Beyond Fama-French Factors: Alpha from Short-Term Signals*

David Blitz
Robeco, d.c.blitz@robeco.com

Matthias X. Hanauer
Robeco, TU Munich, m.hanauer@robeco.com

Iman Honarvar
Robeco, i.honarvar.gheysary@robeco.com

Rob Huisman
Robeco, r.huisman@robeco.com

Pim van Vliet
Robeco, p.van.vliet@robeco.com

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Abstract

Short-term alpha signals are generally dismissed in traditional asset pricing models, primarily due to market friction concerns. However, this paper demonstrates that investors can obtain a significant net alpha by applying a combination of signals to a liquid global universe and with advanced buy/sell trading rules that mitigate transaction costs. The composite model consists of short-term reversal, short-term momentum, short-term analyst revisions, short-term risk, and monthly seasonality signals. The resulting alpha is present in out-of-sample and post-publication periods, across regions, translates into long-only applications, is robust to incorporating implementation lags of several days, and is uncorrelated to traditional Fama-French factors.

Keywords: short-term signals, market frictions, portfolio construction, transaction costs, investments, market efficiency.

JEL Classification: G11, G12, G14

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1. Introduction

Prevailing asset pricing models attempt to describe the cross-section of stock returns with a limited number of fundamental factors, such as size, value, profitability, and investment. Examples are the five-factor model of Fama and French (2015), the q-factor model of Hou, Xue, and Zhang (2015), and the mispricing model of Stambaugh and Yuan (2017).[1] The factors in these models have been rationalized with risk-based explanations (Fama and French, 1993) or with fundamental models (Fama and French, 2015), and their premiums are expected to materialize over a full business cycle. In the short run, however, they can experience large and prolonged drawdowns. There are also concerns that the performance of classic asset pricing factors may have weakened over time; see, e.g., McLean and Pontiff (2016) or Blitz (2020).

High-turnover anomalies are generally dismissed in the asset pricing literature, primarily because of the concern that they may not survive after accounting for transaction costs. Furthermore, they tend to lack risk-based explanations, suggesting they are mispricing phenomena instead. Rather than capturing a large premium that materializes over a long period of time, these short-term signals provide a string of many small consecutive alphas from entirely different portfolios every month. A well-known example is the short-term (one-month) reversal effect of Rosenberg, Reid, and Lanstein (1985), Jegadeesh (1990), and Lehmann (1990), which shows strong returns on paper but is generally considered to be beyond the reach of investors after accounting for market frictions.

A new stream of literature uses machine learning to predict future stock returns. In these studies, short-term signals typically rank among the most important features next to traditional factors, see, e.g., Rasekhschaffe and Jones (2019), Freyberger, Neuhierl, and Weber (2020), and Gu, Kelly, and Xiu (2020). The common conclusion of these studies is that machine learning models substantially outperform comparable linear models with spectacular Sharpe ratios. However, Leung et al. (2021) and Avramov, Cheng, and Metzker (2022) seriously question the efficacy of these models after transaction costs, noting that they rely heavily on short-term signals that result in high turnover. In the quantitative investment community, factor investing is still focused on classic factors such as value, quality, momentum, and low risk. Finally, index providers tend to ignore short-term anomalies, offering only indices that provide exposure to traditional factors and adhering to either semi-annual or quarterly rebalancing frequencies.

In this paper, we argue that short-term signals should not be discarded too easily for a number of reasons. First, the standard academic factor construction methodology, as introduced by Fama and French (1993), gives a disproportionately high weight of 50% to small-caps which only comprise about 10% of total stock market capitalization (cf., Fama and French, 2008). Since trading costs are much higher for small illiquid stocks than for large liquid stocks, it may be more efficient

[1] The Fama and French (2015) five-factor model is often augmented with a mid-turnover momentum factor. Although the momentum premium has also turned out to be "pervasive" (Fama and French, 2008, p. 1653), Fama and French (2018, p. 237) only "reluctantly" include it due to theoretical motivation concerns. Another reason could be that the model focuses on explaining long-term expected returns rather than short-term variation in returns (Fama and French, 2016). Nevertheless, both for the U.S. and international markets, a modified Fama-French six-factor model seems to be the dominant factor model (cf., Barillas and Shanken, 2018, Barillas, Kan, Robotti, and Shanken, 2020, or Hanauer, 2020).

to apply short-term strategies only to stocks where the expected gains outweigh the expected costs.

Second, gross and net performance can be improved substantially by shifting the focus from a single signal to a combination of multiple short-term signals that have been thoroughly established in the literature. Integrating signals with low correlations gives powerful diversification benefits, resulting in higher gross returns and lower volatility. For instance, it is well known that momentum and reversal effects are simultaneously present in the short run. Concentrating on just one of these effects while ignoring the other may therefore be inefficient.

