# Timing the factor zoo *

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**Abstract**

We provide a comprehensive analysis of the timing success for equity risk factors. Our analysis covers over 300 risk factors (factor zoo) and a high dimensional set of predictors. The performance of almost all groups of factors can be improved through timing, with improvements being highest for profitability and value factors. Past factor returns and volatility stand out as the most successful individual predictors of factor returns. However, both are dominated by aggregating many predictors using partial least squares. The median improvement of a timed vs. untimed factor is about 2% p.a. A timed multifactor portfolio leads to a 20% increase in return relative to its untimed counterpart.

**Keywords:** time-varying risk premia, factor investing, partial least squares
**JEL codes:** G10, G12, G14

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# 1 Introduction

Empirical asset pricing research has identified a staggering quantity of priced risk factors. While it may be challenging to rationalize all these factors as independent sources of systematic risk, it is clear that one needs a multifactor model to explain the cross-section of asset returns. In light of the empirical asset pricing literature, it is also uncontroversial that risk premia vary conditionally over time. At the market level, for example, Fama and French (1988) find that returns are predictable by the dividend-price ratio. This opens the arena for market timing, but, in a multifactor world, the more general question concerns the timing of all sources of systematic risk – factor timing. Given the plethora of factors, it is no surprise that a large number of time series predictors for their returns has also been suggested in the literature. The combination of the large numbers of factors and predictors amplifies the empirical challenge in giving an answer to the question - *should investors engage in factor timing?* We carry out a comprehensive analysis using over 300 factors and 39 signals and find that factor timing is indeed possible and profitable. We thereby resolve conflicting findings in the academic literature that result from choosing a smaller subset of factors and/or predictors.

We first establish a benchmark and study the benefits from factor timing in a univariate fashion, i.e. we forecast each factor using each of the 39 signals and then aggregate over the signal class. The analysis reveals that versions of momentum and volatility signals are able to provide improvements on a broad basis. Other signal classes (valuation spreads, characteristic spreads, reversal and issuer-purchaser spread) provide improvements, but the results vary more strongly depending on whether we study improvements in raw returns, alphas or Sharpe ratios. Next, we aim to improve the univariate analysis by aggregating the signals. Many of the predictive signals are highly correlated as they aim to capture the same phenomenon, such as versions of momentum. Since conventional ordinary least squares regression is known to perform rather poorly in such settings, we resort to dimension-reduction techniques to obtain a low dimensional representation of the predictive information. We use partial least squares regression, which provides a data-driven method to aggregate the signals for each factor. However, our setup allows for heterogeneous dynamics across factors. Partial least squares leads to improvements in statistical and economic terms. For the median factor, we achieve an out-of-sample $R^2$ of approximately 0.75% and an improvement of annual returns of 2 percentage points. We correctly forecast the sign of a factor return approximately 56% of the time and most notably the improvements relative to passive buy-and-hold are not confined to a small part of the sample, but accrue almost equally over the full sample.

We also study the benefits of factor timing for multifactor portfolios. We build quintile portfolios of factors, i.e. we go long the factors for which we forecast the highest returns and short the factors for which we forecast the lowest returns. The resulting "high-low" portfolio achieves an annualized Sharpe ratio of 1.3.

This is a significant improvement over merely sorting factors on their historical mean returns, which leads to an annual Sharpe ratio of 0.79.

While previous research on factor timing has taken the factors as given, we look under the hood and study the portfolio composition of optimal factor timing portfolios. This bottom-up approach allows us to answer important questions about the properties of timing portfolios such as turnover as well as their style tilts. This approach also allows us to focus on large stocks. We find that timing portfolios that focus on large stocks exhibit moderate levels of turnover and could likely be implemented in practice. The large-cap timing portfolios achieve an annual average return of approximately 17%, whereas the CRSP value weighted index only averages 12% p.a. over the same period. Nonetheless, the optimal large-cap timing portfolio still contains almost 200 stocks on average, thereby providing sufficient diversification of idiosyncratic risk.

The early literature on factor timing is largely concerned with the market index. While the overall literature on market timing is too large to be summarized here, we refer to the important early contributions of Shiller (1981) and Fama and French (1988). Their early work has been extended to other style factors, such as value by Asness, Friedman, Krail, and Liew (2000) and Cohen, Polk, and Vuolteenaho (2003), who show that the expected return on a value-minus-growth strategy is atypically high at times when its spread in the book-to-market ratio is wide. More recently, Yara, Boons, and Tamoni (2021), show returns for value strategies in individual equities, commodities, currencies, global bonds and stock indexes are predictable by the value spread between stocks ranked in the top percentiles versus those in the bottom.

An important methodological innovation is due to Kelly and Pruitt (2013), who link disaggregated valuation ratios and aggregate market expectations to document high out-of-sample return predictability for value, size, momentum and industry portfolios. Their finding is particularly useful for our setting as we also need to aggregate many predictors to forecast individual time series. Other approaches to aggregate signals are proposed in Leippold and Rueegg (2019), who use momentum in the weights of an integrated scoring approach to form long-only portfolios that outperform. Dichtl, Drobetz, Lohre, Rother, and Vosskamp (2019) use cross-sectional information about factor characteristics to tilt factors and show that the model loads positively on factors with short-term momentum, but avoids factors that exhibit crowding.

Factor volatility as a potential timing signal deserves special mention as it is subject to considerable controversy. DeMiguel, Martın-Utrera, and Uppal (2021) show that a conditional mean-variance multifactor portfolio whose weights on each factor vary with market volatility outperforms out-of-sample. They use the time-varying parametric portfolio framework of Brandt, Santa-Clara, and Valkanov (2009). Their paper is most closely related to existing work on volatility-managed portfolios. Moreira and Muir (2017) show that past factor volatility, estimated from past daily returns, is a useful conditioning variable to choose time-varying exposure to individual factors, in particular the market factor. Cederburg, O'Doherty, Wang, and

Yan (2020) find that the performance benefits of volatility management no longer obtain once more realistic assumptions are made regarding portfolio implementation, such as trading costs. They conclude that, once such frictions are considered, volatility-managed portfolios exhibit lower certainty equivalent returns and Sharpe ratios than do simple investments in the original, unmanaged portfolios. Barroso and Detzel (2021) consider volatility-managed factor portfolios, applying various cost-mitigation strategies. They find that even in this case, realistic estimates of transactions costs render volatility management unprofitable for all factors, except for the market. Reschenhofer and Zechner (2022) show that portfolio performance can be improved significantly when jointly using volatilities of past factor returns and option-implied market volatilities to determine factor exposures. This multi-variate volatility-based factor timing leads to larger improvements when option-implied market returns are right-skewed and exhibit high volatility.

Various implementations of factor momentum have also received considerable attention in the literature. Ehsani and Linnainmaa (2022) show that factor momentum is a likely underlying driver of different forms of classic cross-sectional momentum. Arnott, Clements, Kalesnik, and Linnainmaa (2021) show that factor momentum is also the source of industry momentum. Gupta and Kelly (2019) also provide evidence of factor momentum in many popular asset pricing factors. In contrast, Leippold and Yang (2021) argue that factor momentum can largely be attributed to high unconditional rather than conditional returns.

Haddad, Kozak, and Santosh (2020) extract principal components from 50 popular anomaly portfolios and use the book-to-market ratio to predict future factor returns. They find out-of-sample $R^2$ in the order of 4% on a monthly basis. They also discuss broader asset pricing implications of their findings. In particular, they document that a stochastic discount factor that takes into account timing information is more volatile and has different time series behavior compared to static alternatives, thereby posing new challenges for theories that aim to explain the cross-section of expected returns. Kelly, Malamud, and Pedersen (2021) allow for cross-predictability; they use signals of all securities to predict each security's individual return. They apply a singular value decomposition to summarize the joint dynamics of signals and returns into "principal portfolios". Using a large sample of equity factors and trading signals, they find factor timing strategies based on principal portfolios to perform well overall and across the majority of signals, outperforming the approach of Haddad et al. (2020).

Asness (2016) finds timing strategies that are simply based on the "value" of factors to be very weak historically. Asness, Chandra, Ilmanen, and Israel (2017) look at the general efficacy of value spreads in predicting future factor returns. At first, timing based on valuation ratios seems promising, yet when the authors implement value timing in a multi-style framework that already includes value, they find somewhat disappointing results. They conclude that value timing of factors is too correlated with the value factor itself. Adding further value exposure this way is dominated by an explicit risk-targeted allocation to the value factor. Lee (2017) suggests investors are better off focusing on the underlying rationale of risk premia rather than attempting to time factors. Ilmanen, Israel, Moskowitz, Thapar, and Lee (2021) examine four prominent factors across six asset classes over a century. They find only modest predictability, which could only be exploited in a profitable way for factor timing strategies if trading costs are minimal.

# 2 Data

## 2.1 Factors

Cross-sectional asset pricing has taken a long journey from single-factor models (e.g., Sharpe, 1964) via parsimonious multi-factor models (e.g., Fama and French, 1992) towards a heavily criticized factor zoo (e.g., Cochrane, 2011; Harvey, Liu, and Zhu, 2016). For many factors, their validity in the sense of out-of-sample evidence on the one hand and mere replication on the other hand has come under scrutiny. Chen and Zimmermann (2022) give a positive assessment of preceding academic work. In a massive and open source code replication effort, they reproduce 318 firm-level characteristics. They confirm the original papers' evidence for all but three characteristics and confirm previous findings of performance decaying, but often staying positive out-of-sample.[1] To analyze factor timing, we clearly need a clean data set of portfolios that ideally are associated with positive unconditional risk premia, but time variation in returns. Thus, our starting point is the factor portfolios obtained through applying the methodology of Chen and Zimmermann (2022).

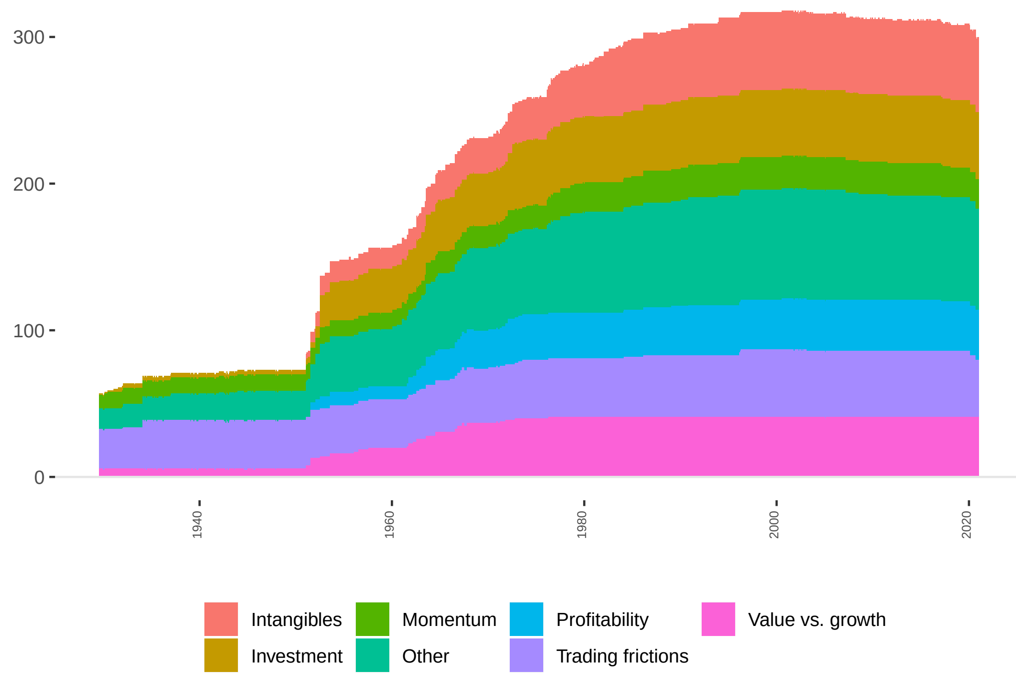
To sort stocks into portfolios, we construct firm characteristics based on data obtained from CRSP, Compustat, IBES, and FRED. Multiple characteristics require specific data to reconstruct the results of the original studies, and are readily available on the authors websites. For each characteristic, we follow Chen and Zimmermann (2022) and replicate portfolios defined in the original paper that introduced the anomaly in the literature. We group similar factors based on their economic interpretation. For factors included in Hou, Xue, and Zhang (2020), we follow their classification. For the remaining factors, we group them into the categories intangibles, investment, momentum, profitability, trading frictions, value vs. growth, and other. Our sample covers the time period from 1926 to 2020. Data availability translates into different starting points for the various characteristics. In general, price-based characteristics have the longest history, with accounting data and analyst forecasts becoming available later in time. Figure 1 plots the number of factors per category over time. Table A.1 provides detailed information on the characteristics, the original studies, and classification into economic categories. Table A.2 provides descriptive statistics of factor category and

[1] Their positive assessment is reinforced by the findings of another open-source project, Jensen, Kelly, and Pedersen (2021).

individual factor returns.

Figure 1: Number of factors per category

This figure shows the number of factors over time. We group factor portfolios into six economic categories based on the firm characteristics used to construct them: Intangibles, Investment, Momentum, Profitability, Trading frictions, Value vs. growth, and Other. Table A.1 provides a description of each individual factor and the assigned factor category.




## 2.2 Timing signals

We use a broad set of timing signals that have been proposed in the literature and group them into six classes: momentum, volatility, valuation spread, characteristics spread, issuer-purchaser spread, and reversal. We here provide a broad overview of the different signals; full details are given in Appendix B.

**Momentum:** Momentum signals are based on the observation that past factor returns over fairly recent periods positively predict future returns. While the classic definition for momentum is cross-sectional and thus less suited for factor timing, we use variations of time series momentum to construct signals. The simplest variants of momentum-based timing signals rely on the sign of prior returns. Thus, we derive momentum signals that assign a weight of $w_{i,t} = \pm 1$, conditional on the sign of the past factor return over an $n$-months horizon. We use look-back periods $n$ equal to 1, 3, 6, and 12 months. Ehsani and Linnainmaa (2022) measure the profitability of factor momentum by taking long and short positions in factors based on prior returns. In further variants of timing signals, we follow Gupta and Kelly (2019), and obtain the weights $w_{i,t}$ of the timed factor portfolios as factor $i$ $n$-months past return, scaled by $m$-months past return volatility. Different values for $n$ and $m$ result in different timing signals. Ehsani and Linnainmaa (2022) measure the profitability of factor momentum by taking long and short positions in factors based on prior returns. Thus, we derive momentum signals that assign a weight of $w_{i,t} = \pm 1$, conditional on the sign of the past factor return over an $n$-months horizon. Finally, we follow Moskowitz, Ooi, and Pedersen (2012) and scale positions such that the timed factor has an ex ante volatility of 40%. In total, we use 16 momentum signals.

**Volatility:** Moreira and Muir (2017) show that realized volatility predicts future volatility but not returns. Investment strategies that condition factor exposure on recent realized volatility tend to outperform. Mirroring the measures analyzed in their paper, we use the realized standard deviation and the variance of daily factor returns over the preceding month to construct timing signals. In a variant, we obtain the variance predictor from an AR(1) process fitted to log variance. Following Cederburg et al. (2020), we estimate a variant that deals with variation in the number of trading days in a month by scaling realized variance with the fraction of the number of trading days in a month and 22. An additional volatility signal is obtained from volatility of market returns instead of factor returns (DeMiguel et al., 2021). Finally, we follow Reschenhofer and Zechner (2022), who find improved predictability when complementing moments estimated from historical data with option-implied information. We thus use the CBOE VIX index and the CBOE SKEW index for signal construction. The different methods result in a total of seven volatility signals.

**Valuation spread:** Stock market valuation ratios are a traditional predictor of aggregate returns, (see, e.g., Campbell and Shiller, 1988). Prices scaled by fundamental variables such as dividends, earnings, or book values contain information about expected returns of the market. If the aggregate valuation level predicts aggregate returns, it seems plausible that the relative valuation of value versus growth stocks should predict their relative returns. Cohen et al. (2003) provide confirming empirical evidence. The value spread – the book-to-market ratio of value stocks minus that of growth stocks – predicts the HML factor return. Similarly, Haddad et al. (2020) use a portfolio's net book-to-market ratio (defined as the difference between the log book-to-market ratio of the long and the short legs) to predict its return. We define value signals similarly, standardizing a factor portfolio's value spread using the rolling and expanding means, respectively. Variants for the value spread differ with respect to the timing of the signals, with variants (i) end of year book and market values, (ii) end of year book value and most recent market value, and (iii) quarterly book and market values. In total, we derive six versions of valuation signals.

**Characteristics spread:** The unconditional factor portfolios result from sorting individual stocks on a specific characteristic. As noted by Huang, Liu, Ma, and Osiol (2010), it is thus intuitive that the spread in the characteristic between the top and the bottom deciles proxies for future return dispersion. To construct the factor-specific characteristic spread, we calculate the difference in the characteristic of the long minus the short leg, and scale the demeaned spread by its standard deviation. We obtain two signal variants, from using a rolling or an expanding mean.

**Reversal:** Moskowitz et al. (2012) document time series momentum at horizons up to 12 months and reversal for longer horizons. We first compute 60 (120) months past returns and obtain two version of reversal signals: The 60 (120) month reversal signal translates into a weight equal to 1 minus the annualized 60 (120) month return.

**Issuer-purchaser spread:** External financing activities such as equity issuance net of repurchases and debt issuance are negatively related to future stock returns (Bradshaw, Richardson, and Sloan, 2006; Pontiff and Woodgate, 2008). Greenwood and Hanson (2012) find that determining which types of firms issue stocks in a given year helps forecasting returns of factor portfolios. In particular, the differences between firms who recently issued vs. repurchased shares predict returns to long–short factor portfolios associated with those characteristics. We construct issuer-purchaser spreads based on three variants for the determination of net issuance: the difference between sales and repurchase of common stock, the change in split-adjusted shares outstanding, and the change in split-adjusted common shares outstanding. The time series are demeaned using rolling or expanding means, and scaled by standard deviation, resulting in 6 signals.

# 3 Empirical analysis

## 3.1 Univariate factor timing

For univariate factor timing, we construct timed factors as versions of the original factor portfolios, using one specific timing signal to scale the returns. More precisely, we obtain

$$f^{\tau_j}_{i,t+1} = w^j_{i,t} f_{i,t+1} \,, \tag{1}$$

where $f^{\tau_j}_{i,t+1}$ is the excess return of the timed factor $i$ from time $t$ to $t+1$, $f_{i,t+1}$ is the excess return of the original factor portfolio, and $w^j_{i,t}$ is the timing weight constructed from signal $j$.[2] We time each one of the

[2]For example, when the signal is a proxy for the portfolio's conditional variance as defined in Moreira and Muir (2017),

$i \in \{1, \ldots, 318\}$ factors at monthly frequency, using $j \in \{1, \ldots, 39\}$ signals, resulting in 12,402 timed factor portfolios.

#### 3.1.1 Timing performance for different types of signals

To evaluate the success of factor timing, we look at the difference in returns, Sharpe ratios and time-series alphas of the timed factor against its untimed version. We denote the timed version of the $i$-th factor (using signal $j$) as $f_i^{\tau_j}$. Our measures of success are then computed as:

$$\Delta \bar{R}_{i,j} = \frac{1}{T} \sum_{t=1}^{T} (f_{i,t+1}^{\tau_j} - f_{i,t+1}) \,. \tag{3}$$

To incorporate risk-adjustment, we also look at the difference in Sharpe ratios, i.e.

$$\Delta SR_{i,j} = SR(f_i^{\tau_j}) - SR(f_i) \,. \tag{4}$$

Some of our timing strategies also make use of leverage, but note that the Sharpe ratios increase proportionally and do not falsely indicate success in such cases.[3] We show the results for differences in returns and Sharpe ratios in Figure 2.

Figure 2 displays the net fraction of significant performance differences, obtained as the fraction of factors with significant positive performance differences between the timed and the untimed portfolios minus the fraction of factors with significant negative performance differences. Panel (a) displays the measure for average returns. We find that timing signals based on momentum lead to the largest improvements. There are some exceptions, such as the signals based on Ehsani and Linnainmaa (2022), which by construction lead to a low average exposure to the original factor. Panel (b) shows that for most signals factor timing on average decreases Sharpe ratios. Only volatility signals are able to improve Sharpe ratios. The top signals are based on the standard deviation of the previous month's daily returns (Moreira and Muir, 2017) and on S&P 500 implied volatility (Reschenhofer and Zechner, 2022). Time series momentum with 12 months lookback period (Moskowitz et al., 2012) also delivers strong performance. All other signals have weaker results.

Another popular measure to assess the performance of timed factors is time-series alpha (see, e.g., Gupta and Kelly, 2019). We estimate the alpha of a timed vs. an untimed factor as:

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$$w_{i,t}^j = \frac{c}{\hat{\sigma}_t^2(f_i)} \,, \tag{2}$$

where $\hat{\sigma}_t^2(f_i)$ is the previous month's realized variance of daily returns, and $c$ a constant that controls the average exposure of the strategy.

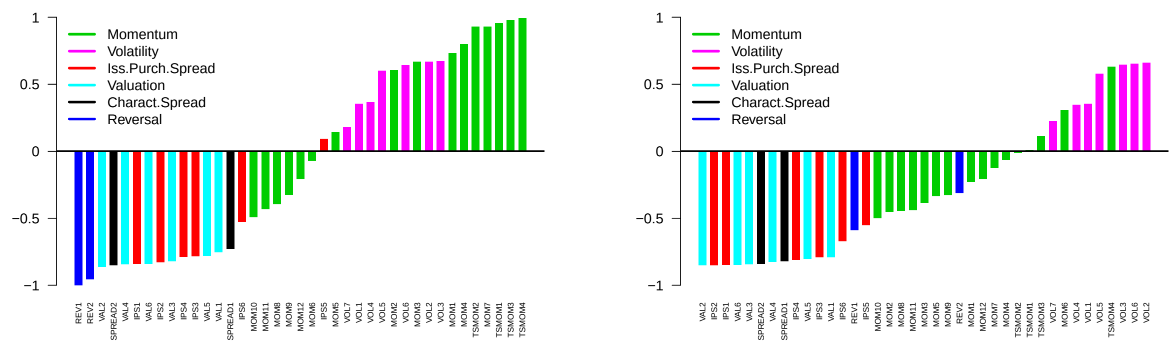
[3] Statistical significance can easily be assessed using the test of Jobson and Korkie (1981) of testing the null that $\Delta SR_{i,j} = 0$.

Figure 2: Net fraction of positive and negative performance differences

This figure shows for each timing signal the fraction of factor portfolios with significant positive performance difference between the timed and untimed factors minus the corresponding fraction of significant negative performance differences. Colors indicate the timing category. Table B.1 provides a description of the individual timing signals and the assigned signal class. Figure (a) displays the net fraction for mean returns, Figure (b) for Sharpe ratios. We determine statistical significance at the 5 percent level. For Sharpe ratios, we use the $z$-statistic from the Jobson and Korkie (1981) test of the null that $SR(f_i^\tau - f_i) = 0$.

(a) Differences in mean return

(b) Differences in Sharpe ratio




$$f_{i,t+1}^{\tau_j} = \alpha_{i,j} + \beta_{i,j} f_{i,t+1} + \epsilon_{t+1} \,. \tag{5}$$

The magnitude of the alpha has to be interpreted with caution, as it may be due to leverage taken by a managed strategy. The statistical significance is not influenced by leverage and implies that the managed strategy expands the efficient frontier. Figure 3 gives a first overview of the univariate timing results.

Figure 3: Fraction of positive and negative alphas

This figure shows the fraction of factor portfolios with positive and negative alphas, respectively, for each timing signal. Colors indicate the signal class. For each factor $i$ and signal $j$ we obtain the alpha $\alpha_{i,j}$ from an OLS regression of timed factor portfolios' excess returns on unmanaged factor portfolio's excess returns: $f_{i,t+1}^{\tau j} = \alpha_{i,j} + \beta_{i,j} f_{i,t+1} + \epsilon_{t+1}$. The dark shaded areas of the bars present the fraction of $\alpha_{i,j}$ significant at the 5 percent level, using $t$-statistics adjusted for heteroscedasticity. Table B.1 provides a description of the individual timing signals and the assigned signal class.

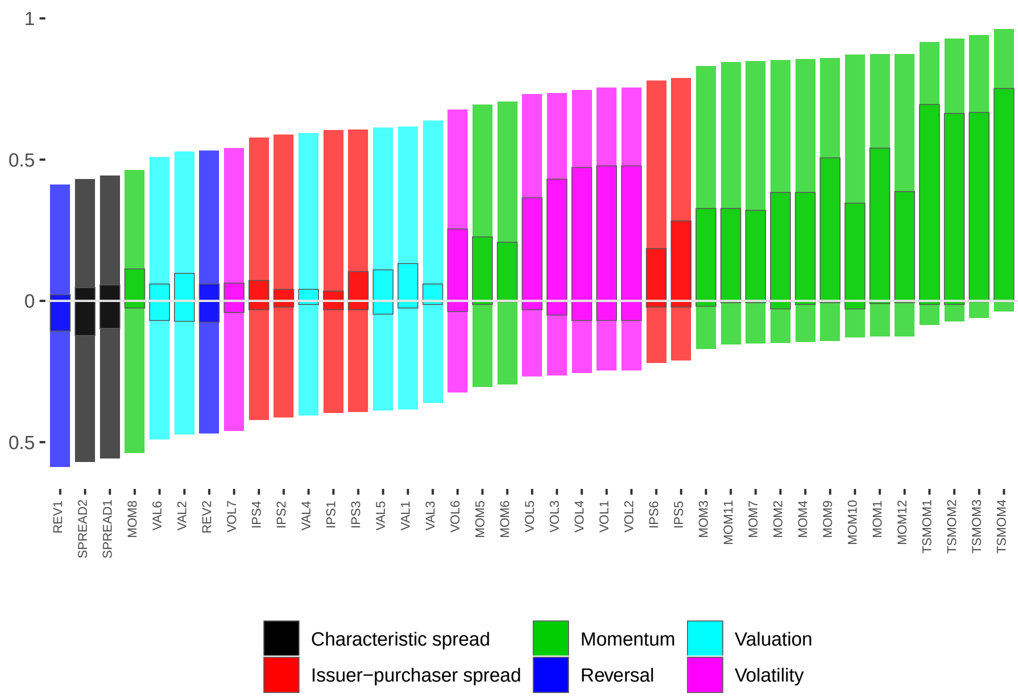



Figure 3 plots the fraction of factor portfolios with positive and negative alphas, respectively, for each timing signal. Each bar has a length of 1; the vertical position of the bar shows the fraction of positive and negative alphas. Areas with dark borders within a bar present the fraction of timed factors with statistically significant $\alpha$. We use a 5 percent significance level, with $t$-statistics adjusted for heteroscedasticity. The signals are ranked according to the fraction of positive alphas. Momentum signals achieve the highest fraction of positive $\alpha$s. More importantly, positive alphas tend to be statistically significant, while there is almost no statistical significance for negative alphas. The single best momentum signal is time series momentum with 12 months lookback period, as defined in Moskowitz et al. (2012). Volatility timing signals achieve performance improvements in the same ballpark as momentum, with high percentages of statistically significant positive alphas. The top signal in this group is the standard deviation of the previous month's daily returns, as described in Moreira and Muir (2017). Timing signals based on valuation, reversal, characteristics spreads and issuer-purchaser spread are less successful.

### 3.1.2 Timing performance for different categories of factors

In the previous analysis, we aggregated the performance across all 318 factors for different timing signals. While some level of aggregation is clearly necessary for tractability, it may mask important heterogeneity in timing success across factors. Factors that capture different sources of risk can potentially be timed with different signals. We therefore use the economic interpretation of factors to group them into seven categories: intangibles, investment, momentum, profitability, trading frictions, value vs. growth, and other.[4] We compile the results for categories of factors in Table 1. The columns show results for all signals, momentum signals, and volatility signals.[5] Panel A displays average $\alpha$s of time-series regressions. We report simple averages over all factors within an economic category and for signals of a given type. Average $t$-statistics in brackets are based on heteroscedasticity-adjusted standard errors.

[4] See Table A.1 for further details.

[5] We relegate details for signals based on the the characteristic spread, issuer-purchaser spread, reversal and valuation to appendix Table C.1.

