total profit minus operating cash flow divided by net profit.

CAPXG: Capital expenditure growth, which is the annual change in capital expenditure divided by 1-year-lagged capital expenditure.

dBe: Change in shareholders' equity, which is the annual change in book equity divided by 1-year-lagged total assets.

dPIA: Changes in PPE and inventory-to-assets, which is the annual change in gross property, plant, and equipment plus the annual change in inventory scaled by 1-year-lagged total assets.

IA: Investment-to-assets, which is the annual change in total assets divided by 1-year-lagged total assets.

IVC: Inventory change, which is the annual change in inventory scaled by two-year average of total assets.

IVG: Inventory growth, which is the annual change in inventory divided by 1-year-lagged inventory.

NOA: Net operating assets, which is operating assets minus operating liabilities scaled by total assets.

ATO: Asset turnover, which is sales divided by 1-year-lagged net operating assets.

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CFOA: Cash flow over assets, which is cash flow from operation scaled by total assets.

CP: Cash productivity, which is market value of tradable shares plus long-term liabilities minus total assets scaled by cash and cash equivalents.

CTA: Cash-to-assets, which is cash and cash equivalents divided by the two-year average of total assets.

CTO: Capital turnover, which is sales divided by 1-year-lagged total assets.

EBIT: Earnings before interests and taxes, which is net profit plus income tax expenses, and plus financial expenses.

EY: Earnings yield, which is earnings before interests and taxes divided by enterprise value.

GM: Gross margins, which is operating revenue minus operating expenses divided by 1-year-lagged operating revenue.

GP: Gross profitability ratio, which is the quarterly operating revenue minus quarterly operating expenses divided by the average of current quarterly total assets and 1-quarter-lagged total assets.

NPOP: Net payout over profits, which is the sum of total net payout (net income minus changes in book equity) divided by total profits.

RNA: Return on net operating assets, which is operating income after depreciation divided by 1-year lagged net operating assets.

ROA: Return on assets, which is quarterly total operating profit divided by the average of current quarterly total assets and 1-quarter-lagged total assets.

ROE: Return on equity, which is quarterly net income divided by the average of current quarterly total shareholders' equity and 1-quarter-lagged shareholders' equity.

ROIC: Return on invested capital, which is t annual earnings before interest and taxes minus non-operating income divided by non-cash enterprise value.

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TBI: Taxable income-to-book income, which is pretax income divided by net income.

Z: Z-score, we follow Dichev (1998) to construct Z-score = 1.2 × (working capital / total assets) + 1.4 × (retained earnings / total assets) + 3.3 × (EBIT / total assets) + 0.6 × (market value of equity / book value of total liabilities) + (sales / total assets).

CHMOM: Change in 6-month momentum, which is cumulative returns from months t-6 to t-1 minus months t-12 to t-7.

INDMOM: Industry momentum, which is the equal weighted average industry 12-month returns.

MOM1M: 1-month momentum, which is one-month cumulative returns.

MOM6M: 6-month momentum, which is 5-month cumulative returns ending one month before month end.

MOM12M: 12-month momentum, which is 11-month cumulative returns ending one month before month end.

MOM36M: 36-month momentum, which is cumulative returns from months t-36 to t-13.

VOLM: Volume Momentum, which is buy- and- hold returns from t-6 through t-1. We limit the sample to high trading volume stocks, i.e., stocks in the highest quintile of average monthly trading volume measured over the past six months.

VOLT: Volume trend, which is five-year trend in monthly trading volume scaled by average trading volume during the same five-year period.

B_DIM: The Dimson beta, we follow Dimson (1979) to use the lead and the lag of the market return along with the current market return to estimate the Dimson beta.

B_DN: Downside beta, we follow Ang, Chen, and Xing (2006) to estimate downside beta as the conditional covariance between a stock's excess return and market excess return, divided by the

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conditional variance of market excess return, which is on condition that market excess return is lower than the average of market excess return.

BETA: Market beta, which is the estimated market beta from weekly returns and equal weighted market returns for 3 years ending month t-1 with at least 52 weeks of returns.

BETASQ: Beta squared, which is market beta squared.

B_FF: Fama and French (1992) beta, we follow Fama and French (1992) to estimate individual stocks' betas by regressing monthly return on the current and recent lag of the market return with a five-year rolling window.