Third, many studies merely consider a very naïve trading strategy by simply constructing fully fresh top and bottom portfolios every month. Novy-Marx and Velikov (2016, 2019) show that more advanced buy and sell rules that only replace stocks if their attractiveness drops below a certain threshold give savings in trading costs that readily outweigh the loss in gross returns. Moreover, trading costs themselves are often substantially overestimated, e.g., by relying on the dated model of Keim and Mahavan (1997) that is based on a sample over the 1991-1993 period. Recent studies such as Novy-Marx and Velikov (2016) and Frazzini, Israel, and Moskowitz (2018) document that sophisticated investors experience considerably lower trading costs than commonly assumed in the literature.

Our main insights can be summarized as follows. First, a composite strategy consisting of short-term reversal, short-term momentum, short-term analyst revisions, short-term risk, and monthly seasonality signals generates economically and statistically highly significant net alphas, at least when efficient trading rules are applied. Second, although the performance of the short-term composite strategy has diminished over time, the alpha remains profitable after costs in the out-of-sample or post-publication periods for the various signals. Third, the results cannot be explained by market frictions such as short-selling limitations or implementation lags. In particular, the performance is just as strong on the long side as on the short side, and the alpha is robust to incorporating an implementation lag of one to two days that would be experienced in a real-time implementation of the strategy. Fourth, the alpha is significant within the separate North America, Europe, Pacific & Japan, and Emerging Markets regions. Finally, we provide evidence consistent with the hypothesis that sentiment-related mispricing partly explains the return predictability, as we find significantly higher returns after high-sentiment periods. Although we also find that the returns are higher after high limits-to-arbitrage periods, limits to arbitrage play only a subordinated role compared to investor sentiment.

While Green, Hand, and Zhang (2017) or Jacobs and Müller (2018) already document that several robust and independent return predictors exist outside prominent benchmark models, we restrict ourselves to short-term signals that are generally dismissed because of investability concerns, in particular their high turnover. We do not claim that our set of short-term signals or their combination is optimal, but merely aim to show that a straightforward combination of several well-known short-term signals can already be highly profitable after costs when using efficient yet straightforward portfolio construction techniques.

Figure 1 gives a visual summary of our main findings. The individual short-term signals have an average Fama-French six-factor model gross alpha of more than 6% per year. However, the high turnover of the signals would lead to a net alpha of less than -2% when considering realistic transaction costs of 25 bps per single trip. Combining the individual signals into a composite boosts the gross alpha by 6% to above 12% per year, but transaction costs still erode more than two-thirds of this return. Applying more sophisticated buy and sell rules on the composite only slightly decreases the gross alpha but lifts the annual net alpha above 6% due to substantially lower turnover.

INSERT FIGURE 1 HERE

Our paper extends the work of De Groot, Huij, and Zhou (2012) and Novy-Marx and Velikov (2016). The former demonstrates that the short-term reversal anomaly can be turned into a profitable investment strategy when applied to the largest, most liquid stocks with efficient buy and sell rules and considering realistic estimates for trading costs. However, the scope and applicability of their approach are limited, as they need to narrow down the universe to the 100 largest US stocks to obtain modest returns net of transaction costs. We add to their work by taking a broad set of well-known short-term signals rather than a single signal and considering a global universe of liquid large-cap stocks.

Novy-Marx and Velikov (2016) study the gross and net performance of a range of low-, mid-, and short-term anomalies for the US and conclude that most of these high-turnover strategies do not provide net alpha. However, in the appendix, they also show that a high-frequency combination based on industry-relative reversals and industry momentum can achieve a significant net alpha when multiple transaction cost mitigation techniques are applied. In this study, we focus on combining a broader set of short-term signals and extending the analysis to a global level. Furthermore, we examine this approach in different regions, consider the alpha stemming from the long and short sides, and account for implementation lags.

Our results imply that high-turnover anomalies are rejected too easily based on market friction arguments. However, many investors may experience other investment barriers which prevent them from harvesting these short-term signals, such as limited access to the necessary data, missing infrastructure to process the data, or the inability to execute the resulting signals in a timely and efficient manner. Short-term signals only present a genuine opportunity to earn alpha beyond common factors to those investors who are able to overcome these barriers. The resulting alpha provides a challenge to market efficiency that is not recognized by prevailing asset pricing models. The fundamental factors in such models effectively describe the cross-section of stock returns over investment horizons of twelve months or longer, but at shorter horizons, a myriad of other dynamics is at play. Since risk-based or fundamental explanations do not appear to be plausible, these are typically considered to be mispricing phenomena, likely stemming from behavioral biases of investors. We conclude that current asset pricing models fail to capture important short-term dynamics because of their overly narrow focus on traditional fundamental factors. The implication for investors is that uncorrelated alpha opportunities exist beyond the common Fama-French factors.