Table 1: Performance impact of factor timing with single signals

This table shows timing success of different signals for individual factors, grouped into economic categories. The columns to the left, middle, and right show results for all signals, momentum signals, and volatility signals, respectively. Panel A displays the annualized average alphas of time-series regressions of a managed factor portfolio on the corresponding unconditional factor portfolio: $f^{\tau_j}_{i,t+1} = \alpha_{i,j} + \beta_{i,j} f_{i,t+1} + \epsilon_{t+1}$. We report simple averages over all factors $f_i$ within an economic category and all signals $\tau_j$ of a given type. We report average $t$-statistics in brackets, where statistical significance is based on heteroscedasticity-adjusted standard errors. $\Delta SR$ shows the average difference in the annualized Sharpe ratio of the timed versus original factor across factor/signal combinations. In brackets, we show the average $z$-statistic from the Jobson and Korkie (1981) test of the null that $\Delta$SR = 0. Panel B reports the percentage of positive (+) and negative (−) alphas. Numbers in brackets are the percentages of positive and negative alphas, respectively, that are statistically significant at the 5% level. Panel C reports the percentage of timed factor/signal combinations with a higher (+) and lower (−) Sharpe ratio; fractions with statistically significant changes in Sharpe ratios are given in brackets. Table C.1 shows results for the remaining timing signal types. We describe the factors and their allocation to an economic category in Table A.1. Table B.1 describes the timing signals.

| | All signals | | Momentum signals | | Volatility signals | |
|---|---|---|---|---|---|---|
| A. Average $\alpha$ and $\Delta SR$ | | | | | | |
| | $\alpha$ | $\Delta SR$ | $\alpha$ | $\Delta SR$ | $\alpha$ | $\Delta SR$ |
| All factors | 3.283 [1.018] | -0.119 [-0.627] | 6.666 [1.696] | 0.011 [-0.157] | 1.448 [1.257] | 0.046 [ 0.562] |
| Intangibles | 2.875 [0.898] | -0.120 [-0.597] | 6.026 [1.619] | 0.016 [-0.089] | 0.860 [0.891] | 0.025 [ 0.307] |
| Investment | 2.311 [0.951] | -0.163 [-0.945] | 5.121 [1.832] | 0.025 [-0.224] | 0.702 [1.112] | 0.018 [ 0.290] |
| Momentum | 4.028 [1.408] | -0.302 [-1.356] | 6.178 [1.343] | -0.146 [-1.094] | 5.111 [3.439] | 0.208 [ 2.494] |
| Other | 3.067 [0.897] | -0.105 [-0.602] | 6.278 [1.627] | 0.005 [-0.152] | 0.814 [0.608] | -0.001 [-0.024] |
| Profitability | 5.098 [1.394] | -0.045 [-0.164] | 10.245 [2.165] | 0.090 [ 0.362] | 2.609 [1.808] | 0.115 [ 1.213] |
| Trading frictions | 2.348 [0.681] | -0.095 [-0.478] | 4.048 [0.902] | -0.044 [-0.449] | 0.953 [0.910] | 0.022 [ 0.287] |
| Value vs. growth | 4.393 [1.318] | -0.088 [-0.528] | 10.076 [2.449] | 0.078 [ 0.208] | 1.799 [1.826] | 0.070 [ 0.987] |
| B. Percentage of positive and negative $\alpha$ | | | | | | |
| | + | − | + | − | + | − |
| All factors | 0.706 [0.277] | 0.294 [0.035] | 0.832 [0.428] | 0.168 [0.012] | 0.706 [0.363] | 0.294 [0.053] |
| Intangibles | 0.700 [0.244] | 0.300 [0.024] | 0.831 [0.406] | 0.169 [0.004] | 0.714 [0.288] | 0.286 [0.049] |
| Investment | 0.707 [0.271] | 0.293 [0.032] | 0.925 [0.452] | 0.075 [0.000] | 0.705 [0.320] | 0.295 [0.043] |
| Momentum | 0.734 [0.337] | 0.266 [0.020] | 0.776 [0.332] | 0.224 [0.014] | 0.883 [0.747] | 0.117 [0.006] |
| Other | 0.690 [0.225] | 0.310 [0.027] | 0.820 [0.385] | 0.180 [0.004] | 0.564 [0.213] | 0.436 [0.055] |
| Profitability | 0.777 [0.367] | 0.223 [0.021] | 0.907 [0.571] | 0.093 [0.007] | 0.792 [0.441] | 0.208 [0.024] |
| Trading frictions | 0.648 [0.217] | 0.352 [0.060] | 0.667 [0.284] | 0.333 [0.057] | 0.668 [0.348] | 0.332 [0.118] |
| Value vs. growth | 0.730 [0.377] | 0.270 [0.057] | 0.904 [0.598] | 0.096 [0.003] | 0.829 [0.526] | 0.171 [0.038] |
| C. Percentage of positive and negative $\Delta SR$ | | | | | | |
| | + | − | + | − | + | − |
| All factors | 0.370 [0.104] | 0.630 [0.245] | 0.409 [0.114] | 0.591 [0.158] | 0.612 [0.209] | 0.388 [0.066] |
| Intangibles | 0.385 [0.074] | 0.615 [0.211] | 0.469 [0.096] | 0.531 [0.130] | 0.588 [0.148] | 0.412 [0.054] |
| Investment | 0.320 [0.115] | 0.680 [0.342] | 0.342 [0.133] | 0.658 [0.217] | 0.587 [0.137] | 0.413 [0.071] |
| Momentum | 0.290 [0.141] | 0.710 [0.397] | 0.267 [0.051] | 0.733 [0.315] | 0.831 [0.623] | 0.169 [0.013] |
| Other | 0.354 [0.079] | 0.646 [0.215] | 0.399 [0.112] | 0.601 [0.132] | 0.463 [0.103] | 0.537 [0.076] |
| Profitability | 0.462 [0.137] | 0.538 [0.184] | 0.554 [0.162] | 0.446 [0.075] | 0.727 [0.318] | 0.273 [0.041] |
| Trading frictions | 0.385 [0.115] | 0.615 [0.222] | 0.360 [0.110] | 0.640 [0.224] | 0.568 [0.208] | 0.432 [0.121] |
| Value vs. growth | 0.385 [0.116] | 0.615 [0.234] | 0.433 [0.114] | 0.567 [0.084] | 0.777 [0.251] | 0.223 [0.049] |

The average annualized alpha across all factors and all signals equals 3.3%. This number is economically large, but there is weak statistical significance and strong heterogeneity between factor categories. Timing profitability factors produces the highest average $\alpha$ of 5.1%. This contrasts with an average $\alpha$ of 2.3% for factors related to trading frictions. Column $\Delta SR$ shows the average difference in the Sharpe ratio of the timed versus original factor. We show the average $z$-statistic from the Jobson and Korkie (1981) test of the null that $\Delta SR = 0$ in brackets. Unsophisticated application of all signals on all factors tends to reduce risk-adjusted returns on average. Using just momentum signals shows more successful factor timing. In particular, average $\alpha$s for profitability and value vs. growth factors are economically high (above 10% p.a.) and statistically significant; the corresponding change in Sharpe ratios is positive. Timing momentum factors with momentum signals is least attractive: Average alphas are statistically insignificant, and the average change in Sharpe ratios is negative. While timing with volatility signals leads to smaller gains in alphas, a higher proportion of alphas is statistically significant. Further, timing with volatility signals enhances Sharpe ratios. Volatility signals work best for momentum factors, where the average Sharpe ratio gain of 0.2 is highly significant.

Panel B reports the percentage of positive (+) and negative (−) $\alpha$s. Numbers in brackets are the percentages of positive and negative $\alpha$s, respectively, that are statistically significant at the 5% level. Our previous findings are reinforced. Momentum signals are associated with a particularly high fraction of positive alphas. This is true in particular for investment, profitability, and value vs. growth factors. For the latter group, roughly 60% of factors have a statistically significant alpha. Importantly, momentum signals produce virtually no statistically significant negative alphas.

We turn to Sharpe ratios in Panel C and report the percentage of timed factor/signal combinations with a higher (+) and lower (−) Sharpe ratio. Fractions with statistically significant changes in Sharpe ratios are given in brackets. Assessing the differences in Sharpe ratio, momentum signals are not able to time factors that well – i.e. no economic category has more than 50% positive differences in the Sharpe ratio. The average change in Sharpe ratios is actually negative. It seems that momentum signals enhance the performance, but increase unpriced risk even more. Strategies based on those signals might be useful if they constitute only a small part of the portfolio. Timing with volatility signals improves Sharpe ratios of 83 percent of momentum factors, with 62 percent being statistically significant.

## 3.2 One factor - many signals

Section 3.1 suggests heterogeneity in timing capabilities: The extent to which factor timing works appears to be factor and signal-specific. Clearly we cannot feasibly analyze the combination of 318 factors × 39 signals in a simple manner but need to resort to appropriate tools for dimension reduction. In a first step of aggregation, we still time each factor individually, but we use multiple signals to make a timing decision. Since many of the signals are highly correlated, it is clear that we cannot simply run a "kitchen sink" regression and expect to obtain sensible predictions. We therefore resort to partial least squares (PLS) as the appropriate signal aggregation technique. We briefly introduce PLS in the next section and refer to Kelly and Pruitt (2013, 2015) for a comprehensive treatment.

#### 3.2.1 Partial least squares

For the aggregation of the right-hand side, we could use principal components analysis (PCA), a well-known statistical approach that is widely applied in finance. Intuitively, PCA extracts $k < J$ linear combinations of the original $J = 39$ signals in a way to explain as much as possible of the variance of the original signals. Yet, our goal is not primarily a parsimonious description of the signals per se, but to find an efficient set of predictors for time-varying factor returns. Hence, we resort to a related technique that is better suited to be used in a regression setting – partial least squares. Kelly and Pruitt (2013) use PLS to successfully predict the market index.[6] The main idea of PLS in our setting is to find linear combinations of the original signals that maximize their covariances with the factor return. More precisely, consider the regression model

$$f_i = W_i \beta_i + \epsilon_i \,, \tag{6}$$

where $f_i$ is a $T \times 1$ vector of factor $i$'s one-period ahead excess returns, and $T$ is the sample length. $W_i$ is a $T \times J$ factor-specific signal matrix that contains $J = 39$ column vectors $w_i^j$, $\beta_i$ is a $J \times 1$ vector of signal sensitivities and $\epsilon_i$ is a $T \times 1$ vector of errors. PLS decomposes $W_i$ such that the first $k$ vectors can be used to predict $f_i$. We can write this as

$$f_i = \left(W_i P_i^k\right) b_i^k + u_i \,. \tag{7}$$

$P_i^k$ is a $J \times k$ matrix with columns $v_m$, $m = 1, \ldots, k$, and $b_i^k$ is a $k \times 1$ vector of sensitivities to the aggregated signals. To find the $v_m$s, we iteratively solve the following problem

$$v_m = \arg\max_v [cov(f_i, W_i v)]^2, \text{ s.t. } v'v = 1, \;\; cov(W_i v, W_i v_n) = 0 \;\forall\; n = 1, 2, ..., m-1 \,.\text{[7]} \tag{8}$$

PLS is well suited for problems such as factor timing as it can deal with highly correlated signals. In particular, a linear combination of the signals can be identified as a useful predictor of factor returns even if it does not explain much of the variation among signals.

[6] Light, Maslov, and Rytchkov (2017) employ PLS successfully for cross-sectional predictions.

[7] Note that we run a separate PLS regression for each factor to capture differential dynamics in factor risk premia. To emphasize this procedure, we could write $v_m^{(i)}$ to emphasize the dependence on $i$. In order to ease the notation, we omit this superscript.

### 3.2.2 Univariate factor timing with PLS

Our approach is to produce one-month ahead forecasts using standard predictive regression of the dominant components of factor returns. For each one of 314 factors,[8] we run four PLS regressions as specified in Eq. (7), where the number of components $k$ equals 1, 2, 3, and 5. We use each factor's first half of the sample to obtain initial estimates, and use the second half to form out-of-sample (OOS) forecasts. To this end, our OOS results are not subject to a look-ahead bias. As in Campbell and Thompson (2008), we use monthly holding periods and calculate out-of-sample $R^2$ as

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T}\left(f_{i,t+1} - \hat{f}_{i,t+1}\right)^2}{\sum_{t=1}^{T}\left(f_{i,t+1} - \bar{f}_{i,t+1}\right)^2}\,, \tag{9}$$

where $\hat{f}_{i,t+1}$ is the predicted value from a predictive regression estimated through period $t$, and $\bar{f}_{i,t+1}$ is the historical average return estimated through period $t$. To assess the economic importance of factor timing, we follow Campbell and Thompson (2008) and compare the average excess return that a buy-and-hold investor will earn from investing in factors without timing, $R^* = \frac{SR^2}{\gamma}$, to the average excess returns earned by an active investor exploiting predictive information through PLS regressions, obtained from

$$R^* = \frac{1}{\gamma}\frac{SR^2 + R^2_{OOS}}{1 - R^2_{OOS}}. \tag{10}$$

We follow Campbell and Thompson (2008) and also assume that $\gamma = 1$, i.e. unit risk aversion.

Table 2 presents statistical and economic measures of timing success in the PLS framework. Panel A reports the average $R^2_{OOS}$ of these regressions and the 25th, 50th, and 75th percentiles. Panel B groups the factors into economic categories and reports the average $R^2_{OOS}$ per category. Panels C and D report average excess returns for all factors and economic categories, respectively.

[8] We lose 4 factors due to lack of sufficient historical data. These are: Activism1, Activism2, Governance, and ProbInformed-Trading.

Table 2: Predictive regressions of factor excess returns

This table shows out-of-sample $R^2_{OOS}$ and active investor excess returns obtained from predictive regressions of factor returns on timing signals. For each one of 314 factors, we run four partial least squares (PLS) regressions, where the number of components equals 1, 2, 3, and 5. Panel A reports the average $R^2_{OOS}$ of these regressions and the 25, 50, and 75 percentiles. Panel B groups the factors into economic categories and reports the average $R^2_{OOS}$ per category. Panel C compares the annualized average excess return $R^*(ORG)$ that a buy-and-hold investor will earn from investing in factors without timing to the average excess returns earned by an active investor exploiting predictive information through PLS regressions, $R^*(PLS)$. We follow Campbell and Thompson (2008) to determine untimed returns $R^* = SR^2/\gamma$, shown in column ORG, and timed returns $R^* = (SR^2 + R^2_{OOS})/(\gamma(1 - R^2_{OOS}))$, shown in columns PLS 1 to PLS 5, assuming unit risk aversion $\gamma$. Panel D displays average active investor returns per economic factor category. We use the first half of the sample to obtain initial estimates, and report only values from out-of-sample regressions using an expanding window. We describe the factors and their allocation to an economic category in Table A.1. Table B.1 describes the timing signals.

| N of components | ORG | PLS 1 | PLS 2 | PLS 3 | PLS 5 |
|---|---|---|---|---|---|
| A. Full sample $R^2_{OOS}$ | | | | | |
| Mean | | 0.754 | -0.218 | -1.044 | -2.058 |
| 25 perc. | | -0.166 | -1.186 | -2.116 | -3.133 |
| 50 perc. | | 0.757 | 0.097 | -0.444 | -1.290 |
| 75 perc. | | 1.793 | 1.285 | 0.886 | 0.352 |
| B. Economic category $R^2_{OOS}$ | | | | | |
| Intangibles | | 0.467 | -0.809 | -1.777 | -2.447 |
| Investment | | 0.789 | -0.175 | -0.572 | -1.365 |
| Momentum | | 0.017 | -1.118 | -1.401 | -1.420 |
| Other | | 0.551 | -0.200 | -1.064 | -2.009 |
| Profitability | | 1.404 | 0.283 | -1.397 | -3.781 |
| Trading frictions | | 0.451 | -0.838 | -1.562 | -2.761 |
| Value vs. growth | | 1.612 | 1.185 | 0.456 | -0.527 |
| C. Full sample R* | | | | | |
| Mean | 2.364 | 3.202 | 2.238 | 1.461 | 0.606 |
| D. Economic category R* | | | | | |
| Intangibles | 1.345 | 1.887 | 0.631 | -0.274 | -0.871 |
| Investment | 3.716 | 4.580 | 3.581 | 3.219 | 2.476 |
| Momentum | 4.706 | 4.773 | 3.724 | 3.440 | 3.437 |
| Other | 1.951 | 2.589 | 1.859 | 1.010 | 0.122 |
| Profitability | 1.626 | 3.133 | 1.978 | 0.408 | -1.228 |
| Trading frictions | 1.538 | 2.039 | 0.748 | 0.149 | -0.781 |
| Value vs. growth | 3.151 | 4.908 | 4.503 | 3.773 | 2.813 |

Table 2 shows the statistical and economic gains of using partial least squares to time factors. The average out-of-sample $R^2_{OOS}$ (over all factor portfolios) for partial least squares predictive regression using just one component (PLS1) equals 0.75%, on a one-month prediction horizon. This corresponds to an increase in the squared Sharpe ratio of about 40% from 2.36 to 3.20 for a mean-variance investor. Thus, timing leads to an increase in excess returns and Sharpe ratios of active investors in single-factor portfolios. The increase in excess returns is pervasive but heterogeneous among economic categories. The largest gains are obtained for the profitability and value vs. growth factor categories. The gain for momentum-based factors is relatively meager.

In practice, risk constraints or other frictions might prohibit an investor from fully exploiting the information of the signals. The results presented in Table 2 may thus appear as an overstatement. To alleviate this concern we construct the simplest possible univariate timing strategies. For each of the 314 factors we time the long and short legs separately. We invest 100% in the long leg if the forecast is positive and earn an excess return of zero otherwise. We separately present the results for the short leg, where we either fully short the stocks in that portfolio or earn an excess return of zero otherwise. Return predictions are made using PLS regressions, where we again vary the number of components. In order to compute performance statistics, we use a two-step procedure: First, we compute statistics for each individual factor separately for its out-of-sample period. Second, we take cross-sectional averages. This means we do not take the perspective of an investor diversified across factors, but an investor who is randomly sampling one factor from the set of 314 factors. We report the average return (R), standard deviation (SD), Sharpe ratio (SR), maximum drawdown (maxDD), turnover, the proportion of months with long positions (N), and the hit rate (fraction of months with a positive return prediction which are correctly followed by a positive factor return).

Table 3 reports performance statistics for untimed factors and univariate factor timing portfolios. Panel A reports results for the long leg. We see that timing individual factors is attractive. It increases average returns from about 4% to 5% p.a. and increases Sharpe ratios from 0.33 to 0.45. Panel B shows results for the short leg of timed factors. It is notoriously hard to predict one-month negative returns for factors that have unconditional positive returns. While the short leg successfully earns returns on average, it is not possible to generate a hit rate above 50%. Panel C reports statistics for long-short portfolios that combine the long and the short legs from Panels A and B. We find that long-short portfolios have a higher return, but only slightly higher Sharpe ratios than timed long-only portfolios. Panel D shows performance over time. Irrespective of the number of components for the PLS regression, the timed strategies beat the untimed performance every single period. Interestingly, there is no performance decay. On the contrary, performance improves as more information becomes available. At the start of the out-of-sample period, from 1975-1989, one component improves the return by 46%, from 4.49% to 6.60%. The following period, from 1990-2004, there is a gain of 49%, from 5.77% to 8.59%. For the last third of our sample, 2005-2020, we find a gain of 67%, from 2.24% to 3.73%.

Table 3: Univariate factor timing

This table shows performance statistics for univariate factor timing portfolios. Panel A reports results for the long leg of timed factors. For each one of 314 factors, the timed portfolio is 100% in the long leg if the forecast is positive and earns an excess return of zero otherwise. Predicted returns come from partial least squares (PLS) regressions, where the number of factors equals 1, 2, 3, or 5. Column ORG shows results for the untimed factors. All statistics are obtained in a two-steps procedure: First, we compute statistics for each individual factor separately for its out-of-sample period. Second, we take cross-sectional averages. We report the annualized average return in percent, annualized standard deviation in percent, annualized Sharpe ratio, maximum drawdown in percent, turnover in percent, the proportion of months with long positions, and the hit rate (fraction of months with a positive return prediction which are correctly followed by a positive factor return). Panel B shows results for the short leg of timed factors, where the timed portfolio is short 100% in the original factor when the predicted return is negative. Panel C reports statistics for long-short portfolios constructed from the long and the short legs of Panels A and B. Panel D shows factor performance over different time periods. We describe the factors and their allocation to an economic category in Table A.1. Table B.1 describes the timing signals.

| N of components | ORG | PLS 1 | PLS 2 | PLS 3 | PLS 5 |
|---|---|---|---|---|---|
| A. Factor performance: long-leg | | | | | |
| R_long | 3.964 | 4.952 | 4.859 | 4.716 | 4.579 |
| SD_long | 12.873 | 10.710 | 10.532 | 10.454 | 10.364 |
| SR_long | 0.334 | 0.448 | 0.450 | 0.439 | 0.429 |
| maxDD_long | 46.023 | 32.707 | 32.516 | 32.743 | 33.030 |
| Turnover_long | | 207.302 | 205.033 | 208.350 | 207.579 |
| N_long | | 74.245 | 71.230 | 70.491 | 68.998 |
| Hit_rate_long | | 79.028 | 76.135 | 75.100 | 73.651 |
| B. Factor performance: short-leg | | | | | |
| R_short | | 0.988 | 0.895 | 0.752 | 0.615 |
| SD_short | | 6.084 | 6.591 | 6.812 | 7.075 |
| SR_short | | 0.094 | 0.074 | 0.053 | 0.036 |
| maxDD_short | | 33.975 | 35.967 | 36.165 | 36.157 |
| Turnover_short | | 79.377 | 94.989 | 100.374 | 108.81 |
| N_short | | 25.755 | 28.77 | 29.509 | 31.002 |
| Hit_rate_short | | 29.858 | 33.161 | 33.547 | 34.946 |
| C. Factor performance: long-short | | | | | |
| R_ls | | 5.941 | 5.755 | 5.467 | 5.193 |
| SD_ls | | 12.840 | 12.841 | 12.853 | 12.866 |
| SR_ls | | 0.485 | 0.473 | 0.446 | 0.421 |
| maxDD_ls | | 37.252 | 38.516 | 39.553 | 40.218 |
| Turnover_ls | | 551.106 | 555.979 | 557.094 | 558.361 |
| Hit_rate_ls | | 56.905 | 56.800 | 56.405 | 56.237 |
| D. Factor performance: ORG and long-short over time | | | | | |
| 05/1975 - 12/1989 | 4.494 | 6.601 | 6.319 | 6.106 | 6.215 |
| 01/1990 - 12/2004 | 5.771 | 8.590 | 8.257 | 7.769 | 7.498 |
| 01/2005 - 12/2020 | 2.237 | 3.728 | 3.621 | 3.335 | 3.032 |

## 3.3 Multifactor timing

The previous analyses show that factor timing can be beneficial even if applied to individual factors. However it is unlikely that a sophisticated investor seeks exposure to only one source of systematic risk. We therefore investigate the gains of factor timing for an investor who seeks exposure to multiple factors. This is also likely a better approximation to the stochastic discount factor.

In the first step, we strive for the simplest possible implementation to utilize the outcome from factor timing regressions. Thus, we form long-leg portfolios, which at any time $t$ is the equally weighted portfolio of all factors which have positive predicted returns for time $t+1$. In contrast to the single-factor portfolios discussed in a previous section, the multi-factor portfolio is always fully invested, but the number of factors it invests in can vary over time. We denote $N_t^+$ the number of factors for which we predict a positive return for period $t+1$. Similarly, the short leg consists of all $N_t^-$ factors with negative predicted returns. Both portfolios are equally weighted. The benchmark portfolio, denoted ORG, is a naive untimed $1/N$ multifactor portfolio. More specifically, we define the benchmark portfolio as

$$f_{t+1}^{ORG} = \frac{1}{N}\sum_{i=1}^{N} f_{i,t+1} \tag{11}$$

and the long leg portfolio of timed factors with positive expected returns as

$$f_{t+1}^{PLS_n} = w_{i,t}^{PLS_n} f_{i,t+1}\,, \tag{12}$$

where $PLS_n$ is the portfolio based on predictions of factor returns with PLS with $n$ components and the weight $w_{i,t}^{PLS_n}$ equals $1/N_t^+$ for all factors with positive predicted returns, and 0 otherwise. The short leg portfolio is defined analogously, consisting of factors with negative predicted returns. For each portfolio, we calculate average return, standard deviation, Sharpe ratio, maximum drawdown and alphas relative to the Fama-French 5-factor plus momentum asset pricing model. For the timed portfolios, we report the average return difference to the benchmark (and its $t$-value) and the difference in Sharpe ratios.

Table 4: Multivariate factor timing portfolio

This table shows performance statistics for multivariate factor timing portfolios. ORG is an untimed portfolio, where all factors available at time $t$ are equally weighted. Panel A reports statistics for the long leg, where portfolios PLS are formed at each point in time as equally weighted portfolios of factors with positive predicted returns. We use partial least squares (PLS) regressions with the number of components equal to 1, 2, 3, and 5, respectively, for prediction. We report annualized return, standard deviation, Sharpe ratio, maximum drawdown, annualized turnover and the average proportion of factors included in the long leg portfolio. Panel B shows risk adjusted performance measures: The alpha from a multifactor regression on the Fama-French five factors plus momentum, its $t$-value and the $R^2$ from the regression. Panel C reports $t$-statistics of the return difference between the predicted and original factor portfolio as well as the Jobson and Korkie (1981) test of Sharpe ratios, with the null hypothesis $\Delta \text{SR} = 0$. Panel D reports statistics for the short leg, where portfolios PLS are formed at each point in time as equally weighted portfolios of factors with negative predicted returns. Panel E shows performance statistics of the corresponding long-short portfolio. We estimate parameters strictly out-of-sample using an expanding window, where only data up to time $t$ are considered to predict returns from $t$ to $t+1$. We use the first half of the sample to obtain initial estimates. We describe the factors and their allocation to an economic category in Table A.1. Table B.1 describes the timing signals.

| N of components | ORG | PLS 1 | PLS 2 | PLS 3 | PLS 5 |
|---|---|---|---|---|---|
| A. Portfolio performance: long-leg | | | | | |
| R_long | 4.942 | 5.844 | 5.818 | 5.658 | 5.554 |
| SD_long | 2.242 | 2.993 | 2.752 | 2.635 | 2.515 |
| SR_long | 2.205 | 1.952 | 2.114 | 2.147 | 2.209 |
| maxDD_long | 3.048 | 5.314 | 4.462 | 3.177 | 3.167 |
| Turnover_long | | 27.786 | 27.442 | 29.636 | 29.170 |
| N_long | | 75.750 | 73.053 | 72.326 | 70.888 |
| B. Risk-adjusted performance | | | | | |
| FF5+M $\alpha$ | 3.877 | 4.523 | 4.689 | 4.597 | 4.564 |
| FF5+M t($\alpha$) | 17.091 | 13.818 | 14.828 | 15.072 | 15.271 |
| R2 | 57.699 | 50.599 | 45.474 | 44.661 | 41.663 |
| C. Timed vs. original | | | | | |
| t($\Delta$R) | | 3.693 | 4.020 | 3.453 | 3.183 |
| $z_{JK}$($\Delta$SR) | | -2.586 | -0.942 | -0.602 | 0.044 |
| D. Portfolio performance: short-leg | | | | | |
| R_short | | 0.902 | 0.876 | 0.716 | 0.612 |
| SD_short | | 1.678 | 1.497 | 1.424 | 1.321 |
| SR_short | | 0.538 | 0.585 | 0.503 | 0.463 |
| maxDD_short | | 35.406 | 34.323 | 29.893 | 26.196 |
| Turnover_short | | 88.126 | 76.704 | 79.474 | 74.516 |
| N_short | | 24.250 | 26.947 | 27.674 | 29.112 |
| E. Portfolio performance: long-short | | | | | |
| R_ls | | 6.747 | 6.695 | 6.374 | 6.167 |
| SD_ls | | 4.304 | 3.822 | 3.594 | 3.334 |
| SR_ls | | 1.567 | 1.752 | 1.773 | 1.850 |
| maxDD_ls | | 8.421 | 7.815 | 6.036 | 4.923 |
| Turnover_ls | | 115.911 | 104.146 | 109.110 | 103.687 |

Table 4 displays the results. For columns denoted as PLS, we use partial least squares regressions and the number of components equal to 1, 2, 3, and 5, respectively, for prediction. We rebalance the portfolios monthly, based on the sign of the factors' $t+1$ predicted returns. Panel A reports portfolio performance of the long leg. Column ORG shows statistics for the untimed equally weighted factor portfolio. This constitutes a tough benchmark with an average return of 4.94% and a Sharpe ratio of 2.2.[9] Nevertheless, the timed portfolios outperform. The portfolio using only one component to predict future returns delivers an annualized return of 5.84% and a Sharpe ratio of 1.95. PLS 5 on the other hand, delivers slightly lower returns, but at a lesser level of risk, translating into a Sharpe ratio of 2.21. Panel B shows risk-adjusted performance measures, i.e. alphas from a multifactor regression on the Fama-French five factors plus momentum, its $t$-value and the $R^2$ from the regression. Alphas are generally large and statistically significant. For the PLS1 long leg, alpha is approximately 4.5% p.a. with a $t$-statistic of 13.8. In Panel C, we report $t$-statistics of the return difference between the timed and the original factor portfolios as well as the Jobson and Korkie (1981) test of Sharpe ratios. We find that although return differences are highly significant even with a small number of partial least squares components, Sharpe ratio differences become only marginally positive when we use 5 components.

The performance of short-leg portfolios is shown in Panel D. Returns are close to 1%. Compared to the long-leg portfolios, the maximum drawdown is considerably larger in magnitude and turnover more than doubles. Hence, short-leg portfolios do not appear as an attractive investment strategy on a stand-alone basis. Panel E shows portfolios that take long minus short positions in all factors based on the predicted sign from the combination of signals. This strategy does in fact improve average returns, but a the cost of higher risk and subsequently lower Sharpe ratios, compared to long-only.