B_FP: Frazzini and Pedersen (2014) beta, we follow Frazzini and Pedersen (2014) to estimate the market beta as the estimated return volatilities for the stock divided by the market return volatilities, multiplied by their return correlation.

B_HS: Hong and Sraer (2015) beta, which is using daily returns to compute the summed-coefficients as market beta with a one-year rolling window.

IVOL: Idiosyncratic return volatility, which is standard deviation of residuals of weekly returns on weekly equal weighted market returns for 3 years prior to month end.

ILLIQ: Illiquidity, which is the average of absolute daily return divided by daily RMB trading volume over the past 12 months ending on June 30 of year t+1.

MAXRET: Maximum daily returns, which is the maximum daily return from returns during calendar month t-1.

PRC: Price, which is the share price at the end of month t-1.

PRCDEL: Price delay, which is the proportion of variation in weekly returns for 36 months ending in month t-1 explained by 4 lags of weekly market returns incremental to contemporaneous market returns.

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RVOL: RMB trading volume, which is the natural log of RMB trading volume times price per share from month t-2.

SIZE: Frim size, which is market value of tradable shares at the end of each month.

STD_RVOL: Volatility of RMB trading volume, which is monthly standard deviation of daily dollar trading volume.

STD_TURN: Volatility of turnover, which is monthly standard deviation of daily share turnover.

RETVOL: Return volatility, which is standard deviation of daily returns from month t-1.

TURN: Share turnover, which is average monthly trading volume for most recent 3 months scaled by number of shares outstanding in current month.

ZEROTRADE: Zero trading days, which is turnover weighted number of zero trading days for most recent 1 month.

AGE: Firm age, which is number of years since a firm's initial public offerings year.

CFD: Cash flow-to-debt, which is earnings before depreciation and extraordinary items divided by the average of current total liabilities and 1-year-lagged total liabilities.

CR: Current ratio, which is current assets divided by current liabilities.

CRG: Current ratio growth, which is annual growth in current ratio.

QR: Quick ratio, which is current assets minus inventory, divided by current liabilities.

QRG: Quick ratio growth, which is annual growth in quick ratio.

SC: Sales-to-cash, which is sales divided by cash and cash equivalents.

SI: Sales-to-inventory, which is sales divided by total inventory.

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Figure 1: Performance of single sorts on 75 firm characteristics

Figure 1 reports value weighted monthly average raw returns of long-short portfolios formed individually by the 75 firm characteristics. The sample is from 2000 to 2016.

