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).

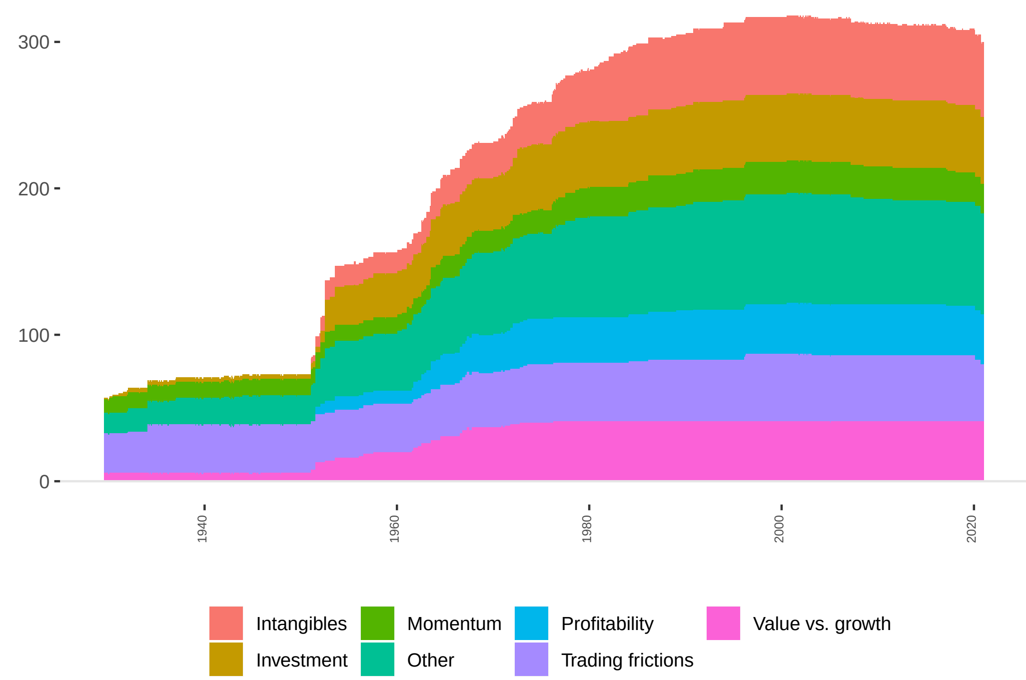
To sort stocks into portfolios, we construct firm characteristics based on data obtained from CRSP, Compustat, IBES, and FRED. Multiple characteristics require specific data to reconstruct the results of the original studies, and are readily available on the authors websites. For each characteristic, 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:

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

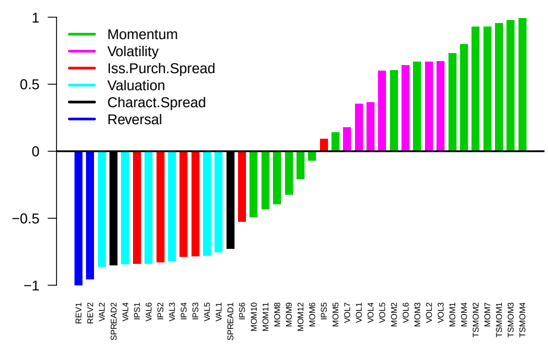
where $\hat{\sigma}_t^2(f_i)$ is the previous month's realized variance of daily returns, and c a constant that controls the average exposure of the strategy.

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

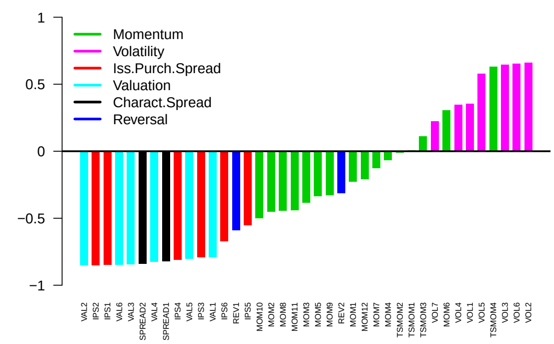
Figure 2: Net fraction of positive and negative performance differences

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: $f^{\tau j}_{i,t+1} = \alpha_{i,j} + \beta_{i,j} f_{i,t+1} + \epsilon_{t+1}$. 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.