2. Data and methodology

2.1 Data

We consider all stocks in the MSCI World standard index at the end of every month from December 1985 to December 2021. This universe is highly investable and comparable to the big-cap universe in academic studies.[2] The average number of stocks over our 36-year sample period is 1,750, varying between a low of 1,296 and a high of 2,065. For all stocks, we gather monthly total returns in US dollars and various characteristics to construct the signals and the six Fama-French control factors. Our main focus is on five short-term signals that have been thoroughly established in the literature. These short-term signals have in common that they are not only updated monthly but are entirely "new" each month. In contrast, a variable such as 12-1 month momentum is also updated monthly, but ten out of the eleven monthly returns in the lookback period overlap from one month to the next, resulting in a much lower turnover. We provide an overview of the five signals in Table 1.

INSERT TABLE 1 HERE

Our first signal is industry-relative reversals. Rosenberg, Reid, and Lanstein (1985), Jegadeesh (1990), and Lehmann (1990) find that stocks with low (high) returns over the previous month tend to outperform (underperform) over the next month. This finding can be interpreted as an investor overreaction phenomenon. Subsequent studies have identified various ways to improve upon the plain vanilla short-term reversal strategy. For instance, Da, Liu, and Schaumburg (2014) and Hameed and Mujtaba Mian (2015) compute industry-relative short-term reversal signals to prevent going against the short-term industry momentum effect of Moskowitz and Grinblatt (1999).[3] Following Novy-Marx and Velikov (2016), we use this enhanced short-term reversal signal. More specifically, industry-relative reversal is defined as a firm's return minus its industry return over the prior month, based on the Global Industry Classification Standard (GICS) Level 3 industries.

Our second signal is one-month industry momentum, as in Moskowitz and Grinblatt (1999). We calculate the industry momentum of a firm by taking the average return of its peers in the same industry over the previous month, again using the GICS Level 3 classification. Our third signal is analysts' earnings revisions measured over the past 30 calendar days, based on Van der Hart, Slagter, and van Dijk (2003). For this signal, we use the IBES point-in-time database and take the number of upwards earnings revisions minus the number of downward earnings revisions

[2] The standard MSCI World index comprises large- and mid-cap stocks across developed markets countries and targets to cover approximately 85% of the free float-adjusted market capitalization in each country. Therefore, this size threshold is even stricter than the academic convention of "big" stocks, which are typically defined as the biggest stocks that account for 90% of the aggregated market capitalization per region (cf., Fama and French, 2012). Before 2001, we do not have access to MSCI World constituents, so we use FTSE Developed as a proxy.

[3] Another enhancement of the standard short-term reversal strategy is the residual short-term reversal strategy of Blitz, Huij, Lansdorp, and Verbeek (2013). This approach adjusts the returns of a stock for its exposures to the market, size, and value factors of Fama and French (1993), estimated over the preceding 36 months, and then scales the residual returns by their volatility over the same period. Using this signal or the raw short-term reversal signal gives a very similar alpha and does not affect our main results (cf., Table A1 in the Appendix).

divided by the total number of analysts over the past 30 calendar days.[4,5] Both effects can be interpreted as investor underreaction phenomena. Hence, combining these two momentum signals with reversal signals can be expected to give powerful diversification benefits, as they exploit conceptually opposite behavioral biases.

Our fourth signal is the same month stock return effect of Heston and Sadka (2008). For the same month stock return strategy, we rank stocks at the end of calendar month T on their average return in calendar month T+1 during the preceding ten years. This phenomenon appears to be a purely seasonal effect since the returns cannot be explained by systematic risk factors, earnings announcements, or dividends.

Our fifth signal is the one-month idiosyncratic volatility variable of Ang, Hodrick, Xing, and Zhang (2006). Idiosyncratic volatility is calculated by regressing the daily returns of a stock over the previous month on the market, size, and value factors of Fama and French (1993) and taking the standard deviation of the regression residuals. The short-term risk signal is negatively related to subsequent stock returns, similar to the well-known long-term low-volatility effect. We refer to Blitz, van Vliet, and Baltussen (2020) for an overview.

Furthermore, we create a composite strategy by first normalizing each of the five short-term metrics cross-sectionally using standard robust z-scores, capped at plus and minus 3, and then averaging these scores. Creating multi-factor composites is common in both academia and the industry, with well-known examples being the F-score of Piotroski (2000), the Mispricing score of Stambaugh, Yu, and Yuan (2015), the Quality composite of Asness, Frazzini, and Pedersen (2019), or the Enhanced Value factor of Blitz and Hanauer (2021).

While combining multiple signals into a composite leads to diversification benefits, composite strategies can also suffer from overfitting and selection biases if the underlying signals have no real power but are signed to have positive in-sample returns (cf., Novy-Marx, 2016). To mitigate these biases, we follow the recommendation of Novy-Marx (2016) and investigate each short-term variable separately. Importantly, we consider well-established short-term variables, refrain from examining more exotic or recently proposed ones, and weight the individual signals equally instead of using an optimized weighting scheme. Furthermore, we also compare the t-statistics of our short-term composite with the critical statistics presented in Novy-Marx (2016) that correct for overfitting and selection biases.