Figure 4 displays the absolute and relative attribution of each factor category to the overall performance of multivariate factor timing portfolios, respectively. The black bars show the performance attribution of each factor category for the untimed equal-weighted factor portfolio. The red bars show performance attribution of each factor category for long-leg portfolios based on PLS1 regressions. Panel (a) shows absolute attribution, i.e., the black (red) bars add up to the total performance of the untimed (timed) portfolio. Panel (b) displays relative attribution, i.e., both the black bars and the red bars add up to a length of 1. We find that each individual category attributes to the overall outperformance of the timed strategy. Factors in the categories Trading frictions and Other (residual factors not grouped into any other category) contribute most to returns on an absolute basis. Groups which already present high absolute returns, such as Momentum and Other, have less impact when we look at the relative return attribution. Profitability, Trading frictions and Value vs. growth, have higher relative contributions in our timing model.

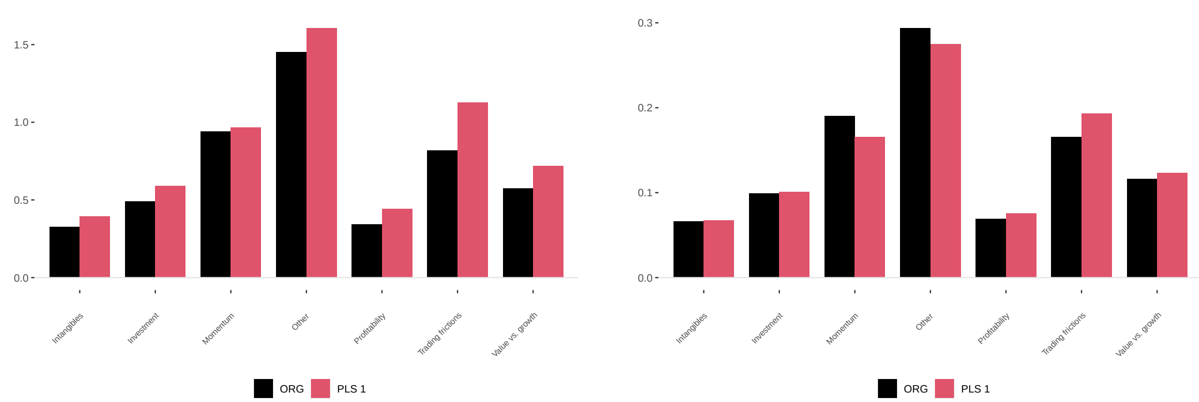
The previous analysis uses only the sign of the prediction, but not the magnitude. We may therefore

[9] Note that these numbers differ from Table 3 because we now report the time-series average of a 1/N portfolio, in contrast to taking time-series averages first, and second cross-sectional averages of the time-series means.

Figure 4: Performance attribution by factor category

Figure (a) displays the absolute attribution of each factor category to the overall performance of multivariate factor timing portfolios in Table 4. Bars show the performance in percent that factors of a specific economic category jointly contribute. Figure (b) displays the relative performance contribution. Bars show the fraction of the overall performance attributed to factors within a specific economic category. Black bars represent the factors of the untimed portfolio (ORG), where all factors available at time $t$ are equally weighted. Red bars (PLS 1) represent the factors in the timed portfolio, which is formed at each point $t$ as an equally weighted portfolio of factors with positive one-month ahead predicted returns, using partial least squares regressions with one component for prediction. We estimate the parameters strictly out-of-sample using an expanding window, where only data up to time $t$ are considered to predict returns from $t$ to $t+1$. We use the first half of the sample to obtain initial estimates. Table A.1 gives a brief description of the firm characteristics and economic category.

(a) Absolute attribution (b) Relative attribution




be underestimating the potential gains from timing in a multifactor portfolio. One easy way to consider magnitudes is to sort factors into portfolios based on the predicted returns. Below we will consider quintile portfolios. Each month $t$ we sort factors into five portfolios based on their $t+1$ predicted excess return. To compare the performance of these portfolios, we use a more sophisticated benchmark than the naive $1/N$ factor portfolio employed in Section 3.3, sorting factors based on their historical average. I.e., we assume that investors expect factors that have historically performed well (poorly), to do so again in the future. This implementation also directly addresses the concern that factor timing might only be successful because we are capturing factors with high unconditional returns. Thus, the benchmark portfolios are formed as

$$f_{t+1}^{ORG_q} = \frac{1}{N^q} w_{i,t}^{ORG_q} f_{i,t+1} \tag{13}$$

where $w_{i,t}^{ORG_q}$ equals $1/N_t^q$ for factors where the historical average return up to $t$ is in the $q$th quintile, and 0 otherwise. The quintile portfolios of timed factors are given by

$$f_{t+1}^{PLS_{q,n}} = w_{i,t}^{PLS_{q,n}} f_{i,t+1} \,, \tag{14}$$

where $PLS_{q,n}$ is the quintile $q$ PLS portfolio with $n$ components and the weight $w_{i,t}^{PLS_{q,n}}$ equals $1/N_t^{q,n}$ for all factors where the $t+1$ return predicted with $PLS_n$ is in the $q$th quintile, and 0 otherwise.

Table 5 displays the results. Panel A reports performance statistics of the quintile and the high-minus-low (HML) portfolios, for the benchmark (ORG). Panel B shows timed factors using PLS1. We find several interesting results. First, sorting factors into portfolios merely based on their historic average leads to a monotonic increase in performance across sorted portfolios. In other words, the expected factor performance seems to be a good predictor for future returns. The High (Low) portfolio, for example, produces an annualized average return of 10.463 (1.161) percent. Hence, portfolio sorts based on the historical average constitute a tough benchmark. The HML portfolio delivers an average return of 9.3% p.a., with a Sharpe ratio of 0.79. Second, timing improves both alphas and Sharpe ratios. The top PLS1-based quintile leads to the highest Sharpe ratio of about 1.96, compared to 1.49 for the top portfolio based on historical averages. Although the HML portfolio has a lower Sharpe ratio than the High portfolio, due to its high standard deviation, it is nevertheless considerably higher than the corresponding benchmark portfolio. The average returns and Sharpe ratios of the timed portfolios are highly statistically significant. Further, we display FF5+Momentum alphas of timed HML portfolios (14.47% for PSL1) that exceed the benchmark (5.5% for ORG) by a wide margin. Third, the return difference between the PLS portfolios and historic average sorted HML factor portfolios are highly significant. The PLS1 HML portfolio minus the ORG HML portfolio produces a $t$-statistic of 5.6, while the difference in Sharpe ratio is also highly significant, with a $z$-statistic of 4.16.

Table 5: Factor timing portfolio sorts

This table shows performance statistics for factor timing portfolio sorts. In each month $t$, we sort factors into 5 portfolios based on their $t+1$ predicted return. Further, we construct a high-minus-low (HML) portfolio. In Panel A, portfolios are constructed based on the historic average. Panel B shows sorts based on partial least squares (PLS) regressions with 1 component. We estimate parameters strictly out-of-sample on expanding windows, where only data up to time $t$ are used to predict returns from $t$ to $t+1$. We use the first half of the sample to obtain initial estimates. We report the annualized mean predicted return (Pred), mean realized return (R), standard deviation (SD), and Sharpe ratio (SR). For the HML portfolio, we display in addition the maximum drawdown (maxDD) and the alpha of the Fama-French five-factor model augmented by the momentum factor (FF5+M$\alpha$). As indicators for statistical significance, we report the $t$-statistic of the mean return, the alpha and the return difference PLS1-ORG, and for Sharpe ratios and differences in Sharpe ratios the Jobson and Korkie (1981) test $z_{JK}$. We describe the factors and their allocation to an economic category in Table A.1. Table B.1 describes the timing signals.

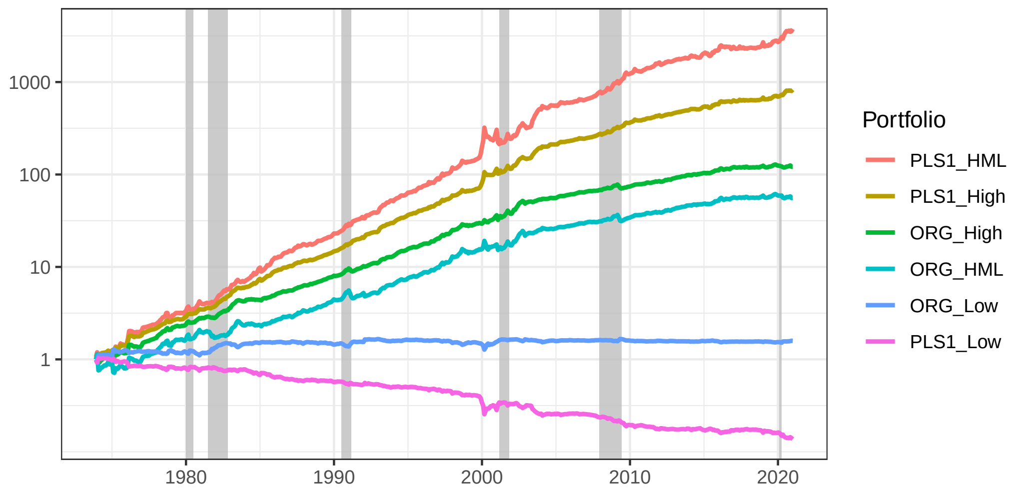
| | Pred | R | SD | SR | maxDD | FF5+M $\alpha$ |
|---|---|---|---|---|---|---|
| A. ORG | | | | | | |
| L | | 1.161 | 6.169 | 0.188 | | |
| 2 | | 3.700 | 3.403 | 1.087 | | |
| 3 | | 4.196 | 3.055 | 1.373 | | |
| 4 | | 5.376 | 5.037 | 1.067 | | |
| H | | 10.463 | 7.025 | 1.489 | | |
| HML | | 9.303 | 11.843 | 0.786 | 37.287 | 5.543 |
| *Statistical significance ($t$, $z_{JK}$)* | | *5.395* | | *4.916* | | *3.677* |
| B. PLS 1 | | | | | | |
| L | -5.802 | -3.929 | 7.410 | -0.530 | | |
| 2 | 1.173 | 2.127 | 3.307 | 0.643 | | |
| 3 | 4.628 | 4.849 | 3.684 | 1.316 | | |
| 4 | 8.212 | 7.477 | 5.123 | 1.459 | | |
| H | 16.718 | 14.598 | 7.477 | 1.952 | | |
| HML | 22.519 | 18.527 | 13.991 | 1.324 | 33.631 | 14.468 |
| *Statistical significance ($t$, $z_{JK}$)* | | *9.094* | | *8.800* | | *8.042* |
| *Statistical significance ($t$, $z_{JK}$) of difference PLS1 - ORG* | | *5.661* | | *4.158* | | |

We further find that our timing approach offers robust performance over time. Figure 5 displays the performance for sorting factors on past average returns and factor timing portfolio sorts.[10] The performance of our timing model using one component (i.e. PLS1) clearly and consistently outperforms portfolios sorted on historical average returns. For the High portfolio, the end-of-period wealth is about ten times larger than the comparable portfolio based on historical averages. Furthermore, we find that the lowest quintile experiences negative returns on average. McLean and Pontiff (2016) find that many anomalies have lower average returns post-publication. And indeed, we find that the performance for ORG gets flatter after the year 2000, i.e., sorting on the historical mean produces a smaller performance spread. Yet sorting on returns predicted from timing signals continues to work at least as well in recent periods as before 2000.

[10] In unreported results we find a monotonic ranking of quintile portfolios, and the economic differences are huge.

Figure 5: Portfolio sort performance

This figure displays the performance for factor timing portfolio sorts. We sort factors into quintile portfolios based on their $t+1$ predicted return and plot performance of the High, Low and High-Low (HML) portfolios. The total return indices are in excess of the risk-free rate. ORG displays results for portfolio sorts based on the historic average. PLS1 shows results for partial least squares regressions with one component. We estimate the parameters strictly out-of-sample using an expanding window, where only data up to time $t$ are considered to predict returns from $t$ to $t+1$. We use the first half of the sample to obtain initial estimates.




Next, we analyze whether the performance is driven by a specific selection of factors. In Table 6, we therefore display the total number of factors per economic category (first column) and the number of factors allocated to each quintile portfolio (subsequent columns). The right part of the table shows the percentage distribution of factors. Again, the first column shows the overall distribution of factors and the subsequent columns report the difference to the overall distribution for each bucket. We see that selecting factors based on historical average performance leads to a strong focus on momentum factors and overweight in profitability and value vs. growth factors, while trading frictions appear least attractive. Timing leads to a more balanced factor structure. Momentum is still overweight, but intangibles and value vs. growth factors are more evenly distributed. Interestingly, investment factors are now under-represented in both the high and low quintiles.

Table 6: Allocation of factors into quintile portfolios and economic categories

This table shows the average distribution of factors into quintile portfolios and economic categories. Allocation of a factor to a portfolio L, 2, 3, 4, and H is based on the $t+1$ predicted return. Panel A reports the distribution based on the historic average. Panel B is based on portfolio sorts using partial least squares (PLS) regressions with 1 component. We estimate the parameters strictly out-of-sample using an expanding window, where only data up to time $t$ are considered to predict returns from $t$ to $t+1$. We use the first half of the sample to obtain initial estimates. The left part of the table reports the number of factors. We display the total number of factors in the first column and each bucket's number of allocated factors in subsequent columns. The right part of the table shows the percentage distribution of factors. We describe the factors and their allocation to an economic category in Table A.1.

| | N of factors | | | | | | % of factors | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A. ORG | Full | L | 2 | 3 | 4 | H | Full | L | 2 | 3 | 4 | H |
| Intangibles | 38 | 9 | 9 | 9 | 6 | 4 | 13 | 3 | 2 | 3 | -2 | -7 |
| Investment | 37 | 8 | 7 | 7 | 7 | 8 | 15 | 0 | 0 | 1 | 1 | -1 |
| Momentum | 18 | 2 | 2 | 4 | 3 | 7 | 8 | -5 | -3 | 0 | 0 | 8 |
| Other | 50 | 11 | 12 | 9 | 10 | 10 | 24 | 1 | 3 | -3 | -1 | -1 |
| Profitability | 29 | 6 | 5 | 4 | 7 | 7 | 10 | -1 | -2 | -2 | 3 | 2 |
| Trading frictions | 38 | 10 | 7 | 9 | 7 | 5 | 18 | 5 | -1 | 4 | -1 | -7 |
| Value vs. growth | 32 | 5 | 6 | 4 | 6 | 11 | 13 | -3 | 0 | -3 | 0 | 6 |
| B. PLS 1 | Full | L | 2 | 3 | 4 | H | Full | L | 2 | 3 | 4 | H |
| Intangibles | 38 | 8 | 9 | 9 | 7 | 6 | 13 | 1 | 2 | 2 | -2 | -3 |
| Investment | 37 | 7 | 8 | 10 | 8 | 5 | 15 | -3 | 2 | 7 | 0 | -6 |
| Momentum | 18 | 2 | 2 | 3 | 4 | 7 | 8 | -4 | -4 | -2 | 2 | 9 |
| Other | 51 | 11 | 11 | 9 | 10 | 10 | 24 | 2 | 1 | -4 | 1 | 0 |
| Profitability | 29 | 6 | 6 | 5 | 5 | 7 | 10 | 1 | 0 | -1 | -1 | 2 |
| Trading frictions | 38 | 10 | 8 | 7 | 7 | 7 | 18 | 5 | 0 | -2 | -1 | -2 |
| Value vs. growth | 31 | 6 | 6 | 6 | 6 | 8 | 13 | -1 | -1 | 0 | 1 | 1 |

Table 7 shows the top holdings for each quintile in our portfolio sorts approach in greater detail. The first panel shows portfolio sorts based on the historical average. We find a very persistent presence of factors in certain quintiles, when the sorting criteria is the expected return. ReturnSkewCAPM and betaCR, for example, are more in the low bucket approximately 9 out of 10 times; STreversal, MomSeasonShort, IntMom, MomOffSeason and IndRetBig end up in the top bucket about 90% of the time. Mediocre factors, such as PriceDelaySlope, Coskewness, MomSeason11YrPlus, remain largely in the second, third and fourth buckets, respectively. Timing, however, results in a more heterogeneous allocation. Even though ReturnSkewCAPM remains the highest top holding in the low bucket, other factors, such as betaCR, drop down to 57 percent. We find similar results for the high bucket, where STreversal, MomSeasonShort, IntMom, MomOffSeason and IndRetBig remain the most frequent holdings, but to a lesser degree.

Table 7: Top 10 factor investments

This table shows the frequency of factor allocation into quintile portfolios. We sort factors into 5 portfolios based on their $t+1$ predicted return. We report the 10 factors with the highest percentage of months a factor is a component of a given quintile portfolio. Panel A shows frequencies in portfolio sorts based on the historic average. Panel B shows portfolio sorts using partial least squares (PLS) regressions with 1 component. We estimate the parameters strictly out-of-sample using an expanding window, where only data up to time $t$ are considered to predict returns from $t$ to $t+1$. We use the first half of the sample to obtain initial estimates. We describe the factors and their allocation to an economic category in Table A.1.

| Acronym | L | Acronym | 2 | Acronym | 3 | Acronym | 4 | Acronym | H |
|---|---|---|---|---|---|---|---|---|---|
| A. ORG | | | | | | | | | |
| ReturnSkewCAPM | 99.117 | PriceDelaySlope | 93.816 | Coskewness | 78.269 | MomSeason11YrPlus | 82.332 | STreversal | 99.647 |
| betaCR | 92.049 | DownsideBeta | 74.382 | zerotradeAlt12 | 72.438 | DolVol | 76.502 | MomSeasonShort | 97.703 |
| BetaDimson | 84.629 | pchdepr | 66.608 | PriceDelayRsq | 72.085 | ShareIss5Y | 75.972 | IntMom | 97.350 |
| BetaFP | 82.155 | ChPM | 65.901 | ReturnSkew | 72.085 | DivInit | 74.912 | MomOffSeason | 96.996 |
| BetaSquared | 81.449 | currat | 65.548 | BetaTailRisk | 66.608 | zerotradeAlt1 | 71.731 | IndRetBig | 94.346 |
| betaRR | 79.859 | ChNNCOA | 63.604 | ResidualMomentum6m | 66.078 | DivYieldST | 69.965 | ResidualMomentum | 84.806 |
| IdioVolCAPM | 78.445 | GrSaleToGrReceivables | 63.251 | DivSeason | 65.724 | Tax | 66.431 | FirmAgeMom | 78.799 |
| ChNCOA | 73.145 | MomOffSeason11YrPlus | 63.251 | VolMkt | 64.311 | IdioVolAHT | 66.254 | MomVol | 76.148 |
| ChNCOL | 72.968 | DelLTI | 61.661 | CompEquIss | 63.781 | ShareVol | 63.251 | Mom12mOffSeason | 74.028 |
| sgr | 72.968 | pchgm_pchsale | 61.484 | Illiquidity | 60.777 | DelCOA | 62.367 | EntMult | 71.731 |
| B. PLS 1 | | | | | | | | | |
| ReturnSkewCAPM | 95.230 | LaborforceEfficiency | 65.018 | DivSeason | 73.322 | DivYieldST | 67.314 | IndRetBig | 87.809 |
| sgr | 71.731 | PriceDelayTstat | 59.717 | ShareIss1Y | 67.668 | VolumeTrend | 60.247 | STreversal | 87.102 |
| ChNCOA | 70.495 | GrSaleToGrReceivables | 56.890 | ShareIss5Y | 63.074 | DelFINL | 59.717 | IntMom | 74.735 |
| ChNCOL | 68.375 | DelLTI | 48.763 | GrSaleToGrInv | 56.714 | DivYield | 52.827 | FirmAgeMom | 67.138 |
| betaCR | 57.244 | GrSaleToGrOverhead | 46.113 | ReturnSkew3F | 54.770 | MomSeason06YrPlus | 51.943 | MomOffSeason | 60.601 |
| BetaSquared | 56.184 | EarningsValueRelevance | 45.583 | ResidualMomentum6m | 49.470 | ReturnSkew | 51.943 | MomSeasonShort | 57.244 |
| FirmAge | 53.534 | PriceDelaySlope | 44.876 | CompositeDebtIssuance | 48.940 | InvestPPEInv | 51.590 | ResidualMomentum | 56.360 |
| DivYieldAnn | 52.297 | ChPM | 44.346 | ChNNCOA | 47.527 | MomSeason11YrPlus | 49.117 | Frontier | 54.770 |
| BetaDimson | 50.353 | EarningsTimeliness | 44.170 | DivInit | 46.643 | MomSeason | 46.643 | MomRev | 53.357 |
| AssetGrowth_q | 49.293 | Coskewness | 43.816 | ConvDebt | 42.933 | MomOffSeason06YrPlus | 44.876 | DolVol | 53.004 |

## 3.4 Stock-level timing portfolios

In all of the previous analyses we have taken factor portfolios as primitives. Since the factors are zero investment portfolios, combinations of them will of course also be zero investment portfolios and the results can be interpreted as proper excess returns. Nonetheless, it is beneficial to take a look "under the hood" to get more insights into the properties of multifactor timing portfolios for multiple reasons. To properly assess turnover of factor timing strategies, we need to compute the actual positions for each security in the portfolio, as the same stock may be in the long leg of one factor portfolio and in the short leg of another portfolio. When implementing dynamic investment strategies in real-world portfolios, investors will clearly transact only on the difference between the desired net position and the current actual holdings. DeMiguel, Martin-Utrera, Nogales, and Uppal (2020) show that many trades cancel out when multiple factors are combined into one portfolio. A second important reason is the real life frictions and constraints investors are facing. For example, leverage or short-sale constraints may inhibit the implementation of the optimal timing portfolio. The only way to gain more insight into these issues is to unpack the timing portfolio and study the multifactor timing portfolios at the individual security level.

To keep track of the net position of stock $i$ in a multifactor timing portfolio, we derive the aggregate weight $w_i$ by aggregating across the $j = 1, ..., N$ factors:

$$w_{i,t} = \sum_{j=1}^{N} w_{i,j,t} \,, \tag{15}$$

where $w_{i,j,t}$ is firm $i$'s weight in factor $j$ at time $t$. We then avoid short positions in individual stocks, and only consider those stocks which receive a positive aggregate weight:

$$w_{i,t}^{+} = \max\left[0, w_{i,t}\right]. \tag{16}$$

Similarly, we derive stock-level weights $w_{i,t}^{PLS,+}$ from the timed factor portfolios.

Table 9 shows the results. Panels A and B report results for small and large-capitalization stocks, respectively, where we split the sample using the median NYSE market equity at the end of June of year $t$ (see Fama and French, 1992). CRSP_VW depicts the value-weighted portfolio using all stocks in the available universe. ORG refers to the non-timed factor weight portfolio based on the original factor definition. PLS1 shows portfolio timing based on partial least squares regressions. Rows denoted as PLS1 | w in top 50% and PLS1 |w in top 20% show portfolios using only a subset of of firms where the aggregate firm-level weights are in the top half and top 20%, respectively.[11] Columns R, SD, SR, maxDD, N and Turn depict the annualized return, standard deviation, Sharpe ratio, maximum drawdown, average number of firms in the portfolio and the annualized turnover.[12]

[11] We re-scale weights to 1.

[12] We define the monthly turnover as the change in weights

$$TO_t = \frac{1}{2} \sum_{i} \left| w_{i,t} - w_{i,t}^{bh} \right| \,, \tag{17}$$

where $w_{i,t}$ is the weight of firm $i$ at time $t$, $w_{i,t}^{bh}$ is the buy and hold weight, i.e. the weight of firm $i$ at time $t$ when no action is taken on the previous period's weight $w_{i,t-1}$. We define $w_{i,t}^{bh}$ as

$$w_{i,t}^{bh} = \frac{mcap_{t-1} w_{i,t-1} \left(1 + r_{i,t}^{exd}\right)}{mcap_t} \,, \tag{18}$$

where $mcap_t$ is the market capitalization of the entire investment universe at time $t$. Note that this can change from $t-1$ to $t$ not only because of performance, but also because of IPOs, SEOs, buybacks, and dividend payments. $r_{i,t}^{exd}$ is the return of firm $i$ excluding dividends from $t-1$ to $t$.

Table 8: Stock-level timing portfolios

This table shows performance statistics for long-only equity portfolios. We aggregate all underlying security weights from all timed factor portfolios. We then retain only firms that have positive total weights. Panel A and B report results for small and large-capitalization stocks in the CRSP universe, where we split the sample in June of year $t$ using the median NYSE market equity and keep firms from July of year $t$ to June of year $t+1$. CRSP_VW is the value-weighted U.S. market return. ORG refers to portfolio weights based on the original factor definition. PLS1 shows portfolio timing based on partial least squares regressions with a single component. We further provide returns for portfolios based on PLS1 where only firms with weights in the top 20% or in the top 50% of all firms in the investment universe are retained. We report annualized mean return (R), standard deviation (SD), Sharpe ratio (SR), maximum drawdown (maxDD), average number of firms in the portfolio (N), and annualized turnover (Turn). The sample period is January 1974 to December 2020. We describe the factors and their allocation to an economic category in Table A.1.

| | R | SD | SR | maxDD | N | Turn |
|---|---|---|---|---|---|---|
| A. Small capitalization stocks | | | | | | |
| CRSP_VW | 12.829 | 20.422 | 0.413 | 55.078 | 3,945 | 7.045 |
| ORG | 24.098 | 21.694 | 0.908 | 57.689 | 2,219 | 286.515 |
| PLS | 26.575 | 22.473 | 0.987 | 52.071 | 2,136 | 364.001 |
| PLS1 \| w in top 50% | 28.080 | 23.171 | 1.022 | 51.634 | 1,068 | 241.198 |
| PLS1 \| w in top 20% | 29.915 | 24.764 | 1.031 | 52.314 | 428 | 202.764 |
| B. large-capitalization stocks | | | | | | |
| CRSP_VW | 9.264 | 15.538 | 0.314 | 51.585 | 929 | 3.487 |
| ORG | 12.045 | 16.145 | 0.474 | 49.138 | 340 | 312.342 |
| PLS1 | 14.369 | 17.528 | 0.569 | 48.443 | 379 | 418.445 |
| PLS1 \| w in top 50% | 14.529 | 17.744 | 0.571 | 48.121 | 190 | 315.070 |
| PLS1 \| w in top 20% | 14.219 | 18.210 | 0.540 | 49.008 | 76 | 292.770 |

We find several interesting results. First, there is a tremendous gain in portfolio performance relative to the market weighted return, even when we just use non-timed factors to form portfolios. When we restrict the sample to small stocks, the annualized return of the untimed portfolio is about 11% p.a. higher than the benchmark, which constitutes an increase of roughly 80%. Results for large-capitalization firms suggest a smaller, but still high absolute (3%) and relative (25%) over-performance. This increase in performance is unmatched by the increase in portfolio risk. Even though the standard deviation increases in all groups, the rise is less pronounced than the return, resulting in much larger Sharpe ratios. The Sharpe ratio for the small (large) sample rises from 0.413 (0.314) to 0.908 (0.474), which is an increase of 120% (50%).

Second, our timing model, denoted as PLS1, further increases the performance and risk-adjusted returns. The small cap portfolio yields an annualized return of 26.6% with a Sharpe ratio of 0.98. Alongside the impressive gain in performance, we find decreasing maximum drawdowns and a reasonable number of firms in the portfolio. However, timing and re-balancing on a monthly basis results in high turnover of roughly 360% per year.

Third, there is merit in focusing on the best in class firms, i.e. firms that have the largest weights across all timed factors. We therefore use a subset of firms in each size sample, retaining only firms with weights above the median and in the top quintile, respectively. Generally speaking, these portfolios have higher returns and higher Sharpe ratios, but also slightly higher standard deviations. The increase in standard deviation might be due to the rise of idiosyncratic risk, reflected by the decrease in the number of firms in the portfolio. For example, in the large-cap sample, the number of firms is on average 190, when we just use firms in the upper half of the weight distribution, and about 76 when we use the highest quintile. Interestingly, we find that these portfolios generate much lower turnover than the base-case PLS1 portfolio. This suggests that firms have, on aggregate across all factors, relatively sticky weights. The strategy that focuses on large-cap stocks with a weight in the top 50% resulting from timing with PLS1, increases the Sharpe ratio by roughly 80% to 0.571 (relative to 0.314 for the market-weight CRSP large-cap universe). With an average number of 190 large-cap stocks in the portfolio and a turnover of 300%, the resulting strategy can very likely be implemented in practice.

### 3.5 Performance in different economic regimes

Next, we analyze the persistence of results across different economic regimes. We split the data along two dimensions. First we split the sample by the implied market volatility, i.e. the CBOE S&P 500 volatility index, into high VIX regimes when the VIX at month $t$ is above the historical median, and vice versa. The number of observations is 164 and 207 months, respectively. Second, we provide statistics for NBER recession and expansions, with 73 and 492 observations, respectively. Table 9 shows the results.

The upper part of the table shows that the naive timing (ORG), using only the historical average of factor returns, already outperforms the market portfolio in both high and low volatility regimes, with a Sharpe ratio slightly higher in low volatility regimes. However, using the factor timing model's weights does improve the return and Sharpe ratio in both regimes.

The lower left-hand part reveals performance statistics during economic turmoil. Most notably, when the economy is in a recession, the return for the sample of small (large) stocks is -11.7% (-12.4%). However, the PLS1 timing model does improve the return tremendously. Small (large) capitalization stock portfolios return roughly 13 (6) percent above and beyond the market. This result is not dwarfed when we investigate the performance during expansions. Here the PLS1 timing portfolio again provides the highest outperformance, with returns being 1.5 and 2.3 percent above the small and large market portfolios, respectively.