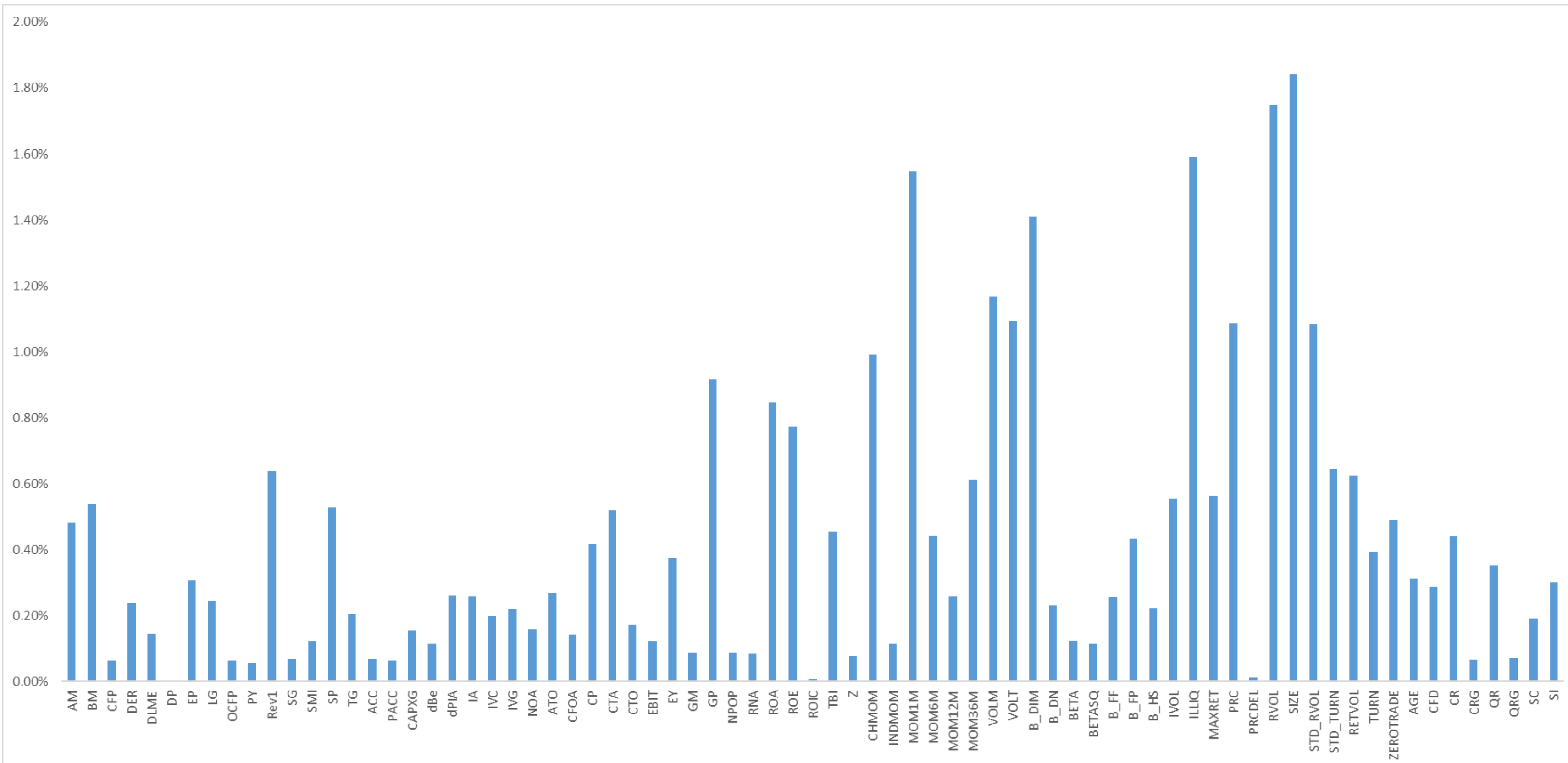

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Figure 2: Loadings on individual characteristics by PLS factor portfolios

Figure 2 reports time-series average loadings of each individual characteristics when calculating the PLS-based factor. The sample period is from 2000 to 2016.