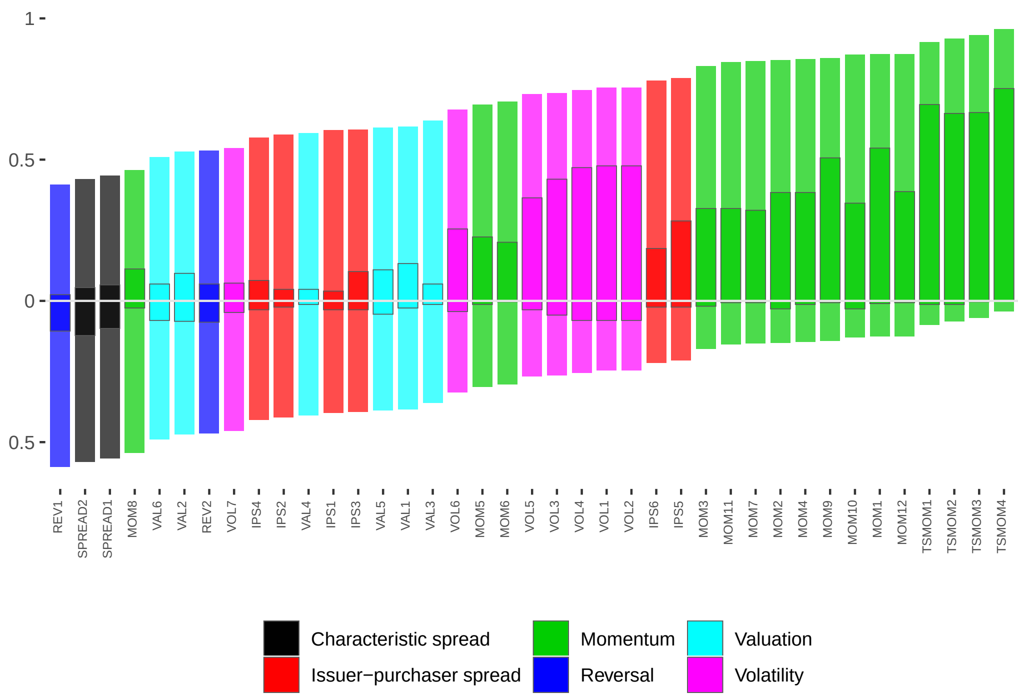


Figure 3 plots the fraction of factor portfolios with positive and negative alphas, respectively, for each timing signal. Each bar has a length of 1; the vertical position of the bar shows the fraction of positive and negative alphas. Areas with dark borders within a bar present the fraction of timed factors with statistically significant α. 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 αs. 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 αs 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 τ_j of a given type. We report average t-statistics in brackets, where statistical significance is based on heteroscedasticity-adjusted standard errors. ΔSR 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 $\Delta\text{SR} = 0$. 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 α and ΔSR						
	α	ΔSR	α	ΔSR	α	ΔSR
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 α						
	+	−	+	−	+	−
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 ΔSR						
	+	−	+	−	+	−
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 α of 5.1%. This contrasts with an average α of 2.3% for factors related to trading frictions. Column ΔSR 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 αs 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 (−) αs. Numbers in brackets are the percentages of positive and negative αs, 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, β_i is a $J \times 1$ vector of signal sensitivities and ϵ_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_ms, 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 γ. 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 α	3.877	4.523	4.689	4.597	4.564
FF5+M t(α)	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(ΔR)		3.693	4.020	3.453	3.183
z_{JK}(ΔSR)		-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.