Table 9: Performance of stock-level timing portfolios during crises

This table shows performance statistics for high (above the historical mean) and low (below historical mean) implied volatility (i.e. CBOE S&P 500 volatility index, VIX) regimes, and NBER recession regimes for long-only equity portfolios. We aggregate all underlying security weights from all timed factor portfolios. We then retain only firms that have positive total weights. Panel A reports results for all securities in the CRSP universe. Panels B and C report performance statistics for small and large-capitalization stocks, where we split the sample in June of year $t$ using the median NYSE market equity and keep firms from July of year $t$ to June of year $t+1$. CRSP_VW is the value-weighted U.S. market return. ORG refers to portfolio weights based on the original factor definition. PLS1 shows portfolio timing based on partial least squares regressions with a single component. We further provide returns for portfolios based on PLS1 where only firms with weights in the top 20% or in the top 50% of all firms in the investment universe are retained. We report annualized mean return (R), standard deviation (SD), and Sharpe ratio (SR). The sample period is January 1990 to December 2020 for VIX regimes and January 1974 to December 2020 for recession regimes. We describe the factors and their allocation to an economic category in Table A.1.

| | *High VIX (N=164)* | | | *Low VIX (N=207)* | | |
|---|---|---|---|---|---|---|
| | R | SD | SR | R | SD | SR |
| A. Small capitalization stocks | | | | | | |
| CRSP_VW | 14.194 | 17.942 | 0.426 | 13.776 | 22.005 | 0.369 |
| ORG | 25.910 | 19.230 | 1.007 | 29.345 | 22.874 | 1.036 |
| PLS1 | 28.277 | 20.020 | 1.085 | 31.883 | 24.713 | 1.061 |
| PLS1 \| w in top 50% | 29.800 | 20.574 | 1.130 | 33.742 | 25.697 | 1.093 |
| PLS1 \| w in top 20% | 31.509 | 21.258 | 1.174 | 36.064 | 27.987 | 1.086 |
| B. large-capitalization stocks | | | | | | |
| CRSP_VW | 10.589 | 15.672 | 0.258 | 8.249 | 16.058 | 0.161 |
| ORG | 12.912 | 15.701 | 0.405 | 12.521 | 15.989 | 0.429 |
| PLS1 | 14.417 | 17.674 | 0.445 | 15.426 | 18.261 | 0.535 |
| PLS1 \| w in top 50% | 14.348 | 18.042 | 0.432 | 15.613 | 18.560 | 0.536 |
| PLS1 \| w in top 20% | 12.951 | 18.709 | 0.342 | 15.292 | 19.306 | 0.499 |
| | *NBER recession (N=73)* | | | *Expansion (N=492)* | | |
| | R | SD | SR | R | SD | SR |
| C. Small capitalization stocks | | | | | | |
| CRSP_VW | −11.743 | 29.601 | −0.608 | 16.475 | 18.493 | 0.668 |
| ORG | 0.200 | 33.264 | −0.182 | 27.644 | 19.241 | 1.223 |
| PLS1 | 2.820 | 30.527 | −0.113 | 30.100 | 20.867 | 1.245 |
| PLS1 \| w in top 50% | 4.090 | 30.857 | −0.070 | 31.639 | 21.654 | 1.271 |
| PLS1 \| w in top 20% | 5.544 | 32.101 | −0.022 | 33.531 | 23.342 | 1.260 |
| D. large-capitalization stocks | | | | | | |
| CRSP_VW | −12.383 | 22.779 | −0.819 | 12.476 | 13.949 | 0.600 |
| ORG | −9.876 | 24.148 | −0.668 | 15.298 | 14.390 | 0.777 |
| PLS1 | −6.191 | 23.360 | −0.533 | 17.419 | 16.336 | 0.815 |
| PLS1 \| w in top 50% | −6.081 | 23.134 | −0.534 | 17.587 | 16.648 | 0.809 |
| PLS1 \| w in top 20% | −6.645 | 22.617 | −0.571 | 17.314 | 17.312 | 0.763 |

### 3.6 Stochastic discount factor

In the previous analysis, we have shown that (i) a parsimonious combination of a multitude of signals is helpful in predicting the time-series of factor returns and (ii) it is possible to construct portfolios that significantly outperform naive factor portfolios. If the underlying source of predictability is related to systematic risk, the time-series predictions of factor returns should also be helpful in pricing the cross-section of factor risk premia. We thus construct a stochastic discount factor (SDF) that makes use of factor return predictions and compare it to an SDF that is based on historical means. Specifically, we construct a mean-variance efficient portfolio $MVEP$ with weights

$$w_t^{MVEP} = \Sigma_t^{-1}(z)E_t(z_{t+1})s_t \tag{19}$$

where $\Sigma_t^{-1}(z)$ is the covariance matrix of the first five principal components $z$ of factor returns, $E_t(z_{t+1})$ is a vector of expected excess returns of the five PCs, and $s_t$ scales the standard deviation of the derived portfolio to that of the market portfolio over the observation window. All components of Eq. (19) are estimated using information up to time $t$. The return of the optimal portfolio is given by

$$r_{t+1}^{MVEP} = w_t^{MVEP} z_{t+1} \tag{20}$$

and the SDF can be obtained from

$$SDF_{t+1} = 1 - w_t^{MVEP}(z_{t+1} - E_t(z_{t+1}))\,. \tag{21}$$

We obtain four SDF variants: We either use historical average returns to obtain the vector of expected returns, or the predictions obtained from timing signals, aggregated through PLS1. For both cases, we use either expanding windows or rolling windows of 120 months of data. We restrict the data to factors where we have complete observations from January 1980 to December 2020, i.e., we exclude factors where return time series start later, end earlier, or have missing values. This gives us 144 factors that are used to construct the SDF and a further 170 factors that do not have full time series. Note that the optimal portfolio and SDF are semi-out-of-sample: Portfolio weights are obtained using covariance matrices and predicted returns using information up to time $t$, which allows to obtain out-of-sample $t+1$ returns. Yet, the selection of 144 factors makes use of full sample information as we exclude factors with missing returns to obtain a balanced panel for PCA analysis.

Table 10: Properties of the efficient portfolio

This table shows properties of mean variance efficient portfolios, obtained from factors with complete observations from January 1980 to September 2020. For estimation of covariances, we use rolling windows of 120 months of data or expanding windows, starting with 120 months, and apply a PCA with 5 components. Expected returns are obtained either from historical averages or predicted returns using PLS1. We report the average return (mean), standard deviation (SD) and Sharpe ratio (SR).

| | Mean | SD | SR |
|---|---|---|---|
| Rolling windows; average returns | 2.58 | 5.23 | 1.71 |
| Rolling windows; predicted returns | 2.90 | 5.49 | 1.83 |
| Expanding windows; average returns | 3.21 | 5.47 | 2.03 |
| Expanding windows; predicted returns | 3.40 | 5.49 | 2.15 |

Table 10 shows that mean-variance efficient portfolios constructed using predicted returns have higher average returns and Sharpe ratios than those constructed using historical average returns. This is the case for rolling and expanding windows. The highest annualized Sharpe ratio of 2.15 is obtained using expanding windows and predicted returns.

## 4 Conclusion

The academic literature has identified many asset pricing factors – the *factor zoo*. It has also analyzed whether risk premia associated with these factors are time-varying and whether it is possible to successfully time investors' exposure to the various risk factors. The evidence on the latter question is inconclusive, as different papers have focused on very different sets of factors and predictive variables. In this paper we conduct a comprehensive analysis of factor timing, simultaneously considering a large set of risk factors and of prediction variables. Our analysis reveals that factor timing is indeed possible. Predictability is not concentrated in short subsamples of the data and does not decay in recent time periods. In short, factor risk premia are robustly predictable. Our evidence reveals that factor timing is greatly beneficial to investors relative to passive "harvesting" of risk premia.

In addition, our results have important implications for asset pricing theories and models. Our results show that there is a large difference between the conditional and unconditional behavior of factor returns and risk premia. In particular, models of constant conditional risk premia are inconsistent with the data. Our findings are also useful for the design of models of the stochastic discount factor. For example, models that imply i.i.d. innovations of the SDF cannot match our empirical findings and are likely to be rejected in the data.

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# Appendices

## A Anomalies

This section describes the details of our dataset. As mentioned in section 2, our dataset is an adapted version using the open source code of Chen and Zimmermann (2022), consisting of over 300 equity portfolios sorted by characteristics. The sample includes NYSE, AMEX, and Nasdaq ordinary common stocks for the time period from 1926 to 2020. The list of firm characteristics can be constructed from CRSP, Compustat, and IBES, FRED data. Multiple characteristics require specific data to reconstruct the results of the original studies, which are readily available on the authors' websites. For each characteristic, Chen and Zimmermann (2022) replicate portfolios used in the original papers that introduced the anomaly in the literature. Table A.1 displays a brief description of the firm characteristics.

Table A.1: Summary of anomaly variables

| Acronym | Description | Original study | Journal | Economic category |
|---|---|---|---|---|
| AbnormalAccruals | Abnormal Accruals | Xie (2001) | AR | Investment |
| AbnormalAccrualsPercent | Percent Abnormal Accruals | Hafzalla, Lundholm, Van Winkle (2011) | AR | Investment |
| AccrualQuality | Accrual Quality | Francis, LaFond, Olsson, Schipper (2005) | JAE | Investment |
| AccrualQualityJune | Accrual Quality in June | Francis, LaFond, Olsson, Schipper (2005) | JAE | Investment |
| Accruals | Accruals | Sloan (1996) | AR | Investment |
| AccrualsBM | Book-to-market and accruals | Bartov and Kim (2004) | RFQA | Investment |
| Activism1 | Takeover vulnerability | Cremers and Nair (2005) | JF | Other |
| Activism2 | Active shareholders | Cremers and Nair (2005) | JF | Intangibles |
| AdExp | Advertising Expense | Chan, Lakonishok and Sougiannis (2001) | JF | Intangibles |
| AgeIPO | IPO and age | Ritter (1991) | JF | Intangibles |
| AM | Total assets to market | Fama and French (1992) | JF | Value vs. growth |
| AMq | Total assets to market (quarterly) | Fama and French (1992) | JF | Value vs. growth |
| AnalystRevision | EPS forecast revision | Hawkins, Chamberlin, Daniel (1984) | FAJ | Momentum |
| AnalystValue | Analyst Value | Frankel and Lee (1998) | JAE | Intangibles |
| AnnouncementReturn | Earnings announcement return | Chan, Jegadeesh and Lakonishok (1996) | JF | Momentum |
| AOP | Analyst Optimism | Frankel and Lee (1998) | JAE | Intangibles |
| AssetGrowth | Asset growth | Cooper, Gulen and Schill (2008) | JF | Investment |
| AssetGrowth-q | Asset growth quarterly | Cooper, Gulen and Schill (2008) | JF | Investment |
| AssetLiquidityBook | Asset liquidity over book assets | Ortiz-Molina and Phillips (2014) | JFQA | Other |
| AssetLiquidityBookQuart | Asset liquidity over book (qtrly) | Ortiz-Molina and Phillips (2014) | JFQA | Other |
| AssetLiquidityMarket | Asset liquidity over market | Ortiz-Molina and Phillips (2014) | JFQA | Other |
| AssetLiquidityMarketQuart | Asset liquidity over market (qtrly) | Ortiz-Molina and Phillips (2014) | JFQA | Other |
| AssetTurnover | Asset Turnover | Soliman (2008) | AR | Other |
| AssetTurnover-q | Asset Turnover | Soliman (2008) | AR | Other |
| Beta | CAPM beta | Fama and MacBeth (1973) | JPE | Trading frictions |
| BetaBDLeverage | Broker-Dealer Leverage Beta | Adrian, Etula and Muir (2014) | JF | Trading frictions |
| betaCC | Illiquidity-illiquidity beta (beta2i) | Acharya and Pedersen (2005) | JFE | Trading frictions |
| betaCR | Illiquidity-market return beta (beta4i) | Acharya and Pedersen (2005) | JFE | Trading frictions |
| BetaDimson | Dimson Beta | Dimson (1979) | JFE | Trading frictions |
| BetaFP | Frazzini-Pedersen Beta | Frazzini and Pedersen (2014) | JFE | Trading frictions |
| BetaLiquidityPS | Pastor-Stambaugh liquidity beta | Pastor and Stambaugh (2003) | JPE | Trading frictions |
| betaNet | Net liquidity beta (betanet,p) | Acharya and Pedersen (2005) | JFE | Trading frictions |
| betaRC | Return-market illiquidity beta | Acharya and Pedersen (2005) | JFE | Trading frictions |
| betaRR | Return-market return illiquidity beta | Acharya and Pedersen (2005) | JFE | Trading frictions |
| BetaSquared | CAPM beta squred | Fama and MacBeth (1973) | JPE | Trading frictions |
| BetaTailRisk | Tail risk beta | Kelly and Jiang (2014) | RFS | Trading frictions |
| betaVIX | Systematic volatility | Ang et al. (2006) | JF | Trading frictions |
| BidAskSpread | Bid-ask spread | Amihud and Mendelsohn (1986) | JFE | Trading frictions |
| BM | Book to market using most recent ME | Rosenberg, Reid, and Lanstein (1985) | JF | Value vs. growth |
| BMdec | Book to market using December ME | Fama and French (1992) | JPM | Value vs. growth |
| BMq | Book to market (quarterly) | Rosenberg, Reid, and Lanstein (1985) | JF | Value vs. growth |
| BookLeverage | Book leverage (annual) | Fama and French (1992) | JF | Value vs. growth |
| BookLeverageQuarterly | Book leverage (quarterly) | Fama and French (1992) | JF | Value vs. growth |
| BPEBM | Leverage component of BM | Penman, Richardson and Tuna (2007) | JAR | Value vs. growth |
| BrandCapital | Brand capital to assets | Belo, Lin and Vitorino (2014) | RED | Intangibles |
| BrandInvest | Brand capital investment | Belo, Lin and Vitorino (2014) | RED | Intangibles |
| CapTurnover | Capital turnover | Haugen and Baker (1996) | JFE | Other |
| CapTurnover-q | Capital turnover (quarterly) | Haugen and Baker (1996) | JFE | Other |
| Cash | Cash to assets | Palazzo (2012) | JFE | Value vs. growth |
| cashdebt | CF to debt | Ou and Penman (1989) | JAR | Other |
| CashProd | Cash Productivity | Chandrashekar and Rao (2009) | WP | Intangibles |
| CBOperProf | Cash-based operating profitability | Ball et al. (2016) | JFE | Profitability |
| CBOperProfLagAT | Cash-based oper prof lagged assets | Ball et al. (2016) | JFE | Profitability |
| CBOperProfLagAT-q | Cash-based oper prof lagged assets qtrly | Ball et al. (2016) | JFE | Profitability |
| CF | Cash flow to market | Lakonishok, Shleifer, Vishny (1994) | JF | Value vs. growth |
| cfp | Operating Cash flows to price | Desai, Rajgopal, Venkatachalam (2004) | AR | Value vs. growth |
| cfpq | Operating Cash flows to price quarterly | Desai, Rajgopal, Venkatachalam (2004) | AR | Value vs. growth |
| CFq | Cash flow to market quarterly | Lakonishok, Shleifer, Vishny (1994) | JF | Value vs. growth |
| ChangeInRecommendation | Change in recommendation | Jegadeesh et al. (2004) | JF | Intangibles |
| ChangeRoA | Change in Return on assets | Balakrishnan, Bartov and Faurel (2010) | NA | Profitability |
| ChangeRoE | Change in Return on equity | Balakrishnan, Bartov and Faurel (2010) | NA | Profitability |
| ChAssetTurnover | Change in Asset Turnover | Soliman (2008) | AR | Profitability |
| ChEQ | Growth in book equity | Lockwood and Prombutr (2010) | JFR | Intangibles |
| ChForecastAccrual | Change in Forecast and Accrual | Barth and Hutton (2004) | RAS | Intangibles |
| ChInv | Inventory Growth | Thomas and Zhang (2002) | RAS | Investment |
| ChInvIA | Change in capital inv (ind adj) | Abarbanell and Bushee (1998) | AR | Investment |
| ChNAnalyst | Decline in Analyst Coverage | Scherbina (2008) | ROF | Intangibles |
| ChNCOA | Change in Noncurrent Operating Assets | Soliman (2008) | AR | Investment |
| ChNCOL | Change in Noncurrent Operating Liab | Soliman (2008) | AR | Investment |
| ChNNCOA | Change in Net Noncurrent Op Assets | Soliman (2008) | AR | Investment |
| ChNWC | Change in Net Working Capital | Soliman (2008) | AR | Profitability |
| ChPM | Change in Profit Margin | Soliman (2008) | AR | Other |
| ChTax | Change in Taxes | Thomas and Zhang (2011) | JAR | Intangibles |
| CitationsRD | Citations to RD expenses | Hirschleifer, Hsu and Li (2013) | JFE | Other |
| CompEquIss | Composite equity issuance | Daniel and Titman (2006) | JF | Investment |

Table A.1 – cont.

| Acronym | Description | Original study | Journal | Economic category |
|---|---|---|---|---|
| CompositeDebtIssuance | Composite debt issuance | Lyandres, Sun and Zhang (2008) | RFS | Investment |
| ConsRecomm | Consensus Recommendation | Barber et al. (2002) | JF | Other |
| ConvDebt | Convertible debt indicator | Valta (2016) | JFQA | Intangibles |
| CoskewACX | Coskewness using daily returns | Ang, Chen and Xing (2006) | RFS | Trading frictions |
| Coskewness | Coskewness | Harvey and Siddique (2000) | JF | Trading frictions |
| CredRatDG | Credit Rating Downgrade | Dichev and Piotroski (2001) | JF | Profitability |
| currat | Current Ratio | Ou and Penman (1989) | JAR | Value vs. growth |
| CustomerMomentum | Customer momentum | Cohen and Frazzini (2008) | JF | Other |
| DebtIssuance | Debt Issuance | Spiess and Affleck-Graves (1999) | JFE | Investment |
| DelayAcct | Accounting component of price delay | Callen, Khan and Lu (2013) | CAR | Other |
| DelayNonAcct | Non-accounting component of price delay | Callen, Khan and Lu (2013) | CAR | Other |
| DelBreadth | Breadth of ownership | Chen, Hong and Stein (2002) | JFE | Intangibles |
| DelCOA | Change in current operating assets | Richardson et al. (2005) | JAE | Investment |
| DelCOL | Change in current operating liabilities | Richardson et al. (2005) | JAE | Investment |
| DelDRC | Deferred Revenue | Prakash and Sinha (2012) | CAR | Profitability |
| DelEqu | Change in equity to assets | Richardson et al. (2005) | JAE | Investment |
| DelFINL | Change in financial liabilities | Richardson et al. (2005) | JAE | Investment |
| DelLTI | Change in long-term investment | Richardson et al. (2005) | JAE | Investment |
| DelNetFin | Change in net financial assets | Richardson et al. (2005) | JAE | Investment |
| DelSTI | Change in short-term investment | Richardson et al. (2005) | JAE | Investment |
| depr | Depreciation to PPE | Holthausen and Larcker (1992) | JAE | Other |
| DivInit | Dividend Initiation | Michaely, Thaler and Womack (1995) | JF | Value vs. growth |
| DivOmit | Dividend Omission | Michaely, Thaler and Womack (1995) | JF | Value vs. growth |
| DivSeason | Dividend seasonality | Hartzmark and Salomon (2013) | JFE | Value vs. growth |
| DivYield | Dividend yield for small stocks | Naranjo, Nimalendran, Ryngaert (1998) | JF | Value vs. growth |
| DivYieldAnn | Last year's dividends over price | Naranjo, Nimalendran, Ryngaert (1998) | NA | Value vs. growth |
| DivYieldST | Predicted div yield next month | Litzenberger and Ramaswamy (1979) | JF | Value vs. growth |
| dNoa | change in net operating assets | Hirshleifer, Hou, Teoh, Zhang (2004) | JAE | Investment |
| DolVol | Past trading volume | Brennan, Chordia, Subra (1998) | JFE | Trading frictions |
| DownRecomm | Down forecast EPS | Barber et al. (2002) | JF | Intangibles |
| DownsideBeta | Downside beta | Ang, Chen and Xing (2006) | RFS | Trading frictions |
| EarningsConservatism | Earnings conservatism | Francis, LaFond, Olsson, Schipper (2004) | AR | Other |
| EarningsConsistency | Earnings consistency | Alwathainani (2009) | BAR | Intangibles |
| EarningsForecastDisparity | Long-vs-short EPS forecasts | Da and Warachka (2011) | JFE | Intangibles |
| EarningsPersistence | Earnings persistence | Francis, LaFond, Olsson, Schipper (2004) | AR | Other |
| EarningsPredictability | Earnings Predictability | Francis, LaFond, Olsson, Schipper (2004) | AR | Other |
| EarningsSmoothness | Earnings Smoothness | Francis, LaFond, Olsson, Schipper (2004) | AR | Other |
| EarningsStreak | Earnings surprise streak | Loh and Warachka (2012) | MS | Other |
| EarningsSurprise | Earnings Surprise | Foster, Olsen and Shevlin (1984) | AR | Momentum |
| EarningsTimeliness | Earnings timeliness | Francis, LaFond, Olsson, Schipper (2004) | AR | Other |
| EarningsValueRelevance | Value relevance of earnings | Francis, LaFond, Olsson, Schipper (2004) | AR | Other |
| EarnSupBig | Earnings surprise of big firms | Hou (2007) | RFS | Momentum |
| EBM | Enterprise component of BM | Penman, Richardson and Tuna (2007) | JAR | Value vs. growth |
| EBM-q | Enterprise component of BM | Penman, Richardson and Tuna (2007) | JAR | Value vs. growth |
| EntMult | Enterprise Multiple | Loughran and Wellman (2011) | JFQA | Value vs. growth |
| EntMult-q | Enterprise Multiple quarterly | Loughran and Wellman (2011) | JFQA | Value vs. growth |
| EP | Earnings-to-Price Ratio | Basu (1977) | JF | Value vs. growth |
| EPq | Earnings-to-Price Ratio | Basu (1977) | JF | Value vs. growth |
| EquityDuration | Equity Duration | Dechow, Sloan and Soliman (2004) | RAS | Value vs. growth |
| ETR | Effective Tax Rate | Abarbanell and Bushee (1998) | AR | Other |
| ExchSwitch | Exchange Switch | Dharan and Ikenberry (1995) | JF | Trading frictions |
| ExclExp | Excluded Expenses | Doyle, Lundholm and Soliman (2003) | RAS | Intangibles |
| FailureProbability | Failure probability | Campbell, Hilscher and Szilagyi (2008) | JF | Other |
| FailureProbabilityJune | Failure probability | Campbell, Hilscher and Szilagyi (2008) | JF | Other |
| FEPS | Analyst earnings per share | Cen, Wei, and Zhang (2006) | WP | Other |
| fgr5yrLag | Long-term EPS forecast | La Porta (1996) | JF | Intangibles |
| fgr5yrNoLag | Long-term EPS forecast (Monthly) | La Porta (1996) | JF | Intangibles |
| FirmAge | Firm age based on CRSP | Barry and Brown (1984) | JFE | Other |
| FirmAgeMom | Firm Age - Momentum | Zhang (2004) | JF | Momentum |
| ForecastDispersion | EPS Forecast Dispersion | Diether, Malloy and Scherbina (2002) | JF | Intangibles |
| ForecastDispersionLT | Long-term forecast dispersion | Anderson, Ghysels, and Juergens (2005) | RFS | Intangibles |
| FR | Pension Funding Status | Franzoni and Marin (2006) | JF | Intangibles |
| FRbook | Pension Funding Status | Franzoni and Marin (2006) | JF | Intangibles |
| Frontier | Efficient frontier index | Nguyen and Swanson (2009) | JFQA | Intangibles |
| Governance | Governance Index | Gompers, Ishii and Metrick (2003) | QJE | Other |
| GP | gross profits / total assets | Novy-Marx (2013) | JFE | Profitability |
| GPlag | gross profits / total assets | Novy-Marx (2013) | JFE | Profitability |
| GPlag-q | gross profits / total assets | Novy-Marx (2013) | JFE | Profitability |
| GrAdExp | Growth in advertising expenses | Lou (2014) | RFS | Intangibles |
| grcapx | Change in capex (two years) | Anderson and Garcia-Feijoo (2006) | JF | Investment |
| grcapx1y | Investment growth (1 year) | Anderson and Garcia-Feijoo (2006) | AR | Investment |
| grcapx3y | Change in capex (three years) | Anderson and Garcia-Feijoo (2006) | JF | Investment |
| GrGMToGrSales | Gross margin growth to sales growth | Abarbanell and Bushee (1998) | AR | Intangibles |
| GrLTNOA | Growth in long term operating assets | Fairfield, Whisenant and Yohn (2003) | AR | Investment |
| GrSaleToGrInv | Sales growth over inventory growth | Abarbanell and Bushee (1998) | AR | Intangibles |
| GrSaleToGrOverhead | Sales growth over overhead growth | Abarbanell and Bushee (1998) | AR | Intangibles |
| GrSaleToGrReceivables | Change in sales vs change in receiv | Abarbanell and Bushee (1998) | AR | Other |
| Herf | Industry concentration (sales) | Hou and Robinson (2006) | JF | Intangibles |
| HerfAsset | Industry concentration (assets) | Hou and Robinson (2006) | JF | Intangibles |
| HerfBE | Industry concentration (equity) | Hou and Robinson (2006) | JF | Intangibles |
| High52 | 52 week high | George and Hwang (2004) | JF | Momentum |
| hire | Employment growth | Bazdresch, Belo and Lin (2014) | JPE | Intangibles |
| IdioRisk | Idiosyncratic risk | Ang et al. (2006) | JF | Trading frictions |
| IdioVol3F | Idiosyncratic risk (3 factor) | Ang et al. (2006) | JF | Trading frictions |
| IdioVolAHT | Idiosyncratic risk (AHT) | Ali, Hwang, and Trombley (2003) | JFE | Trading frictions |
| IdioVolCAPM | Idiosyncratic risk (CAPM) | Ang et al. (2006) | JF | Trading frictions |
| IdioVolQF | Idiosyncratic risk (q factor) | Ang et al. (2006) | JF | Trading frictions |
| Illiquidity | Amihud's illiquidity | Amihud (2002) | JFM | Trading frictions |
| IndIPO | Initial Public Offerings | Ritter (1991) | JF | Intangibles |
| IndMom | Industry Momentum | Grinblatt and Moskowitz (1999) | JFE | Momentum |
| IndRetBig | Industry return of big firms | Hou (2007) | RFS | Momentum |
| IntanBM | Intangible return using BM | Daniel and Titman (2006) | JF | Value vs. growth |
| IntanCFP | Intangible return using CFtoP | Daniel and Titman (2006) | JF | Value vs. growth |
| IntanEP | Intangible return using EP | Daniel and Titman (2006) | JF | Value vs. growth |
| IntanSP | Intangible return using Sale2P | Daniel and Titman (2006) | JF | Value vs. growth |
| IntMom | Intermediate Momentum | Novy-Marx (2012) | JFE | Momentum |
| IntrinsicValue | Intrinsic or historical value | Frankel and Lee (1998) | JAE | Other |
| Investment | Investment to revenue | Titman, Wei and Xie (2004) | JFQA | Investment |
| InvestPPEInv | change in ppe and inv/assets | Lyandres, Sun and Zhang (2008) | RFS | Investment |
| InvGrowth | Inventory Growth | Belo and Lin (2012) | RFS | Investment |
| IO-ShortInterest | Inst own among high short interest | Asquith Pathak and Ritter (2005) | JFE | Other |
| iomom-cust | Customers momentum | Menzly and Ozbas (2010) | JF | Momentum |
| iomom-supp | Suppliers momentum | Menzly and Ozbas (2010) | JF | Momentum |

Table A.1 – cont.