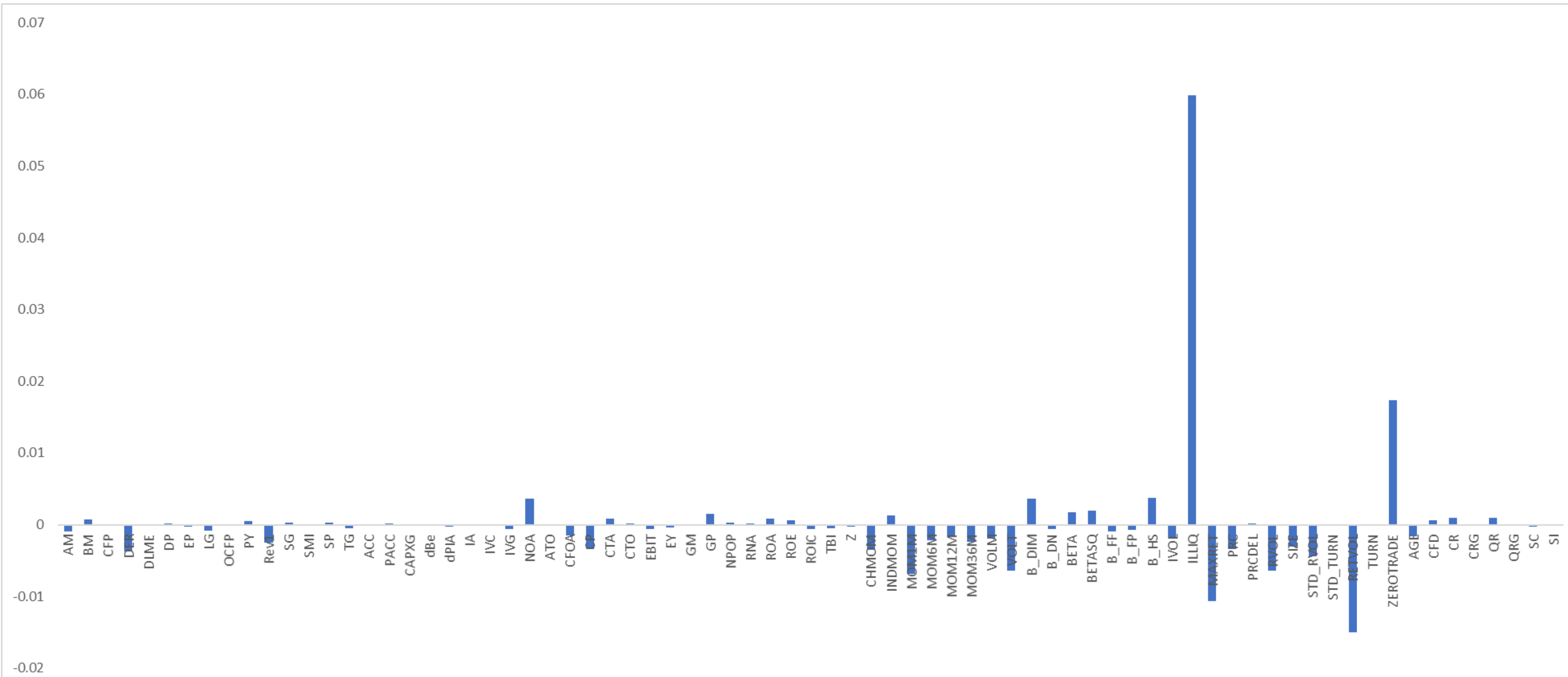

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Table 1: Performance of single sorts on individual characteristics

Table 1 reports monthly average raw returns (in percentage), abnormal returns (FF5 α, in percentage), and their *t*-statistics (in squared brackets) of long-short portfolios formed individually by the 75 firm characteristics. The spread portfolios are equal-weighted in Panel A and value-weighted in Panel B. All variables are named and defined in Appendix B. The sample is from July 2000 to December 2016.

Panel A: Equal-Weighted Portfolios

	AM	BM	CFP	DER	DLME	DP	EP	LG	OCFP	PY
Return	0.42 [1.40]	0.59 [2.49]	0.05 [0.22]	0.04 [0.12]	0.17 [0.58]	0.02 [0.15]	0.12 [0.38]	0.19 [1.43]	0.05 [0.22]	0.23 [1.70]
FF5-α	0.37 [2.15]	0.37 [2.74]	0.36 [2.41]	0.26 [1.03]	0.36 [1.79]	-0.02 [-0.20]	0.55 [3.25]	0.09 [0.76]	0.36 [2.41]	0.33 [2.60]
	Rev1	SG	SMI	SP	TG	ACC	PACC	CAPXG	dBe	dPIA
Return	0.79 [2.18]	0.18 [0.75]	-0.18 [-0.96]	0.29 [1.21]	0.10 [1.01]	-0.07 [-0.46]	0.14 [1.10]	-0.02 [-0.13]	0.20 [0.77]	0.26 [1.78]
FF5-α	0.14 [0.54]	-0.12 [-0.81]	-0.12 [-0.72]	0.35 [2.35]	0.19 [1.96]	0.07 [0.49]	0.11 [0.87]	-0.03 [-0.23]	-0.11 [-0.71]	0.09 [0.85]
	IA	IVC	IVG	NOA	ATO	CFOA	CP	CTA	CTO	EBIT
Return	0.30 [1.48]	0.25 [1.63]	0.16 [1.28]	0.10 [0.58]	0.11 [0.61]	0.01 [0.04]	0.40 [1.54]	0.53 [1.97]	0.04 [0.22]	0.69 [1.48]