We do not claim that our set of short-term signals and their combination is optimal nor that it cannot be further improved upon. Actually, various papers show that these basic signals can be significantly enhanced. For instance, industry momentum appears to be subsumed by connected firm momentum based on shared analyst coverage (Ali and Hirshleifer, 2020).[6] Short-term

[4] Earlier studies such as Stickel (1991) and Chan, Jegadeesh, and Lakonishok (1996) use the change in the consensus earnings forecast. However, this requires an appropriate scaling factor, which should not be a metric that can be zero or negative (like earnings itself), and which should not introduce other effects (like valuation effects when dividing by market capitalization). By using the definition of Van der Hart, Slagter, and van Dijk (2003) we prevent such issues.

[5] The IBES database has been accused of rewriting history by Ljunqvist, Malloy, and Marston (2009), but it turns out that all major discrepancies stem from different ways of dealing with corporate actions and mergers between brokerage firms (cf., Thomson Reuters, 2016).

[6] Alternative lead-lag effects were for instance also documented for customer-supplier links (Cohen and Frazzini, 2008) and for standalone versus more complex firms (Cohen and Lou, 2002).

reversal could be conditioned on share turnover (Medhat and Schmeling, 2022), and the maximum daily return over the past month (MAX) seems to be stronger than idiosyncratic volatility (Bali, Cakici, and Whitelaw, 2011).[7] Analyst earnings revision could be improved by weighting "bold" revisions higher than "herding" revisions (Clement and Tse, 2005), and the same month seasonality effect could be extended with the seasonal reversal (Keloharju et al., 2021) or other calendar effects such as earnings announcements (Frazzini and Lamon, 2007) or dividend month (Hartzmark and Solomon, 2013). Thus, our choice of signals is conservative. We do not include these new signals because they are only recently uncovered and not yet mainstream.

For all individual variables and the multi-signal composite, we apply regional neutrality as in Fama and French (2017), meaning that we rank stocks separately within each of the three main regions: North America, Europe, and Japan & Pacific. As control factors, we construct the Fama and French (2015) factors plus the momentum factor of Jegadeesh and Titman (1993) and Carhart (1997), following the exact same methodology as for our short-term variables. As a result, we prevent potential distortions from differences in the universe, neutrality choices, weighting schemes, etc.[8] The control factors are the market return in excess of the risk-free return, an SMB size factor based on free-float equity market capitalization, an HML value factor based on the book-to-market ratio, an RMW profitability factor based on the gross profits-to-assets ratio, a CMA investment factor based on the 12-month change in total assets, and a WML momentum factor based on the 12-1 month stock returns. Our data source is the Refinitiv platform, where we use the prices, fundamentals (Worldscope), and analyst estimates (IBES) databases.

2.2 Methodology

For our first analysis, we create equally-weighted quintile portfolios by ranking stocks on their signal scores at the end of every month and then computing the returns of the quintile portfolios over the subsequent month. The use of equally-weighted portfolios has been criticized in the literature (see, e.g., Hou, Xue, and Zhang, 2020) because it gives a disproportionately high weight to illiquid small-cap stocks. However, this concern does not apply to our study since we use a universe that only consists of liquid large-cap stocks for which equal-weighting is practically feasible. Furthermore, the drawback of value-weighting is that a small number of ultra-large stocks would heavily dominate the results, e.g., for the global universe, the 50 largest stocks make up about a third of the total index weight and the 100 largest stocks about half, potentially rendering a given factor less effective.

In order to control trading costs, it is critical to prevent unnecessary turnover, which can be accomplished in various ways. DeMiguel, Martin-Utrera, Nogales, and Uppal (2020) show that trading costs can be reduced when implementing multiple anomalies separately because some

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[7] Other skewness-related signals are lottery-type features (Kumar, 2009) or expected skewness (Boyer, Mitton, and Vorkink, 2010).

[8] Furthermore, our analysis starts in 1986, while the standard factor time series for developed markets, available on Kenneth French's website, are only available from June 1990 onwards. If we use the control factors from Kenneth French's website and restrict our analysis to June 1990 to December 2021 period for which these time series are available, our conclusions remain the same (cf., Table A1 in the Appendix).

trades cancel each other out. However, applying different strategies next to each other seems inefficient in itself.[9] Turnover may also be reduced by switching from a monthly to a quarterly or semi-annual rebalancing frequency, as in Jegadeesh and Titman (1993). The drawback of this approach is that stocks that rapidly deteriorate in attractiveness are held too long, while stocks that remain moderately attractive at the rebalancing moment may still be sold too quickly.