| Acronym | Description | Original study | Journal | Economic category |
|---|---|---|---|---|
| KZ | Kaplan Zingales index | Lamont, Polk and Saa-Requejo (2001) | RFS | Intangibles |
| KZ-q | Kaplan Zingales index quarterly | Lamont, Polk and Saa-Requejo (2001) | RFS | Intangibles |
| LaborforceEfficiency | Laborforce efficiency | Abarbanell and Bushee (1998) | AR | Other |
| Leverage | Market leverage | Bhandari (1988) | JFE | Profitability |
| Leverage-q | Market leverage quarterly | Bhandari (1988) | JFE | Profitability |
| LRreversal | Long-run reversal | De Bondt and Thaler (1985) | JF | Other |
| MaxRet | Maximum return over month | Bali, Cakici, and Whitelaw (2010) | JF | Trading frictions |
| MeanRankRevGrowth | Revenue Growth Rank | Lakonishok, Shleifer, Vishny (1994) | JF | Value vs. growth |
| Mom12m | Momentum (12 month) | Jegadeesh and Titman (1993) | JF | Momentum |
| Mom12mOffSeason | Momentum without the seasonal part | Heston and Sadka (2008) | JFE | Other |
| Mom6m | Momentum (6 month) | Jegadeesh and Titman (1993) | JF | Momentum |
| Mom6mJunk | Junk Stock Momentum | Avramov et al (2007) | JF | Momentum |
| MomOffSeason | Off season long-term reversal | Heston and Sadka (2008) | JFE | Other |
| MomOffSeason06YrPlus | Off season reversal years 6 to 10 | Heston and Sadka (2008) | JFE | Other |
| MomOffSeason11YrPlus | Off season reversal years 11 to 15 | Heston and Sadka (2008) | JFE | Other |
| MomOffSeason16YrPlus | Off season reversal years 16 to 20 | Heston and Sadka (2008) | JFE | Other |
| MomRev | Momentum and LT Reversal | Chan and Ko (2006) | JOIM | Momentum |
| MomSeason | Return seasonality years 2 to 5 | Heston and Sadka (2008) | JFE | Other |
| MomSeason06YrPlus | Return seasonality years 6 to 10 | Heston and Sadka (2008) | JFE | Other |
| MomSeason11YrPlus | Return seasonality years 11 to 15 | Heston and Sadka (2008) | JFE | Other |
| MomSeason16YrPlus | Return seasonality years 16 to 20 | Heston and Sadka (2008) | JFE | Other |
| MomSeasonShort | Return seasonality last year | Heston and Sadka (2008) | JFE | Other |
| MomVol | Momentum in high volume stocks | Lee and Swaminathan (2000) | JF | Momentum |
| MRreversal | Medium-run reversal | De Bondt and Thaler (1985) | JF | Other |
| MS | Mohanram G-score | Mohanram (2005) | RAS | Other |
| nanalyst | Number of analysts | Elgers, Lo and Pfeiffer (2001) | AR | Other |
| NetDebtFinance | Net debt financing | Bradshaw, Richardson, Sloan (2006) | JAE | Investment |
| NetDebtPrice | Net debt to price | Penman, Richardson and Tuna (2007) | JAR | Value vs. growth |
| NetDebtPrice-q | Net debt to price | Penman, Richardson and Tuna (2007) | JAR | Value vs. growth |
| NetEquityFinance | Net equity financing | Bradshaw, Richardson, Sloan (2006) | JAE | Investment |
| NetPayoutYield | Net Payout Yield | Boudoukh et al. (2007) | JF | Value vs. growth |
| NetPayoutYield-q | Net Payout Yield quarterly | Boudoukh et al. (2007) | JF | Value vs. growth |
| NOA | Net Operating Assets | Hirshleifer et al. (2004) | JAE | Investment |
| NumEarnIncrease | Earnings streak length | Loh and Warachka (2012) | MS | Momentum |
| OperProf | operating profits / book equity | Fama and French (2006) | JFE | Profitability |
| OperProfLag | operating profits / book equity | Fama and French (2006) | JFE | Profitability |
| OperProfLag-q | operating profits / book equity | Fama and French (2006) | JFE | Profitability |
| OperProfRD | Operating profitability RD adjusted | Ball et al. (2016) | JFE | Profitability |
| OperProfRDLagAT | Oper prof RD adj lagged assets | Ball et al. (2016) | JFE | Profitability |
| OperProfRDLagAT-q | Oper prof RD adj lagged assets (qtrly) | Ball et al. (2016) | JFE | Profitability |
| OPLeverage | Operating leverage | Novy-Marx (2010) | ROF | Intangibles |
| OPLeverage-q | Operating leverage (qtrly) | Novy-Marx (2010) | ROF | Intangibles |
| OptionVolume1 | Option to stock volume | Johnson and So (2012) | JFE | Trading frictions |
| OptionVolume2 | Option volume to average | Johnson and So (2012) | JFE | Trading frictions |
| OrderBacklog | Order backlog | Rajgopal, Shevlin, Venkatachalam (2003) | RAS | Intangibles |
| OrderBacklogChg | Change in order backlog | Baik and Ahn (2007) | Other | Investment |
| OrgCap | Organizational capital | Eisfeldt and Papanikolaou (2013) | JF | Intangibles |
| OrgCapNoAdj | Org cap w/o industry adjustment | Eisfeldt and Papanikolaou (2013) | JF | Intangibles |
| OScore | O Score | Dichev (1998) | JFE | Profitability |
| OScore-q | O Score quarterly | Dichev (1998) | JFE | Profitability |
| PatentsRD | Patents to RD expenses | Hirschleifer, Hsu and Li (2013) | JFE | Other |
| PayoutYield | Payout Yield | Boudoukh et al. (2007) | JF | Value vs. growth |
| PayoutYield-q | Payout Yield quarterly | Boudoukh et al. (2007) | JF | Value vs. growth |
| pchcurrat | Change in Current Ratio | Ou and Penman (1989) | JAR | Investment |
| pchdepr | Change in depreciation to PPE | Holthausen and Larcker (1992) | JAE | Investment |
| pchgm-pchsale | Change in gross margin vs sales | Abarbanell and Bushee (1998) | AR | Other |
| pchquick | Change in quick ratio | Ou and Penman (1989) | JAR | Investment |
| pchsaleinv | Change in sales to inventory | Ou and Penman (1989) | JAR | Other |
| PctAcc | Percent Operating Accruals | Hafzalla, Lundholm, Van Winkle (2011) | AR | Investment |
| PctTotAcc | Percent Total Accruals | Hafzalla, Lundholm, Van Winkle (2011) | AR | Investment |
| PM | Profit Margin | Soliman (2008) | AR | Profitability |
| PM-q | Profit Margin | Soliman (2008) | AR | Profitability |
| PredictedFE | Predicted Analyst forecast error | Frankel and Lee (1998) | JAE | Intangibles |
| Price | Price | Blume and Husic (1972) | JF | Other |
| PriceDelayRsq | Price delay r square | Hou and Moskowitz (2005) | RFS | Trading frictions |
| PriceDelaySlope | Price delay coeff | Hou and Moskowitz (2005) | RFS | Trading frictions |
| PriceDelayTstat | Price delay SE adjusted | Hou and Moskowitz (2005) | RFS | Trading frictions |
| ProbInformedTrading | Probability of Informed Trading | Easley, Hvidkjaer and O'Hara (2002) | JF | Trading frictions |
| PS | Piotroski F-score | Piotroski (2000) | AR | Other |
| PS-q | Piotroski F-score | Piotroski (2000) | AR | Other |
| quick | Quick ratio | Ou and Penman (1989) | JAR | Investment |
| RD | RD over market cap | Chan, Lakonishok and Sougiannis (2001) | JF | Profitability |
| RD-q | RD over market cap quarterly | Chan, Lakonishok and Sougiannis (2001) | JF | Profitability |
| rd-sale | RD to sales | Chan, Lakonishok and Sougiannis (2001) | JF | Other |
| rd-sale-q | RD to sales | Chan, Lakonishok and Sougiannis (2001) | JF | Other |
| RDAbility | RD ability | Cohen, Diether and Malloy (2013) | RFS | Other |
| RDcap | RD capital-to-assets | Li (2011) | RFS | Intangibles |
| RDIPO | IPO and no RD spending | Gou, Lev and Shi (2006) | JBFA | Intangibles |
| RDS | Real dirty surplus | Landsman et al. (2011) | AR | Intangibles |
| realestate | Real estate holdings | Tuzel (2010) | RFS | Intangibles |
| ResidualMomentum | Momentum based on FF3 residuals | Blitz, Huij and Martens (2011) | JEmpFin | Momentum |
| ResidualMomentum6m | 6 month residual momentum | Blitz, Huij and Martens (2011) | JEmpFin | Momentum |
| retConglomerate | Conglomerate return | Cohen and Lou (2012) | JFE | Momentum |
| RetNOA | Return on Net Operating Assets | Soliman (2008) | AR | Profitability |
| RetNOA-q | Return on Net Operating Assets | Soliman (2008) | AR | Profitability |
| ReturnSkew | Return skewness | Bali, Engle and Murray (2015) | Book | Trading frictions |
| ReturnSkew3F | Idiosyncratic skewness (3F model) | Bali, Engle and Murray (2015) | Book | Trading frictions |
| ReturnSkewCAPM | Idiosyncratic skewness (CAPM) | Bali, Engle and Murray (2015) | Book | Trading frictions |
| ReturnSkewQF | Idiosyncratic skewness (Q model) | Bali, Engle and Murray (2015) | Book | Trading frictions |
| REV6 | Earnings forecast revisions | Chan, Jegadeesh and Lakonishok (1996) | JF | Momentum |
| RevenueSurprise | Revenue Surprise | Jegadeesh and Livnat (2006) | JFE | Momentum |
| RIO-Disp | Inst Own and Forecast Dispersion | Nagel (2005) | JF | Other |
| RIO-MB | Inst Own and Market to Book | Nagel (2005) | JF | Other |
| RIO-Turnover | Inst Own and Turnover | Nagel (2005) | JF | Other |
| RIO-Volatility | Inst Own and Idio Vol | Nagel (2005) | JF | Other |
| roaq | Return on assets (qtrly) | Balakrishnan, Bartov and Faurel (2010) | JAE | Profitability |
| roavol | RoA volatility | Francis, LaFond, Olsson, Schipper (2004) | AR | Other |
| RoE | net income / book equity | Haugen and Baker (1996) | JFE | Profitability |
| roic | Return on invested capital | Brown and Rowe (2007) | WP | Profitability |
| salecash | Sales to cash ratio | Ou and Penman (1989) | JAR | Other |
| saleinv | Sales to inventory | Ou and Penman (1989) | JAR | Other |
| salerec | Sales to receivables | Ou and Penman (1989) | JAR | Other |
| secured | Secured debt | Valta (2016) | JFQA | Intangibles |

Table A.1 – cont.

| Acronym | Description | Original study | Journal | Economic category |
|---|---|---|---|---|
| securedind | Secured debt indicator | Valta (2016) | JFQA | Intangibles |
| sfe | Earnings Forecast to price | Elgers, Lo and Pfeiffer (2001) | AR | Value vs. growth |
| sgr | Annual sales growth | Lakonishok, Shleifer, Vishny (1994) | JF | Other |
| sgr-q | Annual sales growth quarterly | Lakonishok, Shleifer, Vishny (1994) | JF | Other |
| ShareIss1Y | Share issuance (1 year) | Pontiff and Woodgate (2008) | JF | Investment |
| ShareIss5Y | Share issuance (5 year) | Daniel and Titman (2006) | JF | Investment |
| ShareRepurchase | Share repurchases | Ikenberry, Lakonishok, Vermaelen (1995) | JFE | Investment |
| ShareVol | Share Volume | Datar, Naik and Radcliffe (1998) | JFM | Trading frictions |
| ShortInterest | Short Interest | Dechow et al. (2001) | JFE | Trading frictions |
| sinAlgo | Sin Stock (selection criteria) | Hong and Kacperczyk (2009) | JFE | Other |
| Size | Size | Banz (1981) | JFE | Other |
| skew1 | Volatility smirk near the money | Xing, Zhang and Zhao (2010) | JFQA | Trading frictions |
| SmileSlope | Put volatility minus call volatility | Yan (2011) | JFE | Trading frictions |
| SP | Sales-to-price | Barbee, Mukherji and Raines (1996) | FAJ | Value vs. growth |
| SP-q | Sales-to-price quarterly | Barbee, Mukherji and Raines (1996) | FAJ | Value vs. growth |
| Spinoff | Spinoffs | Cusatis, Miles and Woolridge (1993) | JFE | Other |
| std-turn | Share turnover volatility | Chordia, Subra, Anshuman (2001) | JFE | Trading frictions |
| STreversal | Short term reversal | Jegadeesh (1989) | JF | Other |
| SurpriseRD | Unexpected RD increase | Eberhart, Maxwell and Siddique (2004) | JF | Intangibles |
| tang | Tangibility | Hahn and Lee (2009) | JF | Intangibles |
| tang-q | Tangibility quarterly | Hahn and Lee (2009) | JF | Intangibles |
| Tax | Taxable income to income | Lev and Nissim (2004) | AR | Profitability |
| Tax-q | Taxable income to income (qtrly) | Lev and Nissim (2004) | AR | Profitability |
| TotalAccruals | Total accruals | Richardson et al. (2005) | JAE | Investment |
| UpRecomm | Up Forecast | Barber et al. (2002) | JF | Intangibles |
| VarCF | Cash-flow to price variance | Haugen and Baker (1996) | JFE | Other |
| VolMkt | Volume to market equity | Haugen and Baker (1996) | JFE | Trading frictions |
| VolSD | Volume Variance | Chordia, Subra, Anshuman (2001) | JFE | Trading frictions |
| VolumeTrend | Volume Trend | Haugen and Baker (1996) | JFE | Other |
| WW | Whited-Wu index | Whited and Wu (2006) | RFS | Other |
| WW-Q | Whited-Wu index | Whited and Wu (2006) | RFS | Other |
| XFIN | Net external financing | Bradshaw, Richardson, Sloan (2006) | JAE | Investment |
| zerotrade | Days with zero trades | Liu (2006) | JFE | Trading frictions |
| zerotradeAlt1 | Days with zero trades | Liu (2006) | JFE | Trading frictions |
| zerotradeAlt12 | Days with zero trades | Liu (2006) | JFE | Trading frictions |
| ZScore | Altman Z-Score | Dichev (1998) | JFE | Profitability |
| ZScore-q | Altman Z-Score quarterly | Dichev (1998) | JFE | Profitability |

This table summarizes the firm characteristics used to construct the long-short anomalies. The columns show the acronym, a brief description, the original study, and the corresponding journal, where we follow Chen and Zimmermann (2022). In the column 'Economic category'we group similar factors based on their economic interpretation. Where available, we use the classification by Hou et al. (2020). For the remaining factors, we group them into the categories intangibles, investment, momentum, profitability, trading frictions, value vs. growth, and other.

## Table A.2: Summary of anomaly variables returns

| Acronym | Economic category | R | t(R) | SD | SR | maxDD | Min | 5% | 95% | Max | Start | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A. Grouped by econ. cat. | | | | | | | | | | | | |
| | Intangibles | 3.540 | 2.520 | 11.126 | 0.362 | 47.184 | -17.730 | -4.237 | 4.880 | 19.268 | 1969-07-06 | 607 |
| | Investment | 3.676 | 3.639 | 7.985 | 0.459 | 41.009 | -10.587 | -3.096 | 3.811 | 14.474 | 1957-08-05 | 762 |
| | Momentum | 8.763 | 5.752 | 15.254 | 0.733 | 56.200 | -37.312 | -5.598 | 6.582 | 21.159 | 1951-07-11 | 830 |
| | Other | 4.730 | 2.724 | 13.073 | 0.340 | 54.467 | -19.024 | -4.891 | 5.900 | 27.260 | 1956-07-03 | 766 |
| | Profitability | 5.028 | 2.819 | 13.450 | 0.381 | 57.680 | -24.590 | -5.183 | 5.790 | 21.285 | 1965-02-15 | 670 |
| | Trading frictions | 4.034 | 2.241 | 15.790 | 0.299 | 61.628 | -23.198 | -6.125 | 6.921 | 35.291 | 1944-02-18 | 917 |
| | Value vs. growth | 4.924 | 3.455 | 12.675 | 0.424 | 54.830 | -22.937 | -4.738 | 5.743 | 24.081 | 1956-05-12 | 776 |
| B. Individual anomalies | | | | | | | | | | | | |
| AbnormalAccruals | Investment | 1.976 | 1.868 | 7.367 | 0.268 | 50.373 | -5.307 | -2.964 | 3.411 | 15.244 | 1972-07-31 | 582 |
| AbnormalAccrualsPercent | Investment | -4.004 | -7.250 | 3.866 | -1.036 | 86.550 | -5.818 | -2.140 | 1.333 | 3.860 | 1972-01-31 | 588 |
| AccrualQuality | Investment | 0.702 | 0.388 | 14.464 | 0.049 | 65.655 | -15.428 | -5.990 | 6.701 | 31.358 | 1957-01-31 | 768 |
| AccrualQualityJune | Investment | 0.646 | 0.358 | 14.395 | 0.045 | 68.988 | -14.969 | -5.733 | 6.809 | 30.395 | 1957-07-31 | 762 |
| Accruals | Investment | 5.022 | 6.651 | 6.250 | 0.804 | 20.468 | -8.761 | -2.194 | 3.471 | 7.165 | 1952-07-31 | 822 |
| AccrualsBM | Investment | 14.974 | 6.299 | 17.854 | 0.839 | 41.987 | -17.393 | -5.982 | 8.985 | 31.215 | 1964-07-31 | 677 |
| Activism1 | Other | 1.713 | 0.768 | 9.034 | 0.190 | 21.330 | -8.014 | -3.689 | 4.234 | 12.648 | 1990-10-31 | 197 |
| Activism2 | Intangibles | 7.032 | 1.763 | 16.157 | 0.435 | 54.174 | -12.828 | -6.804 | 7.906 | 16.228 | 1990-10-31 | 197 |
| AdExp | Intangibles | 5.515 | 2.577 | 16.114 | 0.342 | 53.395 | -20.097 | -5.655 | 6.895 | 43.517 | 1955-07-29 | 680 |
| AgeIPO | Intangibles | 8.995 | 3.316 | 17.173 | 0.524 | 54.993 | -23.749 | -7.144 | 7.796 | 21.436 | 1980-12-31 | 481 |
| AM | Value vs. growth | 5.139 | 3.016 | 14.205 | 0.362 | 70.638 | -28.135 | -5.176 | 7.341 | 20.865 | 1951-07-31 | 834 |
| AMq | Value vs. growth | 8.071 | 3.587 | 16.912 | 0.477 | 74.096 | -40.193 | -5.875 | 8.328 | 21.328 | 1964-07-31 | 678 |
| AnalystRevision | Momentum | 7.801 | 8.734 | 5.981 | 1.304 | 24.575 | -13.810 | -2.132 | 3.265 | 5.551 | 1976-03-31 | 538 |
| AnalystValue | Intangibles | 2.143 | 1.044 | 13.697 | 0.156 | 67.921 | -24.318 | -5.662 | 5.507 | 23.206 | 1976-07-30 | 534 |
| AnnouncementReturn | Momentum | 13.184 | 14.300 | 6.481 | 2.034 | 13.483 | -19.375 | -1.533 | 3.363 | 6.943 | 1971-08-31 | 593 |
| AOP | Intangibles | 1.984 | 1.463 | 9.049 | 0.219 | 34.526 | -9.994 | -3.725 | 4.580 | 11.022 | 1976-07-30 | 534 |
| AssetGrowth | Investment | 10.953 | 7.360 | 12.317 | 0.889 | 35.141 | -9.133 | -3.978 | 6.394 | 28.474 | 1952-07-31 | 822 |
| AssetGrowth_q | Investment | -7.125 | -4.104 | 12.933 | -0.551 | 99.140 | -22.872 | -7.349 | 4.458 | 12.747 | 1965-07-30 | 666 |
| AssetLiquidityBook | Other | 3.255 | 2.535 | 10.735 | 0.303 | 42.858 | -13.004 | -3.874 | 4.672 | 33.696 | 1951-02-28 | 839 |
| AssetLiquidityBookQuart | Other | 2.953 | 1.412 | 15.684 | 0.188 | 66.599 | -19.197 | -7.170 | 6.565 | 38.509 | 1964-10-30 | 675 |
| AssetLiquidityMarket | Other | 10.564 | 7.569 | 10.621 | 0.995 | 34.046 | -15.988 | -3.277 | 5.620 | 17.601 | 1963-02-28 | 695 |
| AssetLiquidityMarketQuart | Other | 8.732 | 5.001 | 13.115 | 0.666 | 47.901 | -14.251 | -4.816 | 6.710 | 19.520 | 1964-08-31 | 677 |
| AssetTurnover | Other | 4.373 | 4.310 | 8.397 | 0.521 | 41.306 | -7.920 | -3.595 | 4.324 | 10.475 | 1952-07-31 | 822 |
| AssetTurnover_q | Other | 6.451 | 4.680 | 10.453 | 0.617 | 31.334 | -12.193 | -4.277 | 5.167 | 16.280 | 1963-07-31 | 690 |
| Beta | Trading frictions | 3.891 | 1.384 | 26.887 | 0.145 | 91.975 | -25.643 | -10.529 | 12.209 | 66.200 | 1929-07-31 | 1,098 |
| BetaBDLeverage | Trading frictions | 3.587 | 1.969 | 12.555 | 0.286 | 49.749 | -15.154 | -5.209 | 6.087 | 17.786 | 1973-07-31 | 570 |
| betaCC | Trading frictions | 4.449 | 3.292 | 12.605 | 0.353 | 61.686 | -11.579 | -4.446 | 5.502 | 29.330 | 1934-01-31 | 1,044 |
| betaCR | Trading frictions | -1.587 | -1.925 | 7.686 | -0.206 | 81.930 | -16.951 | -3.488 | 2.829 | 9.887 | 1934-01-31 | 1,044 |
| BetaDimson | Trading frictions | -0.325 | -0.209 | 14.846 | -0.022 | 87.463 | -20.169 | -6.118 | 5.903 | 47.204 | 1929-07-31 | 1,098 |
| BetaFP | Trading frictions | 0.271 | 0.079 | 32.808 | 0.008 | 99.634 | -27.002 | -13.184 | 14.528 | 83.153 | 1929-07-31 | 1,098 |
| BetaLiquidityPS | Trading frictions | 3.365 | 2.111 | 11.723 | 0.287 | 45.425 | -13.297 | -4.829 | 5.695 | 14.063 | 1966-01-31 | 649 |
| betaNet | Trading frictions | 4.450 | 3.224 | 12.874 | 0.346 | 62.429 | -12.213 | -4.669 | 6.097 | 29.654 | 1934-01-31 | 1,044 |
| betaRC | Trading frictions | -1.017 | -0.639 | 14.838 | -0.069 | 89.604 | -36.464 | -6.683 | 6.306 | 15.996 | 1934-01-31 | 1,044 |
| betaRR | Trading frictions | 1.869 | 0.831 | 20.971 | 0.089 | 90.344 | -21.495 | -8.518 | 9.390 | 55.245 | 1934-01-31 | 1,044 |
| BetaSquared | Trading frictions | -3.400 | -1.223 | 26.596 | -0.128 | 99.935 | -66.200 | -12.162 | 10.505 | 25.817 | 1929-07-31 | 1,098 |
| BetaTailRisk | Trading frictions | 4.290 | 2.709 | 14.942 | 0.287 | 44.177 | -19.120 | -5.867 | 6.466 | 37.067 | 1932-01-30 | 1,068 |
| betaVIX | Trading frictions | 7.167 | 3.328 | 12.723 | 0.563 | 44.428 | -13.073 | -4.288 | 6.959 | 18.266 | 1986-02-28 | 419 |
| BidAskSpread | Trading frictions | 7.873 | 2.443 | 30.825 | 0.255 | 84.230 | -22.807 | -8.812 | 12.451 | 102.674 | 1929-07-31 | 1,098 |
| BM | Value vs. growth | 10.817 | 5.020 | 16.620 | 0.651 | 48.562 | -25.557 | -5.140 | 7.991 | 40.615 | 1961-07-31 | 714 |
| BMdec | Value vs. growth | 8.125 | 6.002 | 11.204 | 0.725 | 43.023 | -16.354 | -4.120 | 5.823 | 18.120 | 1952-07-31 | 822 |
| BMq | Value vs. growth | 11.959 | 4.936 | 18.212 | 0.657 | 52.478 | -28.280 | -5.351 | 8.163 | 39.226 | 1964-07-31 | 678 |
| BookLeverage | Value vs. growth | 1.559 | 1.203 | 10.806 | 0.144 | 61.967 | -13.506 | -4.096 | 4.229 | 28.613 | 1951-07-31 | 834 |
| BookLeverageQuarterly | Value vs. growth | -0.832 | -0.444 | 13.856 | -0.060 | 75.590 | -31.032 | -5.928 | 6.171 | 15.706 | 1966-07-29 | 654 |
| BPEBM | Value vs. growth | 2.024 | 2.723 | 5.685 | 0.356 | 33.062 | -7.161 | -2.355 | 2.713 | 14.380 | 1962-07-31 | 702 |
| BrandCapital | Intangibles | 1.520 | 0.807 | 14.281 | 0.106 | 71.066 | -21.931 | -6.016 | 5.929 | 30.452 | 1955-07-29 | 690 |
| BrandInvest | Intangibles | 4.480 | 1.674 | 19.932 | 0.225 | 71.063 | -24.679 | -8.084 | 8.987 | 40.012 | 1965-07-30 | 666 |
| CapTurnover | Other | 2.629 | 2.368 | 9.156 | 0.287 | 49.854 | -10.745 | -4.058 | 4.341 | 10.646 | 1953-01-30 | 816 |
| CapTurnover_q | Other | 6.572 | 4.065 | 11.936 | 0.551 | 48.146 | -17.783 | -4.505 | 5.518 | 22.782 | 1966-07-29 | 654 |
| Cash | Value vs. growth | 7.705 | 3.137 | 17.236 | 0.447 | 62.280 | -16.820 | -6.668 | 7.818 | 46.972 | 1971-10-29 | 591 |
| cashdebt | Other | -0.247 | -0.140 | 14.696 | -0.017 | 81.409 | -33.187 | -6.402 | 5.038 | 16.617 | 1952-01-31 | 828 |
| CashProd | Intangibles | 3.638 | 2.572 | 11.832 | 0.307 | 58.144 | -27.924 | -4.558 | 6.021 | 15.122 | 1951-01-31 | 840 |
| CBOperProf | Profitability | 5.936 | 3.523 | 12.886 | 0.461 | 53.472 | -14.010 | -5.300 | 6.505 | 17.411 | 1962-07-31 | 702 |
| CBOperProfLagAT | Profitability | 5.176 | 3.218 | 12.249 | 0.423 | 42.409 | -27.702 | -5.954 | 5.064 | 13.288 | 1963-01-31 | 696 |
| CBOperProfLagAT_q | Profitability | 9.091 | 5.741 | 11.151 | 0.815 | 39.919 | -28.827 | -4.442 | 4.766 | 14.235 | 1971-06-30 | 595 |
| CF | Value vs. growth | 4.474 | 2.562 | 14.556 | 0.307 | 50.586 | -36.293 | -5.488 | 5.886 | 17.254 | 1951-07-31 | 834 |
| cfp | Value vs. growth | 3.523 | 1.763 | 15.020 | 0.235 | 70.311 | -32.368 | -6.223 | 6.093 | 16.724 | 1964-07-31 | 678 |
| cfpq | Value vs. growth | 9.781 | 5.407 | 12.565 | 0.778 | 47.498 | -29.978 | -4.275 | 5.664 | 14.110 | 1972-10-31 | 579 |
| CFq | Value vs. growth | 13.434 | 6.362 | 16.264 | 0.826 | 72.984 | -39.397 | -5.160 | 6.670 | 32.551 | 1961-09-29 | 712 |
| ChangeInRecommendation | Intangibles | 6.745 | 7.128 | 4.924 | 1.370 | 7.211 | -6.466 | -1.408 | 2.642 | 6.657 | 1993-12-31 | 325 |
| ChangeRoA | Profitability | 11.065 | 7.787 | 10.393 | 1.065 | 38.746 | -19.908 | -2.886 | 4.576 | 17.454 | 1967-07-31 | 642 |
| ChangeRoE | Profitability | 10.813 | 6.858 | 11.533 | 0.938 | 32.843 | -16.991 | -3.180 | 4.249 | 47.698 | 1967-07-31 | 642 |
| ChAssetTurnover | Profitability | 1.940 | 3.857 | 4.132 | 0.470 | 16.633 | -6.321 | -1.663 | 1.933 | 5.648 | 1953-07-31 | 810 |
| ChEQ | Intangibles | 5.404 | 4.020 | 10.282 | 0.526 | 29.477 | -14.126 | -3.669 | 4.943 | 21.503 | 1962-07-31 | 702 |
| ChForecastAccrual | Intangibles | 2.607 | 3.914 | 4.445 | 0.587 | 10.817 | -5.838 | -1.744 | 2.224 | 5.006 | 1976-07-30 | 534 |
| ChInv | Investment | 7.200 | 8.028 | 7.423 | 0.970 | 24.401 | -6.697 | -2.644 | 4.178 | 15.967 | 1952-07-31 | 822 |
| ChInvIA | Investment | 4.207 | 6.234 | 5.586 | 0.753 | 29.420 | -6.255 | -1.936 | 2.868 | 10.375 | 1952-07-31 | 822 |
| ChNAnalyst | Intangibles | 12.088 | 1.840 | 37.447 | 0.323 | 99.981 | -99.843 | -10.287 | 13.574 | 55.667 | 1976-05-28 | 390 |
| ChNCOA | Investment | -8.536 | -8.978 | 7.898 | -1.081 | 99.820 | -15.440 | -4.346 | 2.315 | 5.331 | 1952-01-31 | 828 |
| ChNCOL | Investment | -4.400 | -5.218 | 7.005 | -0.628 | 97 | -12.220 | -3.453 | 2.570 | 5.754 | 1952-01-31 | 828 |
| ChNNCOA | Investment | 2.716 | 5.350 | 4.203 | 0.646 | 13.783 | -4.704 | -1.723 | 2.279 | 5.299 | 1952-07-31 | 822 |
| ChNWC | Profitability | 1.814 | 4.300 | 3.492 | 0.520 | 24.108 | -4.351 | -1.324 | 1.851 | 6.097 | 1952-07-31 | 822 |
| ChPM | Other | 1.709 | 3.067 | 4.613 | 0.371 | 19.056 | -4.448 | -1.968 | 2.373 | 4.668 | 1952-07-31 | 822 |
| ChTax | Intangibles | 11.678 | 10.049 | 8.870 | 1.317 | 21.738 | -20.135 | -2.648 | 4.727 | 18.141 | 1962-10-31 | 699 |
| CitationsRD | Other | 2.369 | 2.182 | 6.332 | 0.374 | 32.343 | -8.176 | -2.743 | 3.063 | 9.089 | 1977-07-29 | 408 |
| CompEquIss | Investment | 3.805 | 3.068 | 11.763 | 0.323 | 57.380 | -19.376 | -3.639 | 3.766 | 42.241 | 1931-01-31 | 1,080 |
| CompositeDebtIssuance | Investment | 2.813 | 5.327 | 4.241 | 0.663 | 16.535 | -5.517 | -1.810 | 2.180 | 3.866 | 1956-07-31 | 774 |
| ConsRecomm | Other | 5.891 | 2.409 | 12.746 | 0.462 | 42.565 | -12.732 | -5.186 | 6.761 | 19.279 | 1993-11-30 | 326 |
| ConvDebt | Intangibles | 2.831 | 4.260 | 5.561 | 0.509 | 20.422 | -23.012 | -1.979 | 2.489 | 5.700 | 1951-01-31 | 840 |
| CoskewACX | Trading frictions | 4.469 | 3.562 | 9.360 | 0.477 | 35.927 | -11.753 | -3.452 | 4.608 | 19.586 | 1963-07-31 | 668 |
| Coskewness | Trading frictions | 1.131 | 1.152 | 9.390 | 0.120 | 70.164 | -21.274 | -3.578 | 4.210 | 14.991 | 1929-07-31 | 1,098 |
| CredRatDG | Profitability | 8.212 | 3.145 | 14.537 | 0.565 | 56.133 | -23.704 | -6.132 | 6.529 | 12.815 | 1986-02-28 | 372 |
| currat | Value vs. growth | 2.300 | 2.050 | 9.385 | 0.245 | 50.149 | -14.905 | -3.680 | 4.236 | 26.140 | 1951-01-31 | 840 |
| CustomerMomentum | Other | 7.437 | 2.136 | 22.965 | 0.324 | 87.213 | -61.346 | -6.128 | 9.473 | 36.098 | 1977-07-29 | 522 |
| DebtIssuance | Investment | 3.577 | 5.702 | 4.391 | 0.815 | 13.197 | -4.961 | -1.609 | 2.145 | 9.098 | 1972-01-31 | 588 |
| DelayAcct | Other | -1.616 | -0.971 | 10.809 | -0.150 | 69.412 | -15.681 | -4.882 | 4.873 | 12.614 | 1978-07-31 | 506 |
| DelayNonAcct | Other | 0.936 | 0.696 | 8.732 | 0.107 | 38.014 | -9.843 | -4.080 | 4.032 | 10.909 | 1978-07-31 | 506 |
| DelBreadth | Intangibles | 6.880 | 2.899 | 14.976 | 0.459 | 42.848 | -29.964 | -5.476 | 6.541 | 29.975 | 1980-07-31 | 478 |
| DelCOA | Investment | 4.658 | 6.201 | 6.217 | 0.749 | 31.089 | -6.524 | -2.259 | 3.439 | 10.706 | 1952-07-31 | 822 |
| DelCOL | Investment | 2.536 | 3.499 | 5.998 | 0.423 | 32.895 | -6.617 | -2.508 | 3.325 | 6.655 | 1952-07-31 | 822 |
| DelDRC | Profitability | 8.271 | 1.582 | 23.673 | 0.349 | 48.281 | -42.979 | -3.801 | 5.549 | 42.596 | 2000-07-31 | 246 |
| DelEqu | Investment | 5.585 | 3.969 | 10.761 | 0.519 | 36.342 | -8.165 | -3.651 | 5.597 | 21.525 | 1962-07-31 | 702 |
| DelFINL | Investment | 6.152 | 11.461 | 4.443 | 1.385 | 18.264 | -5.483 | -1.545 | 2.520 | 7.868 | 1952-07-31 | 822 |