FF5-α	0.06 [0.42]	0.03 [0.23]	0.07 [0.60]	0.00 [0.00]	0.29 [1.78]	-0.05 [-0.34]	0.22 [1.30]	0.44 [1.89]	0.23 [1.46]	-0.34 [-2.24]
	EY	GM	GP	NPOP	RNA	ROA	ROE	ROIC	TBI	Z
Return	0.00 [-0.01]	0.10 [0.39]	0.61 [1.70]	0.23 [1.93]	0.12 [1.15]	0.62 [1.60]	0.57 [1.49]	-0.24 [-1.05]	0.25 [1.89]	-0.34 [-0.94]
FF5-α	0.59 [3.50]	0.21 [1.06]	0.91 [3.50]	0.22 [1.84]	0.05 [0.49]	1.11 [4.57]	1.10 [4.66]	0.19 [1.44]	0.33 [2.68]	0.43 [3.09]
	CHMOM	INDMOM	MOM1M	MOM6M	MOM12M	MOM36M	VOLM	VOLT	B_DIM	B_DN
Return	1.03 [3.24]	0.09 [0.42]	2.07 [5.07]	0.51 [1.30]	0.39 [0.91]	0.70 [1.98]	1.22 [2.60]	2.13 [6.28]	1.38 [3.94]	-0.03 [-0.09]
FF5-α	1.13 [3.49]	0.19 [0.88]	1.72 [4.11]	0.65 [1.68]	0.27 [0.66]	0.33 [1.26]	1.31 [2.74]	2.37 [7.07]	1.04 [3.32]	0.31 [0.38]
	BETA	BETASQ	B_FF	B_FP	B_HS	IVOL	ILLIQ	MAXRET	PRC	PRCDEL
Return	0.46 [1.13]	0.45 [1.10]	-0.09 [-0.27]	0.32 [0.88]	0.06 [0.14]	0.57 [1.85]	2.31 [5.45]	0.86 [4.08]	1.07 [1.97]	-0.10 [-0.58]
FF5-α	-0.31 [-1.31]	-0.33 [-1.37]	0.32 [1.31]	0.65 [2.26]	0.41 [1.18]	0.42 [1.83]	1.40 [6.21]	0.92 [4.46]	0.61 [1.53]	-0.05 [-0.81]
	RVOL	RETVOL	SIZE	STD_RVOL	STD_TURN	TURN	ZEROTRADE	AGE	CFD	CR
Return	2.18 [5.38]	0.71 [1.87]	1.83 [3.53]	1.53 [8.59]	1.63 [6.05]	1.15 [4.27]	1.37 [4.86]	0.43 [1.78]	0.23 [0.67]	0.43 [1.53]
FF5-α	1.34 [5.00]	1.09 [3.37]	0.45 [2.23]	1.59 [8.72]	1.75 [6.99]	1.26 [5.14]	1.50 [5.73]	0.12 [0.58]	0.52 [2.05]	0.04 [0.19]
	CRG	QR	QRG	SC	SI					
Return	0.17 [1.46]	0.28 [0.99]	0.00 [-0.04]	0.16 [0.67]	0.21 [0.87]					