We address these issues by using the trading cost mitigation approach of De Groot, Huij, and Zhou (2012) and Novy-Marx and Velikov (2016), where the long (short) portfolio consists of the stocks that currently belong to the top (bottom) X% plus the stocks selected in previous months that are still among the top (bottom) Y% of stocks. For instance, with X=10% and Y=50%, the initial long portfolio is simply the top decile, while in subsequent months, the long portfolio consists of all stocks in the top decile plus all the stocks selected in previous months that continuously remained among the top 50% stocks since. The same buy-and-hold trading rules are applied to the short portfolio. For our efficient trading strategy, we apply this approach with various choices for X and Y. Finally, note that the naïve trading strategy that constructs fully fresh top and bottom quantile portfolios every month is a special case with this setup where X and Y are both equal to 20%.

For each of the individual signals and all composite strategies, we compute mean returns and associated t-statistics, as well as the CAPM and Fama-French six-factor alphas and their associated Newey and West (1987) adjusted t-statistics using three lags. Furthermore, we report the regression coefficients for the Fama-French six-factor model, the average number of stocks in the portfolios, and the average annualized strategy turnover. Strategy turnover is calculated as the one-way turnover and, in the case of a long-minus-short factor, the sum of the turnover of the long and short legs. More specifically, one-way portfolio turnover in month *t* for both the long or short portfolio leg is calculated as:

$$Turnover_t = 0.5 \times \sum_i^{N_t} \left| x_{i,t} - \tilde{x}_{i,t-1} \right|, \tag{1}$$

where $x_{i,t}$ is the weight of stock *i* in the respective portfolio leg in month t, N_t amounts to the total number of stocks in the portfolio leg at month t, and $\tilde{x}_{i,t-1}$ is the weight of stock *i* at the end of month $t-1$ resp. at the beginning of month t, right before portfolio rebalance. We compute $\tilde{x}_{i,t-1}$ as:

$$\tilde{x}_{i,t-1} = \frac{x_{i,t-1}(1+r_{i,t-1})}{\sum_j^{N_t} x_{j,t-1}(1+r_{j,t-1})}, \tag{2}$$

[9] For instance, when the fresh top quintile of strategy A is bought, the old top quintile of strategy B is sold, and the two strategies are independent, then about 20% of these trades can likely be crossed. Moreover, if a stock is very attractive according to the first strategy but very unattractive according to the second strategy then a neutral position might actually be most appropriate.

where $r_{i,t}$ is the return of stock i during month t. To illustrate, the one-way turnover is 100% if an entirely fresh portfolio replaces the existing portfolio, while the corresponding two-way turnover (counting both buys and sells) would be 200%.

To assess the net profitability of our short-term strategies, we compute break-even trading cost levels, defined as the average trading costs (in basis-points) at which the net mean return and six-factor alpha become zero as follows:[10]

$$\text{Breakeven TC (bps)} = \frac{\mu}{2 \times \overline{Turnover}} \times 10000, \tag{3}$$

where μ is the gross average mean return or six-factor alpha and $\overline{Turnover}$ is the average turnover as computed in Equation (1).

These break-even trading cost levels can be compared with estimated trading costs for large-cap stocks reported in the literature. De Groot, Huij, and Zhou (2012) use the trading cost model of a large global broker and report costs of 5-25 bps (average 10.9 bps) for the 500 largest US stocks and 20-70 bps (average 32 bps) for the 600 largest European stocks (see their tables 2 and 3). Novy-Marx and Velikov (2016) estimate a 40-70 bps round-trip bid-ask spread for the 500 largest US stocks, which translates into 20-35 bps one-way costs (see their figure 1). Frazzini, Israel, and Moskowitz (2018) report trading costs of 15-16 bps for global developed markets (see their table 2), and Israel, Moskowitz, Ross, and Serban (2021) have 12.6 bps for global, 6.4 bps for the US, and 13.2 bps for developed markets excluding the US (see their table 4). Except for Novy-Marx and Velikov (2016), all these estimates also include the estimated market impact. We note that these estimates could be downward biased, especially for very large trades, due to the endogeneity of the trading and trading size decision.[11] Altogether, 25 bps seems a reasonable conservative estimate for average expected trading costs that sophisticated investors should be able to attain in developed markets large-cap stocks, assuming the trades are not very large.

3. Empirical results

3.1 Individual short-term signals

The top-minus-bottom quintile performance of the individual short-term signals is reported in Table 2. The annualized mean returns range between 5% and 8%, with associated t-statistics between 3 and 7 for all signals except idiosyncratic volatility (iVOL). Since iVOL is structurally long low-risk stocks and short high-risk stocks, it has a highly negative market beta. The CAPM alpha controls for this exposure and is triple the raw return. Considering the CAPM alphas of all five variables, we find a range between 6% and 10% per annum, with associated t-statistics varying between 3 and 8. The six-factor alphas and the associated t-statistics are similar or only

[10] Please note that the break-even trading costs for the Fama-French six-factor model alpha are a conservative estimate as we use gross factor returns to compute this alpha. In reality, factors such as momentum also require a substantial amount of turnover, which decreases their net performance.