Table A.2 – cont.

| Acronym | Economic category | R | t(R) | SD | SR | maxDD | Min | 5% | 95% | Max | Start | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DelLTI | Investment | 1.935 | 3.605 | 4.409 | 0.439 | 18.242 | -4.580 | -1.613 | 1.942 | 9.633 | 1953-07-31 | 810 |
| DelNetFin | Investment | 4.046 | 6.924 | 4.837 | 0.837 | 21.473 | -7.375 | -1.840 | 2.489 | 4.947 | 1952-07-31 | 822 |
| DelSTI | Investment | 0.542 | 0.848 | 4.538 | 0.119 | 40.103 | -3.884 | -1.682 | 2.164 | 8.190 | 1970-07-31 | 606 |
| depr | Other | 5.431 | 3.677 | 12.357 | 0.440 | 51.003 | -14.443 | -4.405 | 5.822 | 30.729 | 1951-01-31 | 840 |
| DivInit | Value vs. growth | 4.054 | 2.990 | 12.970 | 0.313 | 49.172 | -43.755 | -3.727 | 5.101 | 34.573 | 1929-07-31 | 1,098 |
| DivOmit | Value vs. growth | 7.433 | 4.146 | 16.946 | 0.439 | 62.135 | -26.050 | -6.890 | 7.662 | 42.036 | 1929-07-31 | 1,072 |
| DivSeason | Value vs. growth | 3.706 | 14.429 | 2.457 | 1.508 | 6.476 | -3.414 | -0.813 | 1.424 | 4.680 | 1929-07-31 | 1,098 |
| DivYield | Value vs. growth | 7.628 | 3.464 | 21.061 | 0.362 | 77.561 | -31.775 | -8.320 | 9.507 | 88.791 | 1929-07-31 | 1,098 |
| DivYieldAnn | Value vs. growth | -1.306 | -1.287 | 9.710 | -0.135 | 91.044 | -35.937 | -3.336 | 3.135 | 7.769 | 1929-07-31 | 1,098 |
| DivYieldST | Value vs. growth | 6.554 | 8.976 | 6.981 | 0.939 | 17.290 | -11.302 | -1.963 | 3.267 | 34.660 | 1929-07-31 | 1,097 |
| dNoa | Investment | 9.251 | 8.419 | 8.404 | 1.101 | 17.888 | -14.126 | -2.654 | 4.623 | 16.915 | 1962-07-31 | 702 |
| DolVol | Trading frictions | 9.164 | 4.109 | 21.331 | 0.430 | 46.791 | -16.811 | -6.052 | 7.922 | 83.559 | 1929-07-31 | 1,098 |
| DownRecomm | Intangibles | 4.477 | 6.100 | 3.819 | 1.172 | 5.991 | -5.991 | -1.061 | 2.077 | 7.208 | 1993-12-31 | 325 |
| DownsideBeta | Trading frictions | 1.317 | 0.604 | 20.859 | 0.063 | 78.091 | -35.682 | -9.210 | 9.044 | 36.892 | 1929-07-31 | 1,098 |
| EarningsConservatism | Other | -0.046 | -0.091 | 3.945 | -0.012 | 24.520 | -7.691 | -1.775 | 1.762 | 4.180 | 1960-01-29 | 732 |
| EarningsConsistency | Intangibles | 3.118 | 3.803 | 6.735 | 0.463 | 36.496 | -8.200 | -3.047 | 3.239 | 6.818 | 1953-07-31 | 810 |
| EarningsForecastDisparity | Intangibles | 5.295 | 3.518 | 9.399 | 0.563 | 35.356 | -14.629 | -3.599 | 4.209 | 10.182 | 1982-01-29 | 468 |
| EarningsPersistence | Other | -1.665 | -1.688 | 7.641 | -0.218 | 76.584 | -11.517 | -3.704 | 3.353 | 8.554 | 1961-01-31 | 720 |
| EarningsPredictability | Other | -6.669 | -4.644 | 11.123 | -0.600 | 99.146 | -10.177 | -5.641 | 4.293 | 20.682 | 1961-01-31 | 720 |
| EarningsSmoothness | Other | 1.915 | 1.442 | 10.283 | 0.186 | 44.334 | -10.875 | -4.432 | 4.712 | 18.510 | 1961-01-31 | 720 |
| EarningsStreak | Other | 10.655 | 10.064 | 6.367 | 1.673 | 14.726 | -14.726 | -1.678 | 3.672 | 5.792 | 1984-11-30 | 434 |
| EarningsSurprise | Momentum | 8.607 | 9.543 | 6.844 | 1.258 | 32.039 | -13.240 | -2.326 | 3.658 | 9.629 | 1963-06-28 | 691 |
| EarningsTimeliness | Other | 0.559 | 0.904 | 4.823 | 0.116 | 36.643 | -6.167 | -1.969 | 2.269 | 10.844 | 1960-01-29 | 732 |
| EarningsValueRelevance | Other | 0.683 | 1.154 | 4.583 | 0.149 | 29.746 | -6.322 | -2.007 | 2.089 | 4.853 | 1961-01-31 | 720 |
| EarnSupBig | Momentum | 3.925 | 3.082 | 9.664 | 0.406 | 32.411 | -17.367 | -4.074 | 4.276 | 12.992 | 1963-06-28 | 691 |
| EBM | Value vs. growth | 2.546 | 3.505 | 5.556 | 0.458 | 23.888 | -5.635 | -2.281 | 2.856 | 10.374 | 1962-07-31 | 702 |
| EBM_q | Value vs. growth | 7.464 | 5.685 | 9.603 | 0.777 | 28.163 | -17.715 | -3.055 | 4.308 | 21.200 | 1967-04-28 | 642 |
| EntMult | Value vs. growth | 7.700 | 5.418 | 11.848 | 0.650 | 49.869 | -17.387 | -4.551 | 6.280 | 19.392 | 1951-07-31 | 834 |
| EntMult_q | Value vs. growth | -16.156 | -9.121 | 12.955 | -1.247 | 99.994 | -30.493 | -6.224 | 3.222 | 18.873 | 1967-04-28 | 642 |
| EP | Value vs. growth | 3.393 | 2.909 | 9.760 | 0.348 | 41.611 | -15.944 | -3.879 | 4.803 | 17.139 | 1951-01-31 | 840 |
| EPq | Value vs. growth | 13.652 | 12.360 | 8.472 | 1.611 | 37.400 | -13.883 | -2.369 | 4.906 | 12.790 | 1962-03-30 | 706 |
| EquityDuration | Value vs. growth | 4.893 | 2.578 | 14.394 | 0.340 | 66.695 | -16.086 | -6.031 | 7.160 | 20.939 | 1963-07-31 | 690 |
| ETR | Other | -0.609 | -0.800 | 5.908 | -0.103 | 52.348 | -13.621 | -2.026 | 1.763 | 11.243 | 1960-07-29 | 723 |
| ExchSwitch | Trading frictions | 7.486 | 4.924 | 11.596 | 0.646 | 26.117 | -13.520 | -4.582 | 6.374 | 12.930 | 1962-11-30 | 698 |
| ExclExp | Intangibles | 1.438 | 1.049 | 8.307 | 0.173 | 20.432 | -34.727 | -2.163 | 2.663 | 7.241 | 1983-07-29 | 440 |
| FailureProbability | Other | 2.237 | 0.756 | 21.551 | 0.104 | 82.379 | -41.921 | -9.200 | 8.860 | 30.412 | 1968-01-31 | 636 |
| FailureProbabilityJune | Other | -0.584 | -0.204 | 20.970 | -0.028 | 91.037 | -19.760 | -8.391 | 9.824 | 45.198 | 1967-07-31 | 642 |
| FEPS | Other | 8.843 | 2.848 | 20.811 | 0.425 | 80.805 | -31.770 | -7.216 | 10.261 | 31.558 | 1976-02-27 | 539 |
| fgr5yrLag | Intangibles | 1.847 | 0.646 | 17.732 | 0.104 | 68.426 | -27.447 | -6.775 | 7.820 | 18.003 | 1982-07-30 | 462 |
| fgr5yrNoLag | Intangibles | -2.901 | -0.955 | 18.958 | -0.153 | 88.586 | -25.425 | -8.817 | 7.020 | 28.928 | 1982-01-29 | 468 |
| FirmAge | Other | -0.627 | -0.766 | 7.831 | -0.080 | 69.137 | -17.350 | -3.538 | 3.366 | 16.920 | 1929-07-31 | 1,098 |
| FirmAgeMom | Momentum | 14.562 | 7.056 | 19.543 | 0.745 | 85.360 | -43.680 | -7.270 | 8.968 | 32.022 | 1929-07-31 | 1,076 |
| ForecastDispersion | Intangibles | 5.198 | 2.273 | 15.323 | 0.339 | 59.378 | -25.571 | -6.720 | 6.970 | 13.746 | 1976-02-27 | 539 |
| ForecastDispersionLT | Intangibles | -0.210 | -0.125 | 10.478 | -0.020 | 64.888 | -16.820 | -4.310 | 3.542 | 17.539 | 1982-01-29 | 468 |
| FR | Intangibles | -0.760 | -0.397 | 12.033 | -0.063 | 73.811 | -20.101 | -5.593 | 4.640 | 13.236 | 1981-07-31 | 474 |
| FRbook | Intangibles | 0.727 | 0.667 | 6.882 | 0.106 | 47.642 | -10.080 | -3.200 | 3.085 | 7.885 | 1981-02-27 | 479 |
| Frontier | Intangibles | 15.599 | 6.651 | 17.785 | 0.877 | 41.978 | -18.694 | -6.052 | 9.343 | 25.927 | 1963-07-31 | 690 |
| Governance | Other | -1.528 | -0.583 | 10.627 | -0.144 | 62.263 | -11.517 | -4.734 | 4.404 | 12.113 | 1990-10-31 | 197 |
| GP | Profitability | 4.333 | 3.549 | 10.178 | 0.426 | 55.799 | -15.813 | -4.124 | 5.190 | 12.305 | 1951-07-31 | 834 |
| GPlag | Profitability | 2.761 | 2.622 | 8.747 | 0.316 | 36.922 | -8.688 | -4.167 | 4.034 | 11.789 | 1952-01-31 | 828 |
| GPlag_q | Profitability | 8.400 | 4.878 | 12.054 | 0.697 | 56.507 | -22.770 | -4.786 | 5.319 | 10.972 | 1972-01-31 | 588 |
| GrAdExp | Intangibles | 2.849 | 1.503 | 14.123 | 0.202 | 80.327 | -25.982 | -4.973 | 5.514 | 24.665 | 1965-07-30 | 666 |
| grcapx | Investment | 4.065 | 5.625 | 5.937 | 0.685 | 22.295 | -5.778 | -2.317 | 3.218 | 8.255 | 1953-07-31 | 810 |
| grcapx1y | Investment | -1.875 | -2.925 | 5.285 | -0.355 | 83.330 | -7.927 | -2.415 | 2.054 | 13.186 | 1953-01-30 | 816 |
| grcapx3y | Investment | 4.450 | 5.477 | 6.626 | 0.672 | 23.556 | -6.536 | -2.484 | 3.636 | 13.852 | 1954-07-30 | 798 |
| GrGMToGrSales | Intangibles | 2.443 | 3.806 | 5.312 | 0.460 | 19.093 | -5.611 | -2.385 | 2.712 | 5.316 | 1952-07-31 | 822 |
| GrLTNOA | Investment | 2.380 | 3.168 | 6.218 | 0.383 | 21.305 | -8.990 | -2.770 | 3.137 | 8.077 | 1952-07-31 | 822 |
| GrSaleToGrInv | Intangibles | 3.082 | 5.449 | 4.681 | 0.658 | 19.914 | -4.589 | -2.008 | 2.263 | 6.394 | 1952-07-31 | 822 |
| GrSaleToGrOverhead | Intangibles | -0.104 | -0.152 | 5.696 | -0.018 | 50.442 | -12.398 | -2.472 | 2.327 | 9.850 | 1952-07-31 | 822 |
| GrSaleToGrReceivables | Other | 1.481 | 2.945 | 4.163 | 0.356 | 21.693 | -4.096 | -1.686 | 2.015 | 5.631 | 1952-07-31 | 822 |
| Herf | Intangibles | 1.188 | 1.508 | 6.594 | 0.180 | 51.465 | -7.384 | -2.490 | 2.819 | 18.758 | 1951-01-31 | 840 |
| HerfAsset | Intangibles | 0.454 | 0.497 | 7.584 | 0.060 | 61.889 | -11.207 | -2.654 | 3.121 | 30.242 | 1951-12-31 | 829 |
| HerfBE | Intangibles | 1.026 | 1.138 | 7.495 | 0.137 | 52.971 | -11.185 | -2.725 | 2.831 | 28.812 | 1951-12-31 | 829 |
| High52 | Momentum | -0.058 | -0.023 | 23.967 | -0.002 | 99.701 | -69.538 | -9.786 | 7.562 | 18.550 | 1929-07-31 | 1,098 |
| hire | Intangibles | 5.168 | 5.322 | 7.234 | 0.714 | 27.421 | -9.683 | -2.733 | 4.139 | 11.145 | 1965-07-30 | 666 |
| IdioRisk | Trading frictions | 6.260 | 2.660 | 22.511 | 0.278 | 88.132 | -39.119 | -10.011 | 9.601 | 38.075 | 1929-07-31 | 1,098 |
| IdioVol3F | Trading frictions | 5.349 | 2.233 | 22.907 | 0.233 | 91.773 | -43.016 | -9.771 | 9.480 | 39.316 | 1929-07-31 | 1,098 |
| IdioVolAHT | Trading frictions | 2.134 | 0.857 | 23.831 | 0.090 | 96.593 | -43.551 | -11.273 | 9.862 | 35.077 | 1929-07-31 | 1,098 |
| IdioVolCAPM | Trading frictions | 1.057 | 0.373 | 27.100 | 0.039 | 99.137 | -26.001 | -9.600 | 11.392 | 82.801 | 1929-07-31 | 1,098 |
| IdioVolQF | Trading frictions | -3.189 | -0.980 | 23.695 | -0.135 | 97.752 | -25.702 | -9.634 | 10.463 | 52.355 | 1967-02-28 | 636 |
| Illiquidity | Trading frictions | 4.309 | 3.464 | 11.897 | 0.362 | 38.768 | -11.582 | -4.826 | 6.088 | 33.749 | 1929-07-31 | 1,098 |
| IndIPO | Intangibles | 4.646 | 2.673 | 11.743 | 0.396 | 37.676 | -18.905 | -4.542 | 5.156 | 15.404 | 1975-05-30 | 548 |
| IndMom | Momentum | 4.638 | 3.974 | 11.163 | 0.415 | 57.470 | -27.742 | -3.730 | 4.725 | 25.526 | 1929-07-31 | 1,098 |
| IndRetBig | Momentum | 16.529 | 11.663 | 13.557 | 1.219 | 64.652 | -24.055 | -4.223 | 7.183 | 34.887 | 1929-07-31 | 1,098 |
| IntanBM | Value vs. growth | 2.913 | 1.705 | 12.614 | 0.231 | 44.075 | -18.729 | -4.872 | 6.138 | 24.469 | 1966-07-29 | 654 |
| IntanCFP | Value vs. growth | 3.585 | 2.499 | 11.567 | 0.310 | 44.670 | -27.887 | -4.267 | 5.622 | 24.293 | 1956-01-31 | 780 |
| IntanEP | Value vs. growth | 3.242 | 2.781 | 9.365 | 0.346 | 40.047 | -13.871 | -3.601 | 4.412 | 16.625 | 1956-07-31 | 774 |
| IntanSP | Value vs. growth | 4.624 | 2.589 | 14.347 | 0.322 | 62.892 | -13.204 | -5.376 | 6.803 | 23.346 | 1956-07-31 | 774 |
| IntMom | Momentum | 13.308 | 5.545 | 22.958 | 0.580 | 88.552 | -83.162 | -8.599 | 10.886 | 20.057 | 1929-07-31 | 1,098 |
| IntrinsicValue | Other | 3.068 | 1.372 | 14.915 | 0.206 | 60.048 | -24.942 | -5.703 | 6.730 | 17.221 | 1976-07-30 | 534 |
| Investment | Investment | 2.108 | 1.918 | 9.030 | 0.233 | 54.311 | -12.673 | -3.677 | 4.048 | 26.882 | 1953-07-31 | 810 |
| InvestPPEInv | Investment | 6.598 | 8.666 | 6.324 | 1.043 | 28.493 | -7.032 | -2.053 | 3.457 | 13.252 | 1952-01-31 | 828 |
| InvGrowth | Investment | 7.771 | 7.191 | 8.945 | 0.869 | 34.881 | -8.768 | -3.457 | 4.663 | 16.469 | 1952-07-31 | 822 |
| IO_ShortInterest | Other | 34.320 | 4.803 | 45.799 | 0.749 | 70.314 | -58.515 | -17.895 | 24.400 | 46.499 | 1979-11-30 | 493 |
| iomom_cust | Momentum | 7.264 | 3.175 | 13.518 | 0.537 | 44.183 | -33.240 | -4.821 | 6.553 | 15.782 | 1986-02-28 | 419 |
| iomom_supp | Momentum | 7.028 | 2.953 | 14.044 | 0.500 | 39.746 | -22.748 | -5.279 | 6.547 | 20.423 | 1986-02-28 | 418 |
| KZ | Intangibles | 0.843 | 0.618 | 10.444 | 0.081 | 63.554 | -17.243 | -4.576 | 4.615 | 13.567 | 1962-07-31 | 702 |
| KZ_q | Intangibles | -9.538 | -3.017 | 20.075 | -0.475 | 99.661 | -36.364 | -6.295 | 4.441 | 68.723 | 1972-04-28 | 484 |
| LaborforceEfficiency | Other | -0.013 | -0.025 | 4.346 | -0.003 | 44.112 | -5.156 | -2.043 | 2.087 | 5.006 | 1952-07-31 | 822 |
| Leverage | Profitability | 3.853 | 2.299 | 13.969 | 0.276 | 75.307 | -33.085 | -4.922 | 7.008 | 20.942 | 1951-07-31 | 834 |
| Leverage_q | Profitability | 5.283 | 2.342 | 16.651 | 0.317 | 77.886 | -41.682 | -5.998 | 7.953 | 17.376 | 1966-07-29 | 654 |
| LRreversal | Other | 7.929 | 3.658 | 20.733 | 0.382 | 67.396 | -22.419 | -5.603 | 7.674 | 75.696 | 1929-07-31 | 1,098 |
| MaxRet | Trading frictions | 7.166 | 2.682 | 25.561 | 0.280 | 84.963 | -45.188 | -10.793 | 11.013 | 48.034 | 1929-07-31 | 1,098 |
| MeanRankRevGrowth | Value vs. growth | 2.700 | 3.063 | 7.026 | 0.384 | 33.692 | -7.794 | -2.818 | 3.491 | 9.186 | 1957-07-31 | 762 |
| Mom12m | Momentum | 9.296 | 3.130 | 28.413 | 0.327 | 99.532 | -88.699 | -11.678 | 10.508 | 29.484 | 1929-07-31 | 1,098 |
| Mom12mOffSeason | Other | 9.507 | 3.443 | 26.415 | 0.360 | 97.148 | -87.633 | -10.624 | 9.943 | 29.996 | 1929-07-31 | 1,098 |
| Mom6m | Momentum | 6.282 | 2.288 | 26.267 | 0.239 | 99.264 | -77.393 | -9.823 | 8.814 | 32.091 | 1929-07-31 | 1,098 |
| Mom6mJunk | Momentum | 11.686 | 3.346 | 21.627 | 0.540 | 53.689 | -36.607 | -7.183 | 8.839 | 42.169 | 1978-12-29 | 460 |
| MomOffSeason | Other | 11.535 | 5.470 | 20.173 | 0.572 | 63.137 | -14.896 | -5.955 | 9.224 | 59.863 | 1929-07-31 | 1,098 |
| MomOffSeason06YrPlus | Other | 7.854 | 6.034 | 12.286 | 0.639 | 43.147 | -31.543 | -3.781 | 5.546 | 41.583 | 1931-12-31 | 1,069 |
| MomOffSeason11YrPlus | Other | 3.205 | 2.773 | 10.598 | 0.302 | 27.372 | -9.702 | -3.796 | 4.190 | 51.967 | 1936-12-31 | 1,009 |
| MomOffSeason16YrPlus | Other | 3.553 | 3.358 | 9.290 | 0.382 | 40.307 | -9.647 | -3.904 | 4.107 | 22.418 | 1943-12-31 | 925 |
| MomRev | Momentum | 7.454 | 3.507 | 20.322 | 0.367 | 95.380 | -60.502 | -7.601 | 8.663 | 35.977 | 1929-07-31 | 1,097 |

Table A.2 – cont.