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FF5-α	0.07 [0.65]	-0.11 [-0.47]	0.08 [0.69]	-0.10 [-0.48]	0.09 [0.37]

Panel B: Value-Weighted Portfolios

	AM	BM	CFP	DER	DLME	DP	EP	LG	OCFP	PY
Return	0.48 [1.18]	0.54 [1.44]	0.06 [0.21]	0.24 [0.56]	0.14 [0.39]	0.00 [0.01]	0.31 [0.78]	0.24 [1.28]	0.06 [0.21]	0.06 [0.30]
FF5-α	0.45 [2.05]	0.45 [2.30]	0.34 [1.40]	0.30 [1.02]	0.10 [0.40]	0.00 [-0.01]	0.86 [5.31]	0.03 [0.16]	0.34 [1.40]	0.17 [1.04]
	Rev1	SG	SMI	SP	TG	ACC	PACC	CAPXG	dBe	dPIA
Return	0.64 [1.54]	0.07 [0.23]	0.12 [0.53]	0.53 [1.47]	0.21 [1.44]	0.07 [0.34]	0.06 [0.27]	0.15 [0.84]	0.11 [0.37]	0.26 [1.34]
FF5-α	-0.01 [-0.02]	-0.38 [-2.24]	0.12 [0.55]	0.65 [2.84]	0.27 [1.89]	0.19 [1.05]	-0.04 [-0.20]	-0.04 [-0.23]	-0.31 [-1.71]	-0.03 [-0.20]
	IA	IVC	IVG	NOA	ATO	CFOA	CP	CTA	CTO	EBIT
Return	0.26 [1.01]	0.20 [0.87]	0.22 [1.23]	0.16 [0.63]	0.27 [1.18]	0.14 [0.65]	0.42 [1.21]	0.52 [1.79]	0.17 [0.76]	0.12 [0.28]
FF5-α	-0.17 [-0.99]	-0.13 [-0.68]	0.07 [0.44]	0.18 [0.77]	0.47 [2.11]	0.05 [0.21]	0.38 [2.02]	0.44 [2.06]	0.39 [1.83]	-0.76 [-5.45]
	EY	GM	GP	NPOP	RNA	ROA	ROE	ROIC	TBI	Z
Return	0.37 [0.95]	0.09 [0.27]	0.92 [2.32]	0.09 [0.48]	0.08 [0.63]	0.85 [1.98]	0.77 [1.82]	0.01 [0.03]	0.45 [2.58]	0.08 [0.25]
FF5-α	1.03 [5.52]	0.31 [1.33]	1.30 [4.64]	-0.11 [-0.75]	0.00 [-0.01]	1.46 [5.95]	1.39 [5.72]	0.53 [3.26]	0.45 [2.57]	0.69 [4.43]
	CHMOM	INDMOM	MOM1M	MOM6M	MOM12M	MOM36M	VOLM	VOLT	B_DIM	B_DN
Return	0.99 [2.50]	0.11 [0.45]	1.55 [3.35]	0.44 [0.97]	0.26 [0.54]	0.61 [1.48]	1.17 [2.28]	1.09 [2.70]	1.41 [3.12]	0.23 [0.44]
FF5-α	1.02 [2.56]	0.18 [0.68]	1.12 [2.44]	0.54 [1.17]	0.16 [0.33]	0.20 [0.68]	1.23 [2.37]	1.37 [3.41]	0.92 [2.31]	0.57 [1.22]
	BETA	BETASQ	B_FF	B_FP	B_HS	IVOL	ILLIQ	MAXRET	PRC	PRCDEL
Return	0.12 [0.25]	0.11 [0.23]	0.26 [0.59]	0.43 [0.97]	0.22 [0.43]	0.55 [1.45]	1.59 [3.71]	0.56 [2.04]	1.09 [2.02]	0.01 [0.06]
FF5-α	-0.71 [-2.31]	-0.72 [-2.35]	0.73 [2.18]	0.87 [2.41]	0.66 [1.57]	0.35 [1.21]	0.74 [3.39]	0.63 [2.41]	0.47 [1.27]	0.04 [0.54]
	RVOL	RETVOL	SIZE	STD_RVOL	STD_TURN	TURN	ZEROTRADE	AGE	CFD	CR
Return	1.75 [4.02]	0.62 [1.46]	1.84 [3.39]	1.08 [4.22]	0.64 [2.21]	0.39 [1.34]	0.49 [1.67]	0.31 [1.30]	0.29 [0.73]	0.44 [1.30]
FF5-α	0.89 [3.43]	0.92 [2.51]	0.39 [2.12]	1.20 [4.61]	1.01 [3.75]	0.80 [3.06]	0.87 [3.16]	0.23 [1.08]	0.69 [2.84]	0.02 [0.06]
	CRG	QR	QRG	SC	SI					
Return	0.07 [0.39]	0.35 [1.03]	0.07 [0.45]	0.19 [0.66]	0.30 [0.90]					
FF5-α	0.01 [0.07]	-0.11 [-0.42]	0.14 [0.87]	-0.19 [-0.86]	0.20 [0.58]					

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Table 2: Performance of FM factor portfolios

Table 2 shows time series averages (raw returns, Sharpe ratios, CAPM α, FF3 α, FF5 α) and *t*-statistics of monthly equal-weighted (EW) and value-weighted (VW) stock returns on decile portfolios formed by FM estimates expected returns. The columns (10-1) report the statistics for the difference in returns on the top and bottom portfolios. The expected returns are estimated using fitted value of regressions, and the panels correspond to different time series averaging schemes for the slopes of the Fama-MacBeth regression. The sample is from July 2001 to December 2016 for Panel A. For Panel B and C, the sample is from July 2003 to December 2016. The portfolios are rebalanced monthly. All returns and alphas are reported in percentage points.