[11] We thank an anonymous reviewer for raising this point.

slightly lower for most short-term signals because their loadings on the Fama-French factors tend to be small. The exception is again iVOL, which does exhibit some significant loadings on the traditional factors. This results in a lower but still marginally significant (at the 10% level) six-factor alpha. Altogether, the investigated individual signals present strong return predictors rather than signals with no actual power for which a combination would be critical (cf., Novy-Marx, 2016).

INSERT TABLE 2 HERE

Although the investigated short-term signals offer largely unique alphas that are not explained by traditional factors, this comes at the price of a very high turnover between 1300% and 2000% per annum. To put this number into perspective, note that entirely replacing the long portfolio every month gives 100% x 12 = 1200% annual turnover, so the maximum annual turnover for the long-short portfolio is 2400% (all one-way; the round-trip turnover figures are double these amounts). From this, we can infer that the average holding period of stocks is somewhere between one and two months. This high turnover has major consequences because the break-even trading cost levels for retaining positive mean returns or alphas are all below the conservative trading costs estimate of 25 bps.[12] These results confirm the notion that short-term signals are hard to exploit profitably after costs – at least when considered individually and with a naïve trading strategy.

The correlations between the returns of different short-term signals are reported in Table 3 and are generally low or even negative. The highest positive correlation is between analyst revisions and idiosyncratic volatility (0.51), and the highest negative correlation is between industry-relative reversals and industry momentum (-0.58). Overall, these correlations suggest that combining the various short-term signals should give strong diversification benefits.

INSERT TABLE 3 HERE

3.2 The composite strategy

We proceed by examining the performance of the short-term composite strategy. Table 4 reports the performance of the five equally-weighted quintile portfolios. We find a monotonously decreasing return pattern going from the portfolios with the best (Q1) to the worst (Q5) short-term combined scores. The resulting top-minus-bottom quintile has a mean return (CAPM alpha) of more than 12% (14%) with a t-statistic of over 8 (10), which is considerably stronger than for the individual signals. This finding confirms the power of diversification. At over 12%, the six-factor alpha is only slightly lower and remains highly significant, implying that the Fama-French factors have hardly any additional explanatory power. Notably, both the return and alpha spread are similarly driven by the top and the bottom portfolios, implying that the performance does not

[12] The only exception is the break-even trading cost level for the analyst earnings revision signal that is just above 25 bps.

predominantly stem from the short side, which would raise investability concerns due to shorting frictions.

INSERT TABLE 4 HERE

The reported t-statistics also exceed the critical thresholds derived in Novy-Marx (2016) that correct for overfitting and selection biases. The critical t-statistic that corrects for pure overfitting biases in the case of five equally-weighted signals is slightly below 3 for both empirical and theoretical distributions. Similarly, the critical t-statistics that correct for both overfitting and selection (i.e., multi-testing) biases are slightly above 6 when the best 5 out of 100 signals are equal-weighted. With t-statistics above 8, the short-term composite passes not only conventional levels but also these much more conservative levels.

Turnover remains high, at close to 1800% per annum. However, the break-even transaction cost levels now exceed 30 bps due to the stronger performance of the composite signal. Given our assumption that real-life trading costs are around 25 bps, this implies that the multi-signal strategy can generate modest after-cost profits, particularly if investors are able to execute their trades below this conservative threshold. Figure 2 shows the cumulative top-minus-bottom quintile return, CAPM alpha, and Fama and French six-factor alpha of the composite strategy over time. The performance is highly consistent over time without any major drawdowns.

INSERT FIGURE 2 HERE

We next apply the cost-mitigating trading approach to the composite strategy. Every month the long (short) portfolio consists of the stocks that currently belong to the top (bottom) X% plus the stocks selected in previous months that have not deteriorated beyond the top (bottom) Y% since. To ensure that the strategies roughly contain a similar number of stocks, we simultaneously apply stricter thresholds for X when we relax the threshold for Y. More specifically, we use 15%, 10%, and 5% for X, and for Y, we consider 30%, 50%, and 70%, respectively. Consequently, this technique introduces hysteresis into the portfolio construction and lowers turnover. Table 5 shows that for the buy/hold 15/30 strategy, the gross returns slightly increase, while the turnover drops by about a fifth. As a result, the break-even trading costs increase to above 40 bps.

On the other hand, for the buy/hold 10/50 strategy, the gross alpha deteriorates by about 1% per annum, but turnover is almost halved. In this case, the break-even trading costs exceed 55 bps, which is well above our trading costs estimate of 25 bps. Finally, we investigate a 5/70 strategy. Compared to the quintile base case, the turnover decreases by more than two-thirds while the gross return decreases by less than one-third. As a result, the break-even trading cost level of nearly 80 bps is more than twice the base-case level. In sum, these results imply that the composite strategy is highly profitable after costs when efficient trading rules are applied.