| Acronym | Economic category | R | t(R) | SD | SR | maxDD | Min | 5% | 95% | Max | Start | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MomSeason | Other | 9.173 | 6.861 | 12.789 | 0.717 | 58.009 | -27.835 | -4.105 | 6.268 | 24.178 | 1929-07-31 | 1,098 |
| MomSeason06YrPlus | Other | 8.014 | 7.009 | 10.786 | 0.743 | 39.311 | -21.163 | -3.203 | 5.274 | 32.475 | 1932-01-30 | 1,068 |
| MomSeason11YrPlus | Other | 6.435 | 7.117 | 8.287 | 0.777 | 23.154 | -18.298 | -2.924 | 4.337 | 12.701 | 1937-01-30 | 1,008 |
| MomSeason16YrPlus | Other | 6.026 | 6.577 | 8.144 | 0.740 | 16.833 | -8.477 | -2.890 | 3.969 | 17.795 | 1942-01-31 | 948 |
| MomSeasonShort | Other | 10.980 | 6.629 | 15.844 | 0.693 | 76.656 | -54.927 | -5.166 | 6.675 | 43.246 | 1929-07-31 | 1,098 |
| MomVol | Momentum | 10.757 | 3.481 | 29.560 | 0.364 | 99.313 | -68.026 | -11.043 | 11.546 | 37.009 | 1929-07-31 | 1,098 |
| MRreversal | Other | 4.992 | 3.137 | 15.222 | 0.328 | 67.114 | -13.021 | -4.228 | 5.373 | 61.602 | 1929-07-31 | 1,098 |
| MS | Other | 12.290 | 5.003 | 16.464 | 0.746 | 32.814 | -19.743 | -4.647 | 7.197 | 65.859 | 1974-09-30 | 539 |
| nanalyst | Other | -0.634 | -0.483 | 8.795 | -0.072 | 58.317 | -14.030 | -4.092 | 3.846 | 10.109 | 1976-02-27 | 539 |
| NetDebtFinance | Investment | 7.729 | 8.854 | 6.079 | 1.271 | 15.284 | -4.989 | -2.139 | 3.568 | 8.317 | 1972-07-31 | 582 |
| NetDebtPrice | Value vs. growth | 6.727 | 4.133 | 12.343 | 0.545 | 35.617 | -15.666 | -4.773 | 5.217 | 21.375 | 1963-07-31 | 690 |
| NetDebtPrice_q | Value vs. growth | -9.010 | -4.434 | 14.371 | -0.627 | 99.695 | -21.181 | -6.650 | 4.800 | 23.187 | 1970-11-30 | 600 |
| NetEquityFinance | Investment | 10.836 | 5.378 | 14.033 | 0.772 | 53.302 | -26.395 | -5.692 | 6.355 | 18.058 | 1972-07-31 | 582 |
| NetPayoutYield | Value vs. growth | 7.672 | 4.332 | 14.551 | 0.527 | 59.081 | -23.302 | -5.789 | 7.424 | 17.538 | 1953-07-31 | 810 |
| NetPayoutYield_q | Value vs. growth | 5.264 | 2.148 | 18.053 | 0.292 | 64.716 | -30.815 | -7.553 | 8.439 | 36.091 | 1966-10-31 | 651 |
| NOA | Investment | 10.314 | 7.101 | 11.062 | 0.932 | 40.426 | -12.749 | -3.967 | 5.737 | 27.470 | 1963-01-31 | 696 |
| NumEarnIncrease | Momentum | 5.225 | 9.206 | 4.286 | 1.219 | 19.702 | -6.137 | -1.620 | 2.415 | 5.178 | 1964-01-31 | 684 |
| OperProf | Profitability | 4.876 | 3.143 | 11.765 | 0.414 | 54.613 | -25.482 | -4.121 | 4.563 | 19.835 | 1963-07-31 | 690 |
| OperProfLag | Profitability | 2.222 | 1.491 | 11.251 | 0.197 | 55.295 | -27.828 | -4.454 | 4.514 | 19.342 | 1964-01-31 | 684 |
| OperProfLag_q | Profitability | 6.731 | 3.001 | 16.404 | 0.410 | 68.712 | -39.694 | -6.718 | 6.686 | 18.946 | 1967-04-28 | 642 |
| OperProfRD | Profitability | 4.599 | 2.311 | 15.091 | 0.305 | 66.236 | -14.319 | -6.737 | 7.788 | 17.573 | 1963-07-31 | 690 |
| OperProfRDLagAT | Profitability | 1.189 | 0.756 | 13.065 | 0.091 | 72.754 | -28.402 | -6.199 | 4.781 | 12.783 | 1952-01-31 | 828 |
| OperProfRDLagAT_q | Profitability | 10.990 | 4.371 | 17.601 | 0.624 | 67.867 | -45.839 | -7.098 | 7.137 | 19.732 | 1972-01-31 | 588 |
| OPLeverage | Intangibles | 4.744 | 3.818 | 10.357 | 0.458 | 39.750 | -12.354 | -4.142 | 5.035 | 20.604 | 1951-07-31 | 834 |
| OPLeverage_q | Intangibles | 5.831 | 3.274 | 13.118 | 0.445 | 42.393 | -15.361 | -5.231 | 6.544 | 21.029 | 1966-07-29 | 651 |
| OptionVolume1 | Trading frictions | 5.240 | 2.021 | 12.920 | 0.406 | 55.349 | -23.404 | -4.069 | 5.505 | 19.543 | 1996-03-29 | 298 |
| OptionVolume2 | Trading frictions | 3.847 | 1.754 | 10.913 | 0.353 | 24.647 | -9.058 | -2.761 | 2.686 | 36.023 | 1996-04-30 | 297 |
| OrderBacklog | Intangibles | 0.715 | 0.601 | 8.369 | 0.085 | 53.035 | -9.697 | -3.716 | 3.514 | 15.790 | 1971-07-30 | 594 |
| OrderBacklogChg | Investment | 4.194 | 2.567 | 11.378 | 0.369 | 44.392 | -18.400 | -4.450 | 5.326 | 13.777 | 1972-07-31 | 582 |
| OrgCap | Intangibles | 4.573 | 4.160 | 9.165 | 0.499 | 33.984 | -10.615 | -3.832 | 4.604 | 11.703 | 1951-07-31 | 834 |
| OrgCapNoAdj | Intangibles | 7.670 | 4.989 | 12.818 | 0.598 | 48.007 | -17.128 | -4.183 | 6.163 | 33.081 | 1951-07-31 | 834 |
| OScore | Profitability | 8.459 | 3.276 | 18.076 | 0.468 | 65.410 | -42.947 | -7.634 | 8.330 | 20.511 | 1972-01-31 | 588 |
| OScore_q | Profitability | -10.965 | -3.899 | 17.106 | -0.641 | 99.422 | -13.951 | -7.450 | 8.042 | 22.967 | 1984-01-31 | 444 |
| PatentsRD | Other | 2.957 | 2.921 | 5.637 | 0.525 | 20.997 | -4.651 | -2.093 | 2.581 | 10.977 | 1977-07-29 | 372 |
| PayoutYield | Value vs. growth | 2.535 | 2.044 | 10.188 | 0.249 | 55.369 | -9.169 | -4.373 | 5.087 | 16.252 | 1953-07-31 | 810 |
| PayoutYield_q | Value vs. growth | 5.439 | 4.427 | 9.049 | 0.601 | 30.056 | -13.113 | -3.384 | 4.117 | 16.620 | 1966-10-31 | 651 |
| pchcurrat | Investment | 0.109 | 0.192 | 4.697 | 0.023 | 59.192 | -11.203 | -2.183 | 1.840 | 3.711 | 1952-07-31 | 822 |
| pchdepr | Investment | 1.918 | 3.133 | 5.087 | 0.377 | 23.974 | -5.578 | -1.833 | 2.331 | 11.422 | 1952-01-31 | 828 |
| pchgm_pchsale | Other | 2.654 | 4.191 | 5.260 | 0.505 | 17.225 | -7.684 | -2.483 | 2.545 | 4.860 | 1952-01-31 | 828 |
| pchquick | Investment | 1.021 | 1.752 | 4.825 | 0.212 | 56.445 | -11.420 | -2.143 | 2.045 | 3.456 | 1952-07-31 | 822 |
| pchsaleinv | Other | 4.176 | 7.785 | 4.456 | 0.937 | 32.391 | -3.709 | -1.716 | 2.496 | 5.249 | 1952-01-31 | 828 |
| PctAcc | Investment | 4.770 | 4.612 | 7.773 | 0.614 | 22.690 | -8.329 | -2.878 | 4.172 | 12.633 | 1964-07-31 | 678 |
| PctTotAcc | Investment | 3.848 | 4.090 | 5.364 | 0.717 | 20.510 | -7.088 | -1.952 | 2.906 | 5.433 | 1988-07-29 | 390 |
| PM | Profitability | -0.338 | -0.264 | 10.657 | -0.032 | 77.029 | -22.804 | -4.291 | 4.816 | 16.950 | 1951-07-31 | 834 |
| PM_q | Profitability | 7.025 | 2.947 | 18.363 | 0.383 | 66.098 | -47.176 | -8.132 | 7.529 | 20.543 | 1961-09-29 | 712 |
| PredictedFE | Intangibles | 0.009 | 0.004 | 13.560 | 0.001 | 71.065 | -21.731 | -6.157 | 6.248 | 13.841 | 1983-07-29 | 450 |
| Price | Other | 9.713 | 3.106 | 29.918 | 0.325 | 79.409 | -24.709 | -8.140 | 13.004 | 100.833 | 1929-07-31 | 1,098 |
| PriceDelayRsq | Trading frictions | 6.438 | 3.466 | 17.737 | 0.363 | 43.594 | -31.971 | -5.739 | 7.316 | 64.449 | 1929-07-31 | 1,094 |
| PriceDelaySlope | Trading frictions | 2.634 | 2.641 | 9.524 | 0.277 | 25.608 | -11.884 | -3.776 | 4.096 | 29.902 | 1929-07-31 | 1,094 |
| PriceDelayTstat | Trading frictions | 0.464 | 0.588 | 7.526 | 0.062 | 60.189 | -15.351 | -3.374 | 3.116 | 17.205 | 1929-07-31 | 1,094 |
| ProbInformedTrading | Trading frictions | 16.034 | 4.325 | 16.159 | 0.992 | 27.940 | -25.799 | -5.687 | 7.995 | 15.767 | 1984-02-29 | 228 |
| PS | Other | 9.520 | 2.824 | 23.601 | 0.403 | 61.673 | -37.699 | -8.800 | 10.718 | 38.949 | 1972-01-31 | 588 |
| PS_q | Other | 10.286 | 5.751 | 10.880 | 0.945 | 47.416 | -13.940 | -4.492 | 5.216 | 12.435 | 1984-01-31 | 444 |
| quick | Investment | 2.651 | 2.137 | 10.377 | 0.255 | 61.508 | -17.187 | -4.158 | 4.341 | 29.082 | 1951-01-31 | 840 |
| RD | Profitability | 10.822 | 5.567 | 16.206 | 0.668 | 45.119 | -15.353 | -5.082 | 8.037 | 50.778 | 1951-07-31 | 834 |
| RD_q | Profitability | 17.385 | 4.260 | 23.083 | 0.753 | 36.337 | -14.516 | -6.727 | 12.271 | 45.744 | 1989-01-31 | 384 |
| rd_sale | Other | 2.112 | 0.923 | 18.933 | 0.112 | 85.143 | -18.465 | -7.065 | 7.436 | 61.738 | 1952-07-31 | 822 |
| rd_sale_q | Other | 2.777 | 0.672 | 23.002 | 0.121 | 85.224 | -17.849 | -8.758 | 9.696 | 58.856 | 1990-01-31 | 372 |
| RDAbility | Other | 0.127 | 0.079 | 12.805 | 0.010 | 73.118 | -12.956 | -6.043 | 6.068 | 14.978 | 1957-07-31 | 762 |
| RDcap | Intangibles | 5.563 | 2.954 | 11.985 | 0.464 | 39.292 | -9.083 | -4.353 | 6.098 | 20.935 | 1980-07-31 | 486 |
| RDIPO | Intangibles | 7.986 | 3.291 | 16.034 | 0.498 | 54.932 | -26.903 | -6 | 7.171 | 19.231 | 1977-01-31 | 524 |
| RDS | Intangibles | 3.099 | 2.550 | 8.377 | 0.370 | 29.631 | -14.937 | -2.957 | 4.063 | 11.682 | 1973-07-31 | 570 |
| realestate | Intangibles | 3.246 | 2.257 | 10.221 | 0.318 | 36.575 | -15.268 | -4.227 | 4.959 | 11.786 | 1970-07-31 | 606 |
| ResidualMomentum | Momentum | 10.279 | 8.113 | 12.058 | 0.852 | 43.496 | -29.360 | -4.184 | 5.683 | 17.812 | 1930-06-30 | 1,087 |
| ResidualMomentum6m | Momentum | 4.250 | 4.001 | 10.132 | 0.419 | 37.327 | -23.253 | -4.004 | 4.079 | 13.009 | 1930-01-31 | 1,092 |
| retConglomerate | Momentum | 13.997 | 6.753 | 13.433 | 1.042 | 24.048 | -16.426 | -4.368 | 8.037 | 21.581 | 1976-02-27 | 504 |
| RetNOA | Profitability | 0.141 | 0.152 | 7.065 | 0.020 | 47.799 | -10.833 | -2.981 | 2.833 | 17.562 | 1963-07-31 | 690 |
| RetNOA_q | Profitability | 6.997 | 3.255 | 16.123 | 0.434 | 63.183 | -36.101 | -6.855 | 7.057 | 18.418 | 1964-10-30 | 675 |
| ReturnSkew | Trading frictions | 5.820 | 7.715 | 7.216 | 0.806 | 31.453 | -18.157 | -2.099 | 3.169 | 12.179 | 1929-07-31 | 1,098 |
| ReturnSkew3F | Trading frictions | 4.550 | 7.829 | 5.559 | 0.818 | 26.474 | -13.135 | -1.583 | 2.654 | 10.253 | 1929-07-31 | 1,098 |
| ReturnSkewCAPM | Trading frictions | -4.921 | -7.048 | 6.679 | -0.737 | 99.217 | -11.281 | -2.843 | 1.844 | 21.234 | 1929-07-31 | 1,098 |
| ReturnSkewQF | Trading frictions | -2.863 | -4.357 | 4.784 | -0.598 | 80.491 | -8.962 | -2.293 | 1.520 | 10.119 | 1967-02-28 | 636 |
| REV6 | Momentum | 9.534 | 4.131 | 15.368 | 0.620 | 64.114 | -34.365 | -6.128 | 6.317 | 14.066 | 1976-09-30 | 532 |
| RevenueSurprise | Momentum | 7.233 | 8.584 | 6.394 | 1.131 | 18.352 | -12.137 | -1.746 | 2.927 | 14.765 | 1963-06-28 | 691 |
| RIO_Disp | Other | 7.766 | 3.534 | 14.688 | 0.529 | 52.278 | -16.378 | -5.047 | 7.493 | 25.716 | 1976-02-27 | 536 |
| RIO_MB | Other | 8.370 | 4.166 | 15.259 | 0.549 | 70.199 | -19.430 | -5.652 | 7.779 | 26.724 | 1963-01-31 | 692 |
| RIO_Turnover | Other | 4.433 | 2.829 | 14.976 | 0.296 | 64.628 | -20.468 | -6.611 | 7.251 | 18.778 | 1929-07-31 | 1,096 |
| RIO_Volatility | Other | 6.540 | 3.507 | 17.813 | 0.367 | 73.855 | -21.933 | -7.098 | 8.195 | 50.584 | 1929-07-31 | 1,095 |
| roaq | Profitability | 13.804 | 5.206 | 19.575 | 0.705 | 66.879 | -33.620 | -7.489 | 8.434 | 42.393 | 1966-07-29 | 654 |
| roavol | Other | 0.892 | 0.311 | 20.792 | 0.043 | 86.569 | -21.953 | -8.471 | 7.880 | 39.757 | 1968-06-28 | 631 |
| RoE | Profitability | 2.745 | 2.319 | 9.130 | 0.301 | 48.518 | -22.086 | -3.388 | 4.249 | 14.631 | 1961-07-31 | 714 |
| roic | Profitability | 0.333 | 0.161 | 15.832 | 0.021 | 75.953 | -36.024 | -7.025 | 5.713 | 18.188 | 1962-07-31 | 702 |
| salecash | Other | 0.828 | 0.710 | 9.756 | 0.085 | 63.509 | -25.100 | -4.047 | 3.899 | 14.508 | 1951-01-31 | 840 |
| saleinv | Other | 2.481 | 2.989 | 6.943 | 0.357 | 28.359 | -11.825 | -3.104 | 3.137 | 6.522 | 1951-01-31 | 840 |
| salerec | Other | 2.156 | 2.573 | 7.012 | 0.308 | 44.771 | -6.142 | -2.974 | 3.257 | 11.471 | 1951-01-31 | 840 |
| secured | Intangibles | -0.789 | -0.859 | 5.702 | -0.138 | 47.464 | -7.671 | -2.361 | 2.406 | 7.322 | 1982-07-30 | 462 |
| securedind | Intangibles | -0.052 | -0.054 | 6.096 | -0.009 | 51.711 | -7.257 | -2.212 | 2.146 | 13.593 | 1981-01-30 | 480 |
| sfe | Value vs. growth | 5.529 | 1.714 | 21.573 | 0.256 | 88.500 | -54.648 | -8.490 | 9.102 | 21.883 | 1976-04-30 | 537 |
| sgr | Other | -5.431 | -5.847 | 7.716 | -0.704 | 98.533 | -14.800 | -4.258 | 2.937 | 7.272 | 1952-01-31 | 828 |
| sgr_q | Other | 4.117 | 3.150 | 9.980 | 0.412 | 36.258 | -20.083 | -4.513 | 4.033 | 12.006 | 1962-09-28 | 700 |
| ShareIss1Y | Investment | 5.085 | 6.228 | 7.810 | 0.651 | 25.524 | -13.625 | -2.875 | 4.232 | 10.950 | 1929-07-31 | 1,098 |
| ShareIss5Y | Investment | 4.669 | 5.268 | 8.384 | 0.557 | 29.015 | -8.052 | -2.899 | 3.897 | 30.070 | 1931-07-31 | 1,074 |
| ShareRepurchase | Investment | 2.014 | 2.575 | 5.446 | 0.370 | 24.889 | -8.318 | -2.276 | 2.471 | 5.631 | 1972-07-31 | 582 |
| ShareVol | Trading frictions | 5.502 | 3.197 | 16.395 | 0.336 | 77.968 | -29.050 | -7.302 | 7.471 | 28.075 | 1929-07-31 | 1,089 |
| ShortInterest | Trading frictions | 9.553 | 5.975 | 11.068 | 0.863 | 20.305 | -15.606 | -4.439 | 5.620 | 16.318 | 1973-02-28 | 575 |
| sinAlgo | Other | 3.408 | 2.550 | 11.166 | 0.305 | 56.200 | -15.830 | -4.584 | 5.083 | 35.224 | 1951-03-31 | 838 |
| Size | Other | 4.623 | 3.187 | 13.875 | 0.333 | 52.279 | -10.973 | -4.258 | 5.973 | 53.260 | 1929-07-31 | 1,098 |
| skew1 | Trading frictions | 5.853 | 4.086 | 7.151 | 0.818 | 18.390 | -9.273 | -2.320 | 3.658 | 7.431 | 1996-02-29 | 299 |
| SmileSlope | Trading frictions | 14.699 | 10.479 | 7.001 | 2.099 | 4.775 | -4.653 | -1.220 | 4.196 | 15.482 | 1996-02-29 | 299 |
| SP | Value vs. growth | 8.269 | 5.123 | 13.457 | 0.615 | 58.840 | -25.006 | -4.670 | 6.493 | 20.620 | 1951-07-31 | 834 |
| SP_q | Value vs. growth | 12.761 | 6.168 | 15.935 | 0.801 | 66.272 | -36.687 | -4.668 | 7.546 | 30.010 | 1961-09-29 | 712 |
| Spinoff | Other | 3.423 | 2.290 | 14.297 | 0.239 | 62.055 | -20.934 | -4.777 | 5.280 | 54.375 | 1929-07-31 | 1,098 |
| std_turn | Trading frictions | 5.982 | 2.895 | 19.769 | 0.303 | 80.934 | -45.882 | -8.529 | 8.966 | 25.169 | 1929-07-31 | 1,098 |

Table A.2 – cont.

| Acronym | Economic category | R | t(R) | SD | SR | maxDD | Min | 5% | 95% | Max | Start | N |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| STreversal | Other | 35.560 | 13.989 | 24.316 | 1.462 | 50.364 | -36.964 | -4.485 | 14.123 | 79.534 | 1929-07-31 | 1,098 |
| SurpriseRD | Intangibles | 1.044 | 1.412 | 6.136 | 0.170 | 49.918 | -10.417 | -2.360 | 2.650 | 16.462 | 1952-03-31 | 826 |
| tang | Intangibles | 4.304 | 3.219 | 11.188 | 0.385 | 37.320 | -12.065 | -4.163 | 4.874 | 38.744 | 1951-01-31 | 840 |
| tang_q | Intangibles | 6.218 | 4.622 | 9.497 | 0.655 | 52.453 | -9.233 | -3.559 | 4.753 | 27.608 | 1971-03-31 | 598 |
| Tax | Profitability | 4.278 | 5.236 | 6.812 | 0.628 | 34.392 | -16.421 | -2.321 | 3.227 | 11.110 | 1951-07-31 | 834 |
| Tax_q | Profitability | 0.871 | 0.908 | 7.389 | 0.118 | 65.873 | -11.265 | -2.793 | 2.401 | 32.551 | 1961-09-29 | 712 |
| TotalAccruals | Investment | 3.551 | 3.563 | 8.247 | 0.431 | 43.768 | -7.858 | -2.547 | 3.703 | 16.382 | 1952-07-31 | 822 |
| UpRecomm | Intangibles | 4.039 | 5.409 | 3.886 | 1.039 | 8.024 | -6.836 | -1.074 | 2.110 | 4.534 | 1993-12-31 | 325 |
| VarCF | Other | -5.451 | -2.710 | 16.525 | -0.330 | 99.479 | -30.941 | -7.825 | 6.407 | 14.029 | 1953-07-31 | 810 |
| VolMkt | Trading frictions | 3.405 | 1.807 | 18.030 | 0.189 | 80.691 | -31.954 | -7.799 | 8.763 | 21.094 | 1929-07-31 | 1,098 |
| VolSD | Trading frictions | 3.475 | 2.355 | 14.113 | 0.246 | 39.969 | -31.742 | -5.457 | 6.035 | 43.474 | 1929-07-31 | 1,098 |
| VolumeTrend | Other | 6.864 | 5.387 | 12.188 | 0.563 | 29.105 | -25.261 | -3.691 | 5.264 | 45.626 | 1929-07-31 | 1,098 |
| WW | Other | 3.510 | 2.124 | 13.726 | 0.256 | 61.703 | -16.077 | -4.858 | 6.290 | 31.135 | 1952-01-31 | 828 |
| WW_Q | Other | 4.345 | 1.460 | 21.063 | 0.206 | 77.356 | -21.674 | -7.394 | 10.386 | 42.262 | 1970-11-30 | 601 |
| XFIN | Investment | 11.679 | 4.836 | 16.817 | 0.694 | 61.192 | -36.495 | -5.990 | 8.208 | 24.596 | 1972-07-31 | 582 |
| zerotrade | Trading frictions | 6.432 | 3.305 | 18.614 | 0.346 | 46.739 | -27.052 | -7.200 | 7.963 | 67.172 | 1929-07-31 | 1,098 |
| zerotradeAlt1 | Trading frictions | 6.741 | 3.638 | 17.724 | 0.380 | 56.420 | -27.511 | -6.513 | 8.349 | 54.367 | 1929-07-31 | 1,098 |
| zerotradeAlt12 | Trading frictions | 5.162 | 3.390 | 14.564 | 0.354 | 46.510 | -21.010 | -5.145 | 6.463 | 58.400 | 1929-07-31 | 1,098 |
| ZScore | Profitability | -0.120 | -0.055 | 16.524 | -0.007 | 90.674 | -19.919 | -6.548 | 7.211 | 32.341 | 1963-01-31 | 696 |
| ZScore_q | Profitability | -3.014 | -1.176 | 17.989 | -0.168 | 95.687 | -29.248 | -8.667 | 6.516 | 21.465 | 1971-10-29 | 591 |

This table shows descriptive statistics for raw anomaly returns. Panel A shows average statistics for each economic category. Panel B displays individual anomaly statistics. The columns show the acronym, the economic category, the mean return, t-stat of that return, standard deviation, Sharpe ratio, maximum Drawdown, minimum and maximum return, 5 and 95 percentile return, the start of the sample and the number of observations, respectively. Table A.1 gives a brief description of the firm characteristics

# B Timing signals

This section describes the details of our timing signals. For each factor $i$, timing signal $j$ and time $t$ we determine a scaling factor $w_{i,t}^{j}$. The timed factor returns are obtained in the subsequent period as $f_{i,t+1}^{j} = f_{i,t+1} \cdot w_{i,t}^{j}$. Table B.1 provides detailed information about each timing signal. The columns show the acronym, the trading signal class, the original study, the corresponding journal, the original signals' definition and the definition of the scaling factor $w_{i,t}^{j}$ applied in our paper, respectively.

Table B.1: Summary of timing signals

| Acronym | Category | Related literature | Implementation in our paper |
|---|---|---|---|
| MOM1 | Momentum | Gupta and Kelly (2019) | Annualized momentum return from t-1 to t scaled by annualized past return volatility over 3Y, capped at ±2. |
| MOM2 | Momentum | Gupta and Kelly (2019) | Annualized momentum return from t-3 to t scaled by annualized past return volatility over 3Y, capped at ±2. |
| MOM3 | Momentum | Gupta and Kelly (2019) | Annualized momentum return from t-6 to t scaled by annualized past return volatility over 3Y, capped at ±2. |
| MOM4 | Momentum | Gupta and Kelly (2019) | Annualized momentum return from t-12 to t scaled by annualized past return volatility over 10Y, capped at ±2. |
| MOM5 | Momentum | Gupta and Kelly (2019) | Annualized momentum return from t-36 to t scaled by annualized past return volatility over 10Y, capped at ±2. |
| MOM6 | Momentum | Gupta and Kelly (2019) | Annualized momentum return from t-60 to t scaled by annualized past return volatility 10Y, capped at ±2. |
| MOM7 | Momentum | Gupta and Kelly (2019) | Annualized momentum return from t-12 to t-1 scaled by annualized past return volatility over 10Y, capped at ±2. |
| MOM8 | Momentum | Gupta and Kelly (2019) | Annualized momentum return from t-60 to t-12 scaled by annualized past return volatility 10Y, capped at ±2. |
| MOM9 | Momentum | Ehsani, Linnainmaa (2019) | Sign of return from $t-1$ to $t$. |
| MOM10 | Momentum | Ehsani, Linnainmaa (2019) | Sign of return from $t-3$ to $t$. |
| MOM11 | Momentum | Ehsani, Linnainmaa (2019) | Sign of return from $t-6$ to $t$. |
| MOM12 | Momentum | Ehsani, Linnainmaa (2019) | Sign of return from $t-12$ to $t$. |
| VOL1 | Volatility | Moreira and Muir (2017) | Inverse of the variance of daily returns measured in month $t-1$, scaled by the average of all monthly variances of daily returns (using the entire sample). |
| VOL2 | Volatility | Moreira and Muir (2017) | Inverse of the standard deviation of daily returns measured in month $t-1$, scaled by the average of all monthly standard deviations of daily returns (using the entire sample). |
| VOL3 | Volatility | Moreira and Muir (2017) | Inverse of the variance of daily returns measured in month $t-1$, estimated from an AR(1) process for log variance, scaled by the average of all monthly variances of daily returns (using the entire sample). |
| VOL4 | Volatility | Cederburg, O'Doherty, Wang, Yan (2020) | Inverse of the realized variance of daily returns measured in month $t-1$, multiplied by 22 divided by the number of trading days in the month, scaled by the average of all monthly variances of daily returns (using the entire sample). |
| VOL5 | Volatility | DeMiguel, Utrera and Uppal (2021) | Inverse of the annualized standard deviation of daily market returns measured in month $t-1$. |
| VOL6 | Volatility | Reschenhofer and Zechner (2021) | Level of implied volatility (CBOE VIX index) in t-1 is used to scale factor in t. |
| VOL7 | Volatility | Reschenhofer and Zechner (2021) | Level of implied skewness (CBOE SKEW index) in t-1 is used to scale factor in t. |
| REV1 | Reversal | Moskowitz, Ooi, and Pedersen (2012) | 1 minus annualized net return from $t-60$ to $t$. |
| REV2 | Reversal | Moskowitz, Ooi, and Pedersen (2012) | 1 minus annualized net return from $t-120$ to $t$. |
| TSMOM1 | Momentum | Moskowitz, Ooi, and Pedersen (2012) | Sign of return from t-1 to t, multiplied by 40% divided by ex-ante volatility, where ex-ante volatility is the square root of exponentially weighted moving average of squared daily returns. |
| TSMOM2 | Momentum | Moskowitz, Ooi, and Pedersen (2012) | Sign of return from t-3 to t, multiplied by 40% divided by ex-ante volatility, where ex-ante volatility is the square root of exponentially weighted moving average of squared daily returns. |
| TSMOM3 | Momentum | Moskowitz, Ooi, and Pedersen (2012) | Sign of return from t-6 to t, multiplied by 40% divided by ex-ante volatility, where ex-ante volatility is the square root of exponentially weighted moving average of squared daily returns. |
| TSMOM4 | Momentum | Moskowitz, Ooi, and Pedersen (2012) | Sign of return from t-12 to t, multiplied by 40% divided by ex-ante volatility, where ex-ante volatility is the square root of exponentially weighted moving average of squared daily returns. |
| VAL1 | Valuation | Campbell and Shiller (1988), Cohen, Polk, and Vuolteenaho (2003), Haddad, Kozak, and Santosh (2020) | We first calculate the BTM spread as the difference of log book-to-market ratio of long minus short leg. The signal is obtained as the difference of the BTM spread at time $t$ minus the expanding mean BTM spread up to time $t-1$, scaled by the standard deviation of the difference. |

Table B.1 – cont.

| Acronym | Category | Related literature | Implementation in our paper |
|---|---|---|---|
| VAL2 | Valuation | Campbell and Shiller (1988), Cohen, Polk, and Vuolteenaho (2003), Haddad, Kozak, and Santosh (2020) | We first calculate the BTM spread as the difference of log book-to-market ratio of long minus short leg. The signal is obtained as the difference of the BTM spread at time $t$ minus the 5 year rolling mean BTM spread up to time $t-1$, scaled by the standard deviation of the difference. |
| VAL3 | Valuation | Campbell and Shiller (1988), Cohen, Polk, and Vuolteenaho (2003), Haddad, Kozak, and Santosh (2020) | We first calculate the BTM spread as the difference of log book-to-market ratio of long minus short leg using the book-value of December of last year. The signal is obtained as the difference of the BTM spread at time $t$ minus the expanding mean BTM spread up to time $t-1$, scaled by the standard deviation of the difference. |
| VAL4 | Valuation | Campbell and Shiller (1988), Cohen, Polk, and Vuolteenaho (2003), Haddad, Kozak, and Santosh (2020) | We first calculate the BTM spread as the difference of log book-to-market ratio of long minus short leg using the book-value of December of last year. The signal is obtained as the difference of the BTM spread at time $t$ minus the 5 year rolling mean BTM spread up to time $t-1$, scaled by the standard deviation of the difference. |
| VAL5 | Valuation | Campbell and Shiller (1988), Cohen, Polk, and Vuolteenaho (2003), Haddad, Kozak, and Santosh (2020) | We first calculate the BTM spread as the difference of log book-to-market ratio of long minus short leg using quarterly book-values. The signal is obtained as the difference of the BTM spread at time $t$ minus the expanding mean BTM spread up to time $t-1$, scaled by the standard deviation of the difference. |
| VAL6 | Valuation | Campbell and Shiller (1988), Cohen, Polk, and Vuolteenaho (2003), Haddad, Kozak, and Santosh (2020) | We first calculate the BTM spread as the difference of log book-to-market ratio of long minus short leg using quarterly book-values. The signal is obtained as the difference of the BTM spread at time $t$ minus the 5 year rolling mean BTM spread up to time $t-1$, scaled by the standard deviation of the difference. |
| SPREAD1 | Characteristic spread | Huang, Liu, Ma, Osiol (2011) | Difference of characteristic of long minus short leg, then SD calculated from difference, then spread minus expanding mean scaled by standard deviation. |
| SPREAD2 | Characteristic spread | Huang, Liu, Ma, Osiol (2011) | Difference of characteristic of long minus short leg, then SD calculated from difference, then spread minus rolling mean scaled by standard deviation. |
| IPS1 | Issuer-purchaser spread | Greenwood and Hanson (2012) | Difference of the average for net equity issuers versus repurchasers (from original paper: YoY change in net stock issuance (NS) as the change in log split-adjusted shares outstanding from Compustat (CSHO × AJEX)) of long minus short leg, then SD calculated from difference, then spread minus expanding mean scaled by standard deviation. |
| IPS2 | Issuer-purchaser spread | Greenwood and Hanson (2012) | Difference of the average for net equity issuers versus repurchasers (from original paper: YoY change in net stock issuance (NS) as the change in log split-adjusted shares outstanding from Compustat (CSHO × AJEX)) of long minus short leg, then SD calculated from difference, then spread minus rolling mean scaled by standard deviation. |
| IPS3 | Issuer-purchaser spread | Pontiff and Woodgate (2008) | Difference of the average for net equity issuers versus repurchasers (Growth in number of shares between t-18 and t-6. Number of shares is calculated as shrout/cfacshr to adjust for splits from CRSP (SHROUT × CFACSHR)) of long minus short leg, then SD calculated from difference, then spread minus expanding mean scaled by standard deviation. |
| IPS4 | Issuer-purchaser spread | Pontiff and Woodgate (2008) | Difference of the average for net equity issuers versus repurchasers (Growth in number of shares between t-18 and t-6. Number of shares is calculated as shrout/cfacshr to adjust for splits.from CRSP (SHROUT × CFACSHR)) of long minus short leg, then SD calculated from difference, then spread minus rolling mean scaled by standard deviation. |
| IPS5 | Issuer-purchaser spread | Bradshaw, Richardson, Sloan (2006) | Difference of the average for net equity issuers versus repurchasers (Sale of common stock (sstk) minus purchase of common stock (prstkc), scaled by average total assets (at) from years t and t-1. Exclude if absolute value of ratio is greater than 1.) of long minus short leg, then SD calculated from difference, then spread minus expanding mean scaled by standard deviation. |
| IPS6 | Issuer-purchaser spread | Bradshaw, Richardson, Sloan (2006) | Difference of the average for net equity issuers versus repurchasers (Sale of common stock (sstk) minus purchase of common stock (prstkc), scaled by average total assets (at) from years t and t-1. Exclude if absolute value of ratio is greater than 1.) of long minus short leg, then SD calculated from difference, then spread minus rolling mean scaled by standard deviation. |

This table summarizes the timing signals used to time the long-short anomalies. The columns show the acronym, the category, a brief description, the original study, the corresponding journal, the original definition and the definition used in this paper, respectively.