Panel A: Averaging of slopes over past 12 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	0.83	2.10	1.27	0.95	1.29	1.37	1.10	0.56	1.57	1.01	0.66	1.06	1.22	0.91
t-stats	1.08	2.75	3.75		3.79	3.91	3.26	0.78	2.26	2.61		2.76	3.10	2.37

Panel B: Averaging of slopes over past 24 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.39	2.44	1.05	0.81	1.08	1.32	1.08	1.08	1.60	0.52	0.34	0.59	0.96	0.65
t-stats	1.62	2.88	2.96		3.04	3.72	3.19	1.35	2.05	1.26		1.42	2.32	1.64

Panel C: Averaging of slopes over past 36 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.39	2.31	0.92	0.73	0.95	1.25	1.07	1.04	1.43	0.39	0.26	0.45	0.82	0.67
t-stats	1.62	2.72	2.67		2.72	3.77	3.33	1.29	1.83	0.97		1.12	2.13	1.77

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Table 3: Performance of PCA factor portfolios

Table 3 shows time series averages (raw returns, Sharpe ratios, CAPM α, FF3 α, FF5 α) and *t*-statistics of monthly equal-weighted (EW) and value-weighted (VW) stock returns on decile portfolios formed by PCA estimates expected returns. The columns (10-1) report the statistics for the difference in returns on the top and bottom portfolios. The expected returns are estimated using principal component analysis, and the panels correspond to different time series averaging schemes for the slopes of the first principal component. The sample is from July 2001 to December 2016 for Panel A. For Panel B and C, the sample is from July 2003 to December 2016. The portfolios are rebalanced monthly. All returns and alphas are reported in percentage points.

Panel A: Averaging of slopes over past 12 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.55	1.55	0.00	0.00	0.14	1.00	0.49	1.08	1.07	-0.02	0.00	0.13	1.09	0.56
t-stats	1.82	2.24	-0.01		0.27	2.05	1.01	1.32	1.58	-0.03		0.22	2.08	1.06

Panel B: Averaging of slopes over past 24 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.98	1.98	0.01	0.00	0.14	1.05	0.29	1.35	1.39	0.04	0.02	0.17	1.19	0.46
t-stats	2.17	2.41	0.01		0.23	2.02	0.58	1.53	1.78	0.07		0.27	2.14	0.85

Panel C: Averaging of slopes over past 36 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.97	2.10	0.13	0.06	0.28	1.24	0.44	1.34	1.37	0.03	0.01	0.17	1.28	0.51
t-stats	2.14	2.56	0.22		0.46	2.45	0.92	1.51	1.77	0.05		0.27	2.42	1.01

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Table 4: Performance of PLS factor portfolios

Table 4 shows time series averages and *t*-statistics of monthly equal-weighted (EW) and value-weighted (VW) stock returns on decile portfolios formed by sorting firms on PLS based factor model. The time series averages include raw returns, Sharpe ratios (SR), CAPM α, FF3 α, FF5 α, and market adjusted returns (L-SMKT). The PLS factor is constructed with different averaging of β^a over the most recent 12 months (in Panel A), 24 months (in Panel B), and 36 months (in Panel C). The sample is from July 2001 to December 2016 for Panel A, and F from July 2003 to December 2016 for Panel B and C. The portfolios are rebalanced monthly. All returns and alphas are reported in percentage points.

Panel C: Averaging of β^a over past 12 months

	EW portfolios								VW portfolios							
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	L-SMKT	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	L-SMKT
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	0.36	2.96	2.60	1.52	2.62	2.33	2.12	1.42	0.17	2.12	1.95	1.03	1.98	1.68	1.44	1.28
t-stats	0.47	3.76	5.98		6.00	5.26	4.79	4.31	0.23	2.86	4.07		4.13	3.45	2.97	3.03

Panel E: Averaging of β^a over past 24 months

	EW portfolios								VW portfolios							
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	L-SMKT	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	L-SMKT
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	0.89	3.70	2.82	1.48	2.88	2.64	2.40	1.51	0.86	2.65	1.79	0.81	1.82	1.50	1.19	1.27
t-stats	1.02	4.09	5.43		5.51	5.09	4.62	3.93	1.06	3.04	2.97		3.01	2.53	2.02	2.33

Panel F: Averaging of β^a over past 36 months

	EW portfolios								VW portfolios							
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	L-SMKT	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	L-SMKT
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	0.70	3.61	2.91	1.66	2.96	3.07	2.72	1.41	0.92	2.58	1.66	0.81	1.71	1.82	1.41	1.12
t-stats	0.81	4.09	6.10		6.17	6.91	6.13	3.90	1.12	3.02	2.96		3.02	3.50	2.71	2.21

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Table 5: Performance of FC factor portfolios

Table 5 shows time series averages (raw returns, Sharpe ratios, CAPM α, FF3 α, FF5 α) and *t*-statistics of monthly equal-weighted (EW) and value-weighted (VW) stock returns on decile portfolios formed by FC estimates expected returns. The columns (10-1) report the statistics for the difference in returns on the top and bottom portfolios. The expected returns are estimated using equal-weighted fitted value of regressions, and the panels correspond to different time series averaging schemes for the slopes of OLS regressions. The sample is from July 2001 to December 2016 for Panel A. For Panel B and C, the sample is from July 2003 to December 2016. The portfolios are rebalanced monthly. All returns and alphas are reported in percentage points.