INSERT TABLE 5 HERE

So far, we have only computed break-even transaction cost levels that would render the strategies' mean returns or six-factor alphas negative. Figure 3 visualizes the net alpha of the composite for a continuous range of transaction costs. Although the 10/50 strategy has a lower gross alpha than the simple top-minus-bottom quintile strategy, the net alpha already becomes more profitable for trading costs above 5 bps. For higher transaction costs, the gap widens quickly, while the 15/30 strategy dominates the naïve approach for all trading cost levels. Although the more aggressive 15/30 strategy is more profitable for trading cost levels below 11 bps, the more restrained 10/50 strategy yields a higher net performance for more realistic trading cost levels. If trading cost levels exceed 30 bps, the 5/70 strategy generates the highest net alphas.

INSERT FIGURE 3 HERE

The figure also shows for which level of transaction cost the net alphas would become insignificant (both at the 1% and 5% significance level).[13] While the net alpha of a naïve implementation becomes insignificant at the 1% (5%) significance level for trading costs of 26 bps (28 bps), the 15/30, 10/50, and 5/70 approaches can bear trading costs of 32 (35), 44 (47), or even 56 (61) bps, respectively. For the conservative trading costs estimate of 25 bps, we observe net alphas ranging from slightly above 3% for the base case to more than 6% for the 10/50 approach. Altogether, we conclude that the composite strategy is able to generate economically and statistically significant net alphas, at least when efficient trading rules are applied.

3.3 Out-of-sample and post-publication performance

So far, we have only investigated the performance of the composite strategy in the entire sample period from December 1985 to December 2021. However, it is unlikely that investors would have been able to construct this strategy back in 1985 as the individual signals were only published later. Thus, our conclusions partly depend on in-sample and pre-publication results.[14] This consideration matters as McLean and Pontiff (2016) document a decline in the out-of-sample and post-publication performance of 97 academic variables compared to their in-sample performance. While Jacobs and Müller (2020) find that the United States is the only one out of 29 investigated countries with a reliable post-publication decline, Figure 2 also indicates some decline in the performance of the short-term composite after 2003.[15]

Following McLean and Pontiff (2016), we investigate the out-of-sample and post-publication performance of the short-term composite strategy and compare it with the in-sample and pre-publication performance, respectively. More specifically, the out-of-sample performance (post-publication) starts now in August 1995 (September 1999) when the out-of-sample (post-publication) period for industry momentum begins (cf., Table 1). Subsequently, we add analyst earnings revisions (June 1999, resp. March 2003), idiosyncratic volatility (January 2001, resp. March 2006), same month stock return seasonality (January 2003, resp. March 2008), and industry-relative reversal (April 2009, resp. April 2014). Similarly, we compute the in-sample and pre-publication performance of the short-term composite strategy, which starts as a composite of

[13] The figure should be read as follows. Each line presents one of the four portfolio construction approaches. The first dot at the top left of each line marks the gross six-factor alpha of the strategy. When following the line to the bottom right, the next two dots mark the net alpha and transaction cost levels when the strategies become insignificant at the 1% and 5% significant levels. The last dot for each strategy show at which trading cost level the net alpha becomes negative.

[14] We thank two anonymous reviewers for raising this point.

[15] The attenuation of prominent anomalies has also been documented by Chordia, Subrahmanyam, and Tong (2014) and Green et al. (2017) document a sharp decrease in return predictability after 2003.

all five signals in December 1985. Subsequently, we remove signal by signal when their in-sample and pre-publication samples end.

INSERT TABLE 6 HERE

Table 6 contrasts the in-sample and pre-publication performance of the short-term composite strategy with the out-of-sample and post-publication performance for the 20/20 and 10/50 trading rules. As expected, the average return and six-factor alpha of more than 12% for the in-sample and pre-publication periods are somewhat higher than the corresponding values for the full sample period. The only exception is the six-factor alpha of the composite strategy for the 10/50 trading approach. The associated t-statistics are lower, but this also stems from the shorter lengths of these samples.

The out-of-sample and post-publication returns and alphas are around 8%, equivalent to performance decays between 18% and 40% compared to their in-sample and pre-publication counterparts. However, with values above 3 for the mean returns and above 5 for the six-factor alphas, the t-statistics still exceed the critical value derived in Novy-Marx (2016), which corrects for overfitting biases in the case of five equally-weighted signals. Furthermore, the net alphas remain positive and significant when assuming transaction costs of 25 bps per single trip (as in Figure 1), at least when the more sophisticated buy and sell rules are applied. Similarly, the break-even transaction costs remain above 25 bps and 45 bps for the 20/20 and 10/50 approaches, respectively.[16]

These results imply that the short-term composite strategy is also profitable after costs for the out-of-sample and post-publication periods of the single signals, also keeping in mind that trading costs have generally declined over time. While the individual signals suffer from some performance decay, the advantage of using a composite is that more and more signals become available over time. This suggests that continuous enhancement of investment strategies is crucial to maintaining their profitability in practice.