# C Additional results

Table C.1: Percentage of positive and negative signals

| | Characteristic spread | | Issuer-purchaser spread | |
|---|---|---|---|---|
| A. Average $\alpha$ and $\Delta SR$ | | | | |
| | $\alpha$ | $\Delta SR$ | $\alpha$ | $\Delta SR$ |
| All factors | -1.029 [-0.291] | -0.379 [-2.076] | 1.389 [0.507] | -0.329 [-1.599] |
| Intangibles | -0.170 [-0.120] | -0.347 [-1.740] | 1.045 [0.432] | -0.324 [-1.477] |
| Investment | -0.554 [-0.438] | -0.467 [-2.549] | 0.508 [0.226] | -0.454 [-2.268] |
| Momentum | -3.680 [-0.394] | -0.792 [-4.388] | 0.864 [0.448] | -0.723 [-3.567] |
| Other | -1.199 [-0.390] | -0.348 [-1.861] | 1.642 [0.586] | -0.261 [-1.266] |
| Profitability | -0.505 [ 0.013] | -0.284 [-1.623] | 1.415 [0.649] | -0.250 [-1.255] |
| Trading frictions | -0.417 [-0.018] | -0.220 [-1.157] | 2.322 [0.492] | -0.216 [-0.945] |
| Value vs growth | -2.070 [-0.677] | -0.417 [-2.548] | 1.574 [0.704] | -0.305 [-1.590] |
| B. Percentage of positive and negative $\alpha$ | | | | |
| | + | − | + | − |
| All factors | 0.437 [0.052] | 0.563 [0.110] | 0.658 [0.120] | 0.342 [0.027] |
| Intangibles | 0.462 [0.028] | 0.538 [0.057] | 0.654 [0.091] | 0.346 [0.025] |
| Investment | 0.283 [0.054] | 0.717 [0.076] | 0.572 [0.098] | 0.428 [0.054] |
| Momentum | 0.455 [0.023] | 0.545 [0.114] | 0.591 [0.091] | 0.409 [0.000] |
| Other | 0.453 [0.040] | 0.547 [0.127] | 0.704 [0.100] | 0.296 [0.016] |
| Profitability | 0.571 [0.014] | 0.429 [0.071] | 0.657 [0.186] | 0.343 [0.033] |
| Trading frictions | 0.500 [0.109] | 0.500 [0.109] | 0.659 [0.120] | 0.341 [0.025] |
| Value vs growth | 0.354 [0.085] | 0.646 [0.220] | 0.707 [0.179] | 0.293 [0.028] |
| C. Percentage of positive and negative $\Delta SR$ | | | | |
| | + | − | + | − |
| All factors | 0.164 [0.049] | 0.836 [0.524] | 0.217 [0.057] | 0.783 [0.420] |
| Intangibles | 0.094 [0.019] | 0.906 [0.387] | 0.217 [0.028] | 0.783 [0.368] |
| Investment | 0.174 [0.120] | 0.826 [0.696] | 0.138 [0.101] | 0.862 [0.616] |
| Momentum | 0.000 [0.000] | 1.000 [0.773] | 0.045 [0.008] | 0.955 [0.727] |
| Other | 0.207 [0.033] | 0.793 [0.487] | 0.251 [0.044] | 0.749 [0.373] |
| Profitability | 0.257 [0.000] | 0.743 [0.471] | 0.276 [0.043] | 0.724 [0.352] |
| Trading frictions | 0.217 [0.087] | 0.783 [0.359] | 0.297 [0.087] | 0.703 [0.301] |
| Value vs growth | 0.110 [0.061] | 0.890 [0.671] | 0.195 [0.069] | 0.805 [0.382] |

| | Reversal | | Valuation | |
|---|---|---|---|---|
| D. Average $\alpha$ and $\Delta SR$ | | | | |
| | $\alpha$ | $\Delta SR$ | $\alpha$ | $\Delta SR$ |
| All factors | 0.005 [-0.156] | -0.005 [-0.301] | 0.825 [ 0.272] | -0.400 [-1.923] |
| Intangibles | -0.058 [-0.329] | -0.008 [-0.420] | 0.645 [ 0.200] | -0.406 [-1.808] |
| Investment | -0.014 [-0.492] | -0.004 [-0.590] | 0.230 [ 0.081] | -0.540 [-2.565] |
| Momentum | 0.014 [-0.131] | -0.012 [-0.516] | 4.102 [ 1.289] | -0.827 [-3.609] |
| Other | 0.012 [-0.044] | -0.006 [-0.212] | 0.995 [ 0.344] | -0.314 [-1.524] |
| Profitability | 0.165 [-0.057] | 0.000 [-0.283] | 1.471 [ 0.547] | -0.322 [-1.554] |
| Trading frictions | 0.049 [ 0.460] | 0.003 [ 0.432] | 1.158 [ 0.323] | -0.236 [-1.055] |
| Value vs growth | -0.091 [-0.549] | -0.012 [-0.704] | -1.267 [-0.391] | -0.414 [-2.465] |
| E. Percentage of positive and negative $\Delta SR$ | | | | |
| | + | − | + | − |
| All factors | 0.472 [0.041] | 0.528 [0.091] | 0.583 [0.083] | 0.417 [0.040] |
| Intangibles | 0.377 [0.019] | 0.623 [0.047] | 0.563 [0.063] | 0.437 [0.031] |
| Investment | 0.391 [0.033] | 0.609 [0.196] | 0.507 [0.058] | 0.493 [0.014] |
| Momentum | 0.455 [0.068] | 0.545 [0.136] | 0.780 [0.311] | 0.220 [0.000] |
| Other | 0.520 [0.033] | 0.480 [0.080] | 0.613 [0.060] | 0.387 [0.018] |
| Profitability | 0.486 [0.071] | 0.514 [0.029] | 0.695 [0.133] | 0.305 [0.024] |
| Trading frictions | 0.663 [0.076] | 0.337 [0.011] | 0.605 [0.069] | 0.395 [0.036] |
| Value vs growth | 0.378 [0.012] | 0.622 [0.171] | 0.415 [0.033] | 0.585 [0.159] |
| F. Percentage of positive and negative $\Delta SR$ | | | | |
| | + | − | + | − |
| All factors | 0.447 [0.041] | 0.553 [0.134] | 0.181 [0.044] | 0.819 [0.458] |
| Intangibles | 0.387 [0.019] | 0.613 [0.094] | 0.189 [0.013] | 0.811 [0.437] |
| Investment | 0.348 [0.022] | 0.652 [0.185] | 0.170 [0.087] | 0.830 [0.649] |
| Momentum | 0.409 [0.136] | 0.591 [0.227] | 0.023 [0.000] | 0.977 [0.667] |
| Other | 0.487 [0.020] | 0.513 [0.133] | 0.213 [0.036] | 0.787 [0.378] |
| Profitability | 0.429 [0.057] | 0.571 [0.100] | 0.176 [0.024] | 0.824 [0.405] |
| Trading frictions | 0.652 [0.054] | 0.348 [0.011] | 0.290 [0.080] | 0.710 [0.279] |
| Value vs growth | 0.366 [0.049] | 0.634 [0.244] | 0.089 [0.049] | 0.911 [0.553] |

*Caption on the following page*

This table shows timing abilities of different signals for individual factors, grouped into economic categories. The upper columns to the left and right show results for characteristic spread and issuer-purchaser spread signals, respectively. The lower columns to the left and right show results for reversal and valuation signals, respectively. Panels A and D display the average alphas of time-series regressions of a managed factor portfolio on the corresponding unconditional factor portfolio: $f^{\tau_j}_{i,t+1} = \alpha_{i,j} + \beta_{i,j} f_{i,t+1} + \epsilon_{t+1}$. We report simple averages over all untimed factors $f_i$ within an economic category and all signals $\tau_j$ of a given type. We report average t-statistics in brackets, where statistical significance is based on heteroscedasticity-adjusted standard errors. $\Delta SR$ shows the average difference in the Sharpe ratio of the timed versus original factor across factor/signal combinations. In brackets, we show the average z-statistic from the Jobson and Korkie (1981) test of the null that $\Delta\text{SR} = 0$. Panels B and E report the percentage of positive (+) and negative (−) alphas. Numbers in brackets are the percentages of positive and negative alphas, respectively, that are statistically significant at the 5% level. Panels C and F report the percentage of timed factor/signal combinations with a higher (+) and lower (−) Sharpe ratio; fractions with statistically significant changes in Sharpe ratios are given in brackets. We describe the factors and their allocation to an economic category in Table A.1. Table B.1 describes the timing signals.

Table C.2: Factor timing portfolio sorts: top and bottom 10 factors

| | Pred | R | SD | SR | t | $z_{JK}$ | maxDD | FF5+M $\alpha$ | t($\alpha$) | $R^2$ | t($\Delta$R) | $z_{JK}(\Delta$SR) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A. ORG | | | | | | | | | | | | |
| L | | -2.161 | 8.342 | -0.259 | | | | | | | | |
| H | | 14.839 | 9.064 | 1.637 | | | | | | | | |
| HML | | 17.000 | 14.912 | 1.140 | 7.829 | 7.449 | 37.977 | 14.130 | 7.593 | 35.669 | | |
| B. PLS 1 | | | | | | | | | | | | |
| L | -12.251 | -7.975 | 10.973 | -0.727 | | | | | | | | |
| H | 24.388 | 18.882 | 9.500 | 1.988 | | | | | | | | |
| HML | 36.639 | 26.857 | 18.655 | 1.440 | 9.887 | 9.885 | 47.318 | 22.067 | 8.915 | 27.262 | 4.439 | 2.199 |
| C. PLS 2 | | | | | | | | | | | | |
| L | -15.121 | -8.590 | 10.479 | -0.820 | | | | | | | | |
| H | 28.026 | 17.817 | 10.602 | 1.681 | | | | | | | | |
| HML | 43.147 | 26.407 | 19.273 | 1.370 | 9.410 | 9.125 | 48.879 | 22.829 | 8.509 | 19.943 | 3.729 | 1.523 |
| D. PLS 3 | | | | | | | | | | | | |
| L | -16.803 | -7.973 | 10.657 | -0.748 | | | | | | | | |
| H | 30.132 | 17.501 | 9.991 | 1.752 | | | | | | | | |
| HML | 46.936 | 25.474 | 18.569 | 1.372 | 9.422 | 9.274 | 47.504 | 21.688 | 8.575 | 23.347 | 3.531 | 1.570 |
| E. PLS 5 | | | | | | | | | | | | |
| L | -19.280 | -7.297 | 10.181 | -0.717 | | | | | | | | |
| H | 32.637 | 18.529 | 10.573 | 1.752 | | | | | | | | |
| HML | 51.917 | 25.826 | 18.049 | 1.431 | 9.827 | 9.477 | 41.638 | 23.528 | 9.297 | 18.782 | 3.477 | 1.821 |

This table shows performance statistics for factor timing portfolio sorts. In each month $t$, based on predicted returns for period $t+1$, we sort the top and bottom 10 factors into portfolios H and L, respectively. Further, we construct a high-minus-low (HML) portfolio. In Panel A, portfolios are constructed based on the historic average. Panels B, C, D, and E show sorts based on partial least squares (PLS) regressions with 1, 2, 3, and 5 components, respectively. We estimate parameters strictly out-of-sample on expanding windows, where only data up to time $t$ are used to predict returns from $t$ to $t+1$. We use the first half of the sample to obtain initial estimates. We report the annualized predicted return (Pred), realized return (R), standard deviation (SD), and Sharpe ratio (SR). For the HML portfolio, we display t-statistics of the mean return, the Jobson and Korkie (1981) test $z_{JK}$ of statistical significance of Sharpe ratios, the maximum drawdown maxDD, the alpha of the Fama-French five-factor model augmented by the momentum factor FF5+M$\alpha$, its t-statistic t($\alpha$), and $R^2$. The last two columns show t-statistics of the return difference between the predicted and original HML factor portfolio t($\Delta$R) as well as the test on the difference in Sharpe ratios between the predicted and original HML portfolios, $z_{JK}(\Delta$SR). We describe the factors and their allocation to an economic category in Table A.1. Table B.1 describes the timing signals.

Table C.3: Factor timing portfolio sorts: top and bottom 10 factors investments

| Acronym | Top % | Acronym | Bottom % |
|---|---|---|---|
| A. ORG | | | |
| STreversal | 99.647 | ChNCOA | 71.025 |
| IntMom | 79.859 | sgr | 58.304 |
| IndRetBig | 79.152 | AssetGrowth_q | 57.597 |
| FirmAgeMom | 60.954 | EntMult_q | 55.830 |
| Frontier | 58.481 | NetDebtPrice_q | 50.883 |
| AccrualsBM | 53.357 | ChNCOL | 47.703 |
| MomVol | 48.233 | ReturnSkewCAPM | 31.449 |
| MomSeasonShort | 34.629 | EarningsPredictability | 29.152 |
| AssetGrowth | 33.039 | KZ_q | 27.915 |
| IO_ShortInterest | 29.329 | BetaFP | 26.325 |
| B. PLS 1 | | | |
| STreversal | 79.152 | ChNCOA | 48.233 |
| IndRetBig | 53.357 | ReturnSkewCAPM | 43.993 |
| IntMom | 40.636 | BetaSquared | 40.989 |
| IO_ShortInterest | 37.102 | EntMult_q | 39.929 |
| Price | 35.689 | IdioVolCAPM | 28.269 |
| MomSeasonShort | 29.152 | VarCF | 27.739 |
| BidAskSpread | 28.092 | AssetGrowth_q | 27.208 |
| AccrualsBM | 26.325 | EarningsPredictability | 25.795 |
| MaxRet | 24.735 | NetDebtPrice_q | 25.088 |
| Frontier | 24.205 | BetaFP | 24.028 |
| C. PLS 2 | | | |
| STreversal | 72.968 | ChNCOA | 38.869 |
| IndRetBig | 43.993 | BetaSquared | 35.689 |
| IO_ShortInterest | 34.982 | EntMult_q | 33.392 |
| Price | 33.922 | ReturnSkewCAPM | 33.392 |
| IntMom | 28.975 | IdioVolCAPM | 30.212 |
| BidAskSpread | 27.915 | NetDebtPrice_q | 28.092 |
| MomOffSeason | 22.968 | BetaFP | 27.208 |
| MaxRet | 21.201 | VarCF | 24.205 |
| Frontier | 20.671 | EarningsPredictability | 23.852 |
| MomSeasonShort | 20.318 | IdioVolQF | 20.848 |

This table shows allocation statistics for factor timing portfolio sorts. We sort the top and bottom 10 factors into high and low portfolios based on their $t+1$ predicted return, respectively. Panel A shows frequencies in portfolio sorts based on the historic average. Panels B and C show portfolio sorts using partial least squares (PLS) regressions with 1 and 2 components, respectively. We estimate the parameters strictly out-of-sample using an expanding window, where only data up to time $t$ are considered to predict returns from $t$ to $t+1$. We use the first half of the sample to obtain initial estimates. The left part of the table reports the percentage allocation of factors in the top portfolio. The right part of the table shows the percentage allocation of factors in the bottom portfolio. We describe the factors and their allocation to an economic category in Table A.1.

In order to understand the heterogeneity in timing success better, we illustrate the timing of selected individual factors in Table C.4. Specifically, we highlight the best and worst univariate factor timing results. Panel A displays the 10 factors with the highest and lowest t-stats of the return difference between timed and untimed factors as defined in Eq. (3), respectively. We sort the factors on their average return difference. We find that certain factors can be timed particularly well. For example, the quarterly return for net debt to price (NetDebtPrice_q) improves by 29 percentage points when the factor is timed. In contrast, factors to the right have worse performance when timed. For example, Change in order backlog (OrderBacklogChg) has an unconditional average return of 4.1%, but timed -1.5%. Overall, Panel A shows that large performance increases are much more common than substantial decreases through timing. In Panel B, we show the 10 factors with the highest and lowest average timed returns, respectively, sorted on average timed returns. We find that institutional ownership among high short interest (IO_ShortInterest), short term reversal (STreversal), industry return of big firms (IndRetBig), and firm age - momentum (FirmAgeMom) produce the largest annualized returns out-of-sample, but not all outperform their untimed factors. Panel C selects factors conditional on the sign of average returns of the original factor and sorts them on the difference between timed and untimed factor returns. The left (right) panel considers only factors with on average negative (positive) original factor returns but positive (negative) timed returns. We find that for some factors, a (considerable) negative unconditional return can be transformed into substantial positive timed return. In contrast, it is rarely the case that a positive unconditional risk premium turns negative through poor timing decisions. While some time returns are indeed negative, only one factor out of 314 has significantly negative return differences (OrderBacklogChg).

## Table C.4: Best and worst univariate timing results (using PLS1)

This table shows the factors with the best and worst univariate timing results. Panel A displays the 10 factors with the highest and lowest t-stats of the mean difference between timed and untimed factor returns $\Delta R = f_i^{\tau_j}$ - $f_i$, respectively. The factors are sorted on the average return difference. Panel B shows the 10 factors with the highest and lowest average timed returns, respectively, sorted on the average timed returns. Panel C selects factors conditional on the sign of average returns and sorts them on the difference between timed and untimed factor returns. The left (right) columns consider only factors with on average negative (positive) original factor returns but positive (negative) timed returns. We describe the factors in Table A.1.

| | $f_i$ | $f_i^{\tau_j}$ | ΔR | t-stat. | | $f_i$ | $f_i^{\tau_j}$ | ΔR | t-stat. |
|---|---|---|---|---|---|---|---|---|---|
| A. Factors sorted on ΔR | | | | | | | | | |
| *Highest* | | | | | *Lowest* | | | | |
| NetDebtPrice_q | -15.047 | 14.001 | 29.048 | 4.255 | OrderBacklogChg | 4.128 | -1.538 | -5.667 | -2.598 |
| EntMult_q | -12.265 | 14.128 | 26.394 | 6.562 | sinAlgo | 7.802 | 4.342 | -3.460 | -2.027 |
| AssetGrowth_q | -9.272 | 11.237 | 20.508 | 4.424 | STreversal | 28.535 | 25.257 | -3.278 | -4.171 |
| ChNCOA | -9.123 | 9.107 | 18.230 | 6.261 | realestate | 4.028 | 2.314 | -1.714 | -1.879 |
| EarningsPredictability | -7.407 | 9.764 | 17.170 | 4.227 | DivInit | 4.845 | 3.251 | -1.594 | -3.374 |
| sgr | -7.028 | 6.659 | 13.687 | 5.006 | ChangeInRecommendation | 2.569 | 1.127 | -1.443 | -2.411 |
| ChNCOL | -6.077 | 5.741 | 11.818 | 4.747 | OrgCap | 3.811 | 2.400 | -1.411 | -1.948 |
| betaRC | -2.655 | 5.743 | 8.398 | 2.792 | ShareVol | 5.344 | 4.141 | -1.203 | -1.857 |
| ReturnSkewCAPM | -3.043 | 2.901 | 5.944 | 3.503 | SmileSlope | 9.863 | 8.828 | -1.035 | -1.848 |
| LRreversal | 6.626 | 11.775 | 5.149 | 3.115 | AnalystRevision | 2.740 | 1.869 | -0.871 | -1.900 |
| B. Factors sorted on timed returns | | | | | | | | | |
| *Highest* | | | | | *Lowest* | | | | |
| IO_ShortInterest | 41.780 | 39.263 | -2.518 | -0.924 | OrderBacklogChg | 4.128 | -1.538 | -5.667 | -2.598 |
| STreversal | 28.535 | 25.257 | -3.278 | -4.171 | DelayAcct | -1.996 | -1.189 | 0.808 | 0.214 |
| IndRetBig | 21.205 | 21.501 | 0.296 | 1.846 | FRbook | -2.143 | -1.067 | 1.076 | 0.528 |
| FirmAgeMom | 21.324 | 20.273 | -1.051 | -1.800 | BrandInvest | 3.259 | -0.652 | -3.911 | -0.906 |
| SP_q | 11.306 | 17.683 | 6.377 | 1.807 | DelayNonAcct | 1.467 | -0.440 | -1.907 | -0.803 |
| OperProfRDLagAT_q | 12.231 | 16.691 | 4.460 | 1.281 | EBM | 0.806 | -0.430 | -1.236 | -0.907 |
| Frontier | 18.367 | 16.484 | -1.883 | -1.622 | GrSaleToGrOverhead | -0.887 | -0.175 | 0.712 | 0.462 |
| roaq | 12.133 | 16.451 | 4.318 | 0.917 | PctTotAcc | 0.291 | -0.073 | -0.364 | -0.494 |
| FEPS | 6.418 | 16.401 | 9.984 | 1.476 | Tax_q | -2.448 | -0.023 | 2.425 | 1.248 |
| IntMom | 16.368 | 16.132 | -0.236 | -1.518 | EarningsTimeliness | 1.429 | -0.003 | -1.432 | -1.159 |
| C. Factors sorted on ΔR, conditional on sign of returns | | | | | | | | | |
| *Highest, conditional on* $f_i \leq 0$ & $f_i^{\tau_j} \geq 0$ | | | | | *Lowest, conditional on* $f_i \geq 0$ & $f_i^{\tau_j} \leq 0$ | | | | |
| NetDebtPrice_q | -15.047 | 14.001 | 29.048 | 4.255 | OrderBacklogChg | 4.128 | -1.538 | -5.667 | -2.598 |
| EntMult_q | -12.265 | 14.128 | 26.394 | 6.562 | BrandInvest | 3.259 | -0.652 | -3.911 | -0.906 |
| AssetGrowth_q | -9.272 | 11.237 | 20.508 | 4.424 | DelayNonAcct | 1.467 | -0.440 | -1.907 | -0.803 |
| ChNCOA | -9.123 | 9.107 | 18.230 | 6.261 | EarningsTimeliness | 1.429 | -0.003 | -1.432 | -1.159 |
| EarningsPredictability | -7.407 | 9.764 | 17.170 | 4.227 | EBM | 0.806 | -0.430 | -1.236 | -0.907 |
| sgr | -7.028 | 6.659 | 13.687 | 5.006 | PctTotAcc | 0.291 | -0.073 | -0.364 | -0.494 |
| ChNCOL | -6.077 | 5.741 | 11.818 | 4.747 | | | | | |
| betaRC | -2.655 | 5.743 | 8.398 | 2.792 | | | | | |
| ReturnSkewCAPM | -3.043 | 2.901 | 5.944 | 3.503 | | | | | |
| AbnormalAccrualsPercent | -2.118 | 1.433 | 3.551 | 2.390 | | | | | |

Table C.5: Stock-level timing portfolios: sub-periods

| | R | SD | SR | maxDD | N | Turn |
|---|---|---|---|---|---|---|
| *01/1974 – 12/1989* | | | | | | |
| A. Small capitalization stocks | | | | | | |
| CRSP_VW | 15.544 | 20.522 | 0.375 | 37.069 | 4,096 | 6.214 |
| ORG | 25.603 | 22.596 | 0.785 | 33.573 | 2,328 | 342.482 |
| PLS1 | 26.480 | 22.598 | 0.824 | 33.868 | 2,274 | 394.312 |
| PLS1 \| w in top 50% | 27.526 | 23.013 | 0.855 | 33.269 | 1,137 | 269.696 |
| PLS1 \| w in top 20% | 28.660 | 23.796 | 0.874 | 32.605 | 455 | 230.593 |
| B. Large capitalization stocks | | | | | | |
| CRSP_VW | 9.439 | 16.749 | 0.095 | 36.349 | 826 | 3.055 |
| ORG | 11.622 | 17.100 | 0.220 | 38.021 | 242 | 382.296 |
| PLS1 | 14.353 | 19.034 | 0.341 | 34.867 | 292 | 469.213 |
| PLS1 \| w in top 50% | 14.216 | 19.283 | 0.330 | 34.991 | 146 | 365.556 |
| PLS1 \| w in top 20% | 12.979 | 19.997 | 0.256 | 35.367 | 59 | 341.432 |
| *01/1990 – 12/2004* | | | | | | |
| C. Small capitalization stocks | | | | | | |
| CRSP_VW | 12.919 | 20.061 | 0.441 | 36.448 | 4,860 | 8.011 |
| ORG | 31.024 | 19.894 | 1.355 | 25.512 | 2,725 | 252.508 |
| PLS1 | 35.130 | 22.840 | 1.360 | 26.930 | 2,637 | 329.877 |
| PLS1 \| w in top 50% | 37.540 | 24.038 | 1.392 | 28.072 | 1,319 | 223.195 |
| PLS1 \| w in top 20% | 40.597 | 26.545 | 1.376 | 32.156 | 528 | 189.374 |
| D. Large capitalization stocks | | | | | | |
| CRSP_VW | 9.495 | 14.860 | 0.365 | 46.857 | 1,049 | 3.970 |
| ORG | 14.215 | 14.349 | 0.707 | 25.688 | 377 | 259.971 |
| PLS1 | 16.073 | 16.764 | 0.716 | 39.570 | 405 | 387.365 |
| PLS1 \| w in top 50% | 16.352 | 17.183 | 0.715 | 42.149 | 202 | 291.684 |
| PLS1 \| w in top 20% | 16.002 | 17.882 | 0.667 | 49.008 | 81 | 272.711 |
| *01/2005 – 12/2020* | | | | | | |
| E. Small capitalization stocks | | | | | | |
| CRSP_VW | 10.017 | 20.730 | 0.425 | 55.078 | 2,937 | 6.976 |
| ORG | 16.092 | 22.277 | 0.668 | 57.689 | 1,636 | 262.139 |
| PLS1 | 18.651 | 21.863 | 0.798 | 52.071 | 1,527 | 365.524 |
| PLS1 \| w in top 50% | 19.768 | 22.331 | 0.831 | 51.634 | 764 | 229.428 |
| PLS1 \| w in top 20% | 21.161 | 23.784 | 0.839 | 52.314 | 306 | 187.343 |
| F. Large capitalization stocks | | | | | | |
| CRSP_VW | 8.873 | 14.966 | 0.512 | 51.585 | 920 | 3.469 |
| ORG | 10.436 | 16.800 | 0.549 | 49.138 | 406 | 291.121 |
| PLS1 | 12.788 | 16.709 | 0.693 | 48.443 | 443 | 396.551 |
| PLS1 \| w in top 50% | 13.135 | 16.698 | 0.714 | 48.121 | 222 | 286.244 |
| PLS1 \| w in top 20% | 13.793 | 16.648 | 0.756 | 45.999 | 89 | 262.661 |

This table shows performance statistics for long-only equity portfolio for different time periods: Jan 1974 to Dec 1989, Jan 1990 to Dec 2004, and Jan 2005 to Dec 2020. We aggregate all underlying security weights from all timed factor portfolios. We then retain only firms that have positive total weights. Panels A, D, and G report results for all securities in the CRSP universe. Panels B, E, and H report performance statistics for small capitalization stocks. Panels C, F, and I report performance statistics for large capitalization stocks. The split according to capitalization is based on median NYSE market equity from June of year $t$; we keep firms from July of year $t$ to June of year $t+1$. CRSP_VW is the value-weighted U.S. market return. ORG refers to portfolio weights based on the original factor definition. PLS1 shows portfolio timing based on partial least squares regressions with a single component. We further provide returns for portfolios based on PLS1 where only firms with weights in the top 20% or in the top 50% of all firms in the investment universe are retained. We report annualized mean return (R), standard deviation (SD), Sharpe ratio (SR), maximum drawdown (maxDD), average number of firms in the portfolio (N), and annualized turnover (Turn). We describe the factors and their allocation to an economic category in Table A.1.