Panel A: Averaging of slopes over past 12 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	0.96	2.04	1.08	0.64	1.09	1.06	0.87	0.73	1.47	0.74	0.41	0.76	0.72	0.55
t-stats	1.24	2.70	2.53		2.56	2.41	1.99	1.01	2.07	1.60		1.65	1.52	1.15

Panel B: Averaging of slopes over past 24 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.62	2.25	0.64	0.39	0.71	0.78	0.57	1.13	1.34	0.21	0.11	0.28	0.35	0.11
t-stats	1.85	2.67	1.42		1.59	1.69	1.24	1.41	1.71	0.41		0.55	0.67	0.21

Panel C: Averaging of slopes over past 36 months

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.55	2.07	0.52	0.34	0.63	1.06	0.75	1.15	1.31	0.15	0.08	0.26	0.72	0.35
t-stats	1.74	2.53	1.24		1.52	2.71	1.96	1.39	1.71	0.30		0.53	1.53	0.76

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Table 6: Performance of PLS factor portfolios formed by different factor categories

Table 6 shows time series averages (raw returns, Sharpe ratios, CAPM α, FF3 α, FF5 α) and t-statistics of monthly equal-weighted (EW) and value-weighted (VW) stock returns on decile portfolios formed by sorting firms on PLS based factor model. We construct PLS factor portfolios based on six factor categories (value-versus-growth, investment, profitability, momentum, trading frictions, intangibles). The factor is constructed with time series averaging of β^{α} over the past 12 months. The sample is from July 2001 to December 2016. The portfolios are rebalanced monthly. All returns and alphas are reported in percentage points.

Panel A: Value-versus-growth														
	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.22	1.56	0.34	0.33	0.31	0.07	0.07	0.71	1.07	0.36	0.29	0.33	-0.03	0.07
t-stats	1.67	2.05	1.31		1.19	0.32	0.29	1.05	1.48	1.13		1.01	-0.12	0.26
Panel B: Investment														
	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.42	1.61	0.19	0.29	0.17	0.20	0.06	0.98	0.99	0.01	0.01	0.00	0.04	-0.13
t-stats	1.87	2.06	1.16		1.04	1.24	0.39	1.41	1.38	0.06		0.01	0.17	-0.58
Panel C: Profitability														
	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.04	2.05	1.02	0.67	1.04	1.32	0.96	0.47	1.41	0.94	0.58	0.96	1.25	0.93
t-stats	1.34	2.72	2.64		2.68	3.38	2.49	0.67	2.01	2.29		2.32	3.02	2.23
Panel D: Momentum														

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	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	0.44	1.90	1.46	1.10	1.48	1.57	1.38	0.15	1.24	1.10	0.67	1.11	1.23	1.06
t-stats	0.57	2.43	4.33		4.36	4.66	4.11	0.20	1.66	2.65		2.66	2.95	2.55

Panel E: Trading Frictions

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	0.67	2.91	2.24	1.39	2.27	2.00	1.90	0.30	2.17	1.86	1.07	1.92	1.77	1.52
t-stats	0.84	3.67	5.47		5.53	4.80	4.51	0.40	3.00	4.23		4.37	3.95	3.38

Panel F: Intangibles

	EW portfolios							VW portfolios						
	Raw Returns			SR	CAPM-α	FF3-α	FF5-α	Raw Returns			SR	CAPM-α	FF3-α	FF5-α
	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)	1	10	(10-1)	(10-1)	(10-1)	(10-1)	(10-1)
Means	1.31	1.94	0.63	0.46	0.60	0.42	0.12	0.82	1.37	0.54	0.38	0.52	0.24	-0.02
t-stats	1.80	2.40	1.83		1.74	1.24	0.36	1.23	1.84	1.50		1.43	0.67	-0.05

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