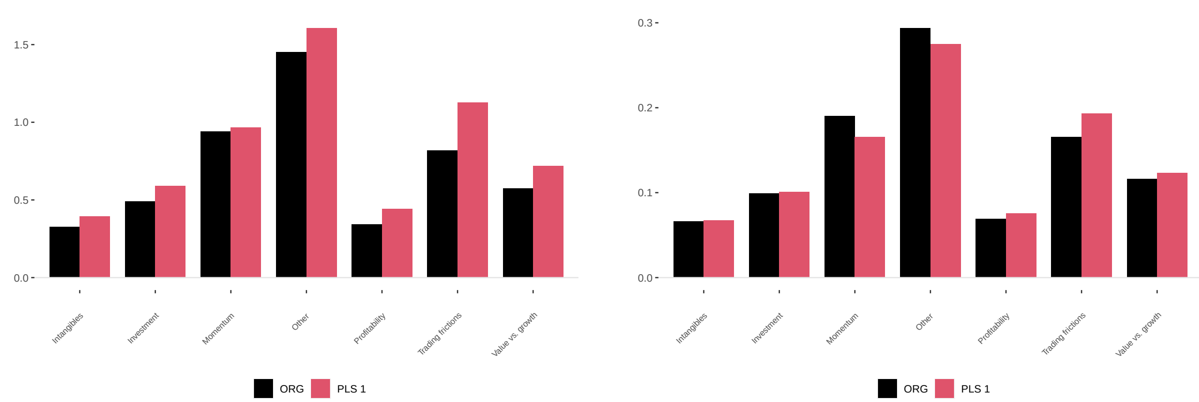
The previous analysis uses only the sign of the prediction, but not the magnitude. We may therefore

[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 qth 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 qth 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+Mα). 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.

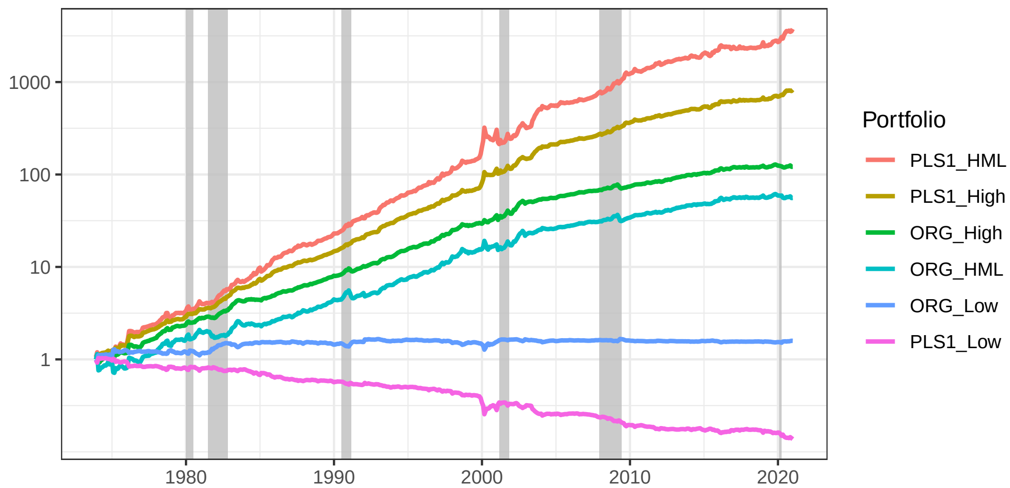
	Pred	R	SD	SR	maxDD	FF5+M α
A. ORG						
L		1.161	6.169	0.188		
2		3.700	3.403	1.087		
3		4.196	3.055	1.373		
4		5.376	5.037	1.067		
H		10.463	7.025	1.489		
HML		9.303	11.843	0.786	37.287	5.543
Statistical significance (t, z_{JK})		*5.395*		*4.916*		*3.677*
B. PLS 1						
L	-5.802	-3.929	7.410	-0.530		
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	7.117	8.287	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 $\times$ 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 $\times$ 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 $\times$ 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 $\times$ 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 α and ΔSR				
	α	ΔSR	α	ΔSR
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 α				
	+	−	+	−
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 ΔSR				
	+	−	+	−
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 α and ΔSR				
	α	ΔSR	α	ΔSR
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 ΔSR				
	+	−	+	−
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 ΔSR				
	+	−	+	−
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: $f_{i,t+1}^{\tau_j} = \alpha_{i,j} + \beta_{i,j} f_{i,t+1} + \epsilon_{t+1}$. We report simple averages over all untimed factors f_i within an economic category and all signals τ_j of a given type. We report average t-statistics in brackets, where statistical significance is based on heteroscedasticity-adjusted standard errors. ΔSR 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 α	t(α)	R^2	t(ΔR)	$z_{JK}(\Delta$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+Mα, its t-statistic t(α), and R^2. The last two columns show t-statistics of the return difference between the predicted and original HML factor portfolio t(ΔR) 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.