3.4. Other investment frictions

As mentioned before, short-term signals are often dismissed because of market friction concerns. The previous section demonstrated that the alpha of the short-term composite strategy is not subsumed by transaction costs. In this section, we address other investment frictions.

First, we focus on the long side of the composite strategy. So far, we have analyzed top-minus-bottom strategies, but in practice shorting individual stocks is not without frictions. On the one hand, shorting stocks involves additional costs, particularly shorting fees. Shorting costs are

[16] As another robustness check, Table A2 in the Appendix reports net results for the second half of the sample, starting in January 2004. The 10/50 strategy is shown for global markets, as well as for the US separately. Consistent with the out-of-sample and post-publication results, the alphas generally hold up well, with most t-statistics remaining economically and statistically significant. However, for the US market in isolation the net alpha (after 25 bp costs per trade) is insignificant over this recent period, with the net outperformance even being negative. This echoes the finding of Jacobs and Müller (2020) that post-publication performance decay is a major concern for the US market but much less so for international markets. It also underlines the importance of further minimizing the implementation shortfall and continued innovation with new and improved signals.

estimated to be between 20 and 45 bps per year for easily borrowable stocks, but these costs can easily exceed 100 bps for harder-to-borrow stocks (cf., D'Avolio 2002, Cohen, Diether, and Malloy, 2007, Beneish, Lee, and Nichols, 2015, or Porras Prado, Saffi, and Sturgess, 2016). Moreover, shorting is not always feasible due to missing shorting supply (cf., Beneish et al., 2015). Therefore, we rerun the analysis in Table 5 with the top portfolio and report the results in Table 7. We observe that mean returns, CAPM alphas, and Fama-French six-factor alphas are roughly half for all four portfolio construction approaches. However, as the turnover and volatility of the returns (not reported) are also approximately halved, t-values and break-even trading costs remain nearly unchanged (on average, we find 3.5bps lower break-even trading costs). Therefore, shorting frictions cannot explain the abnormal returns of the short-term composite, and our base results remain strong in long-only applications.

INSERT TABLE 7 HERE

Second, a real-time application of the strategy would involve an implementation lag as most of the signals implicitly assume that we can simultaneously observe and trade on a signal. While some studies consider implementation lags (e.g., Jegadeesh, 1990, Blitz et al., 2013, Medhat and Schmeling, 2022), most papers do not consider implementation lags. We investigate the effect of implementing the signal with lags ranging from one to ten trading days.

INSERT FIGURE 4 HERE

Figure 4 shows that the performance decreases monotonically with a longer implementation lag. For example, while a hypothetical immediate implementation would yield a gross six-factor alpha of more than 11% (with break-even trading costs of about 60 bps), a fast but realistically feasible implementation lag of one day decreases the net alpha by 1.5% and break-even trading costs to 53 bps. Lagging the signal by two or three trading days still results in break-even costs above 40 bps, but implementation lags of a week or longer question the significance of the real-life returns for the short-term composite signal. This result is not surprising for a strategy that is based on short-term signals. In reality, however, professional investors should be able to limit the implementation delay to one day at most.

3.5 Robustness tests

To check the robustness of the results, we conduct three follow-up tests, again using the buy/hold 10/50 strategy as our base case.

First, we analyze to what extent our results depend on the number of included short-term signals in the composite. Therefore, we compute the break-even trading cost for all possible multiple-signal composites for two-, three-, or four-signal combinations[17], take the average and compare it with the average break-even costs for a single-signal strategy (as in Section 3.1) and our five-signal composite introduced in Section 3.2. In all cases, we use the 10/50 portfolio construction rule. Figure 5 visualizes the diversifying effect of adding more signals. The average break-even costs for individual signals are slightly above 30 bps and monotonously increase when more

[17] The number of possible combinations with n signals is $\binom{5}{n}$.

signals are added. For example, the average break-even costs for three-signal composites are already nearly 50 bps and increase to 55bps for the average four-signal composites. These results show that our results do not critically depend on the five-signal composite that we use in the main analysis.

INSERT FIGURE 5 HERE

Second, we investigate the performance of the composite strategy within the three separate regions North America, Europe, and Japan & Pacific. Columns one to three in Table 8 show that the mean returns, CAPM alphas, and six-factor model alphas are all significant and range between 9% and 15%, 11% and 18%, and 10% and 15%, respectively. The composite strategy performs best in Europe, followed by North America and Japan & Pacific. However, even for Europe, the t-statistics for the six-factor alpha are not as strong as for the global strategy, which highlights the benefits of diversifying across regions. In line with the returns, the break-even trading costs are highest for Europe at nearly 75 bps, which is well above the conservative trading costs estimate of 25 bps. As actual trading costs are generally the lowest in North America, the break-even trading costs of more than 50 bps indicate that the strategy should also be highly profitable after costs in this region. The profitability of the strategy is lowest for the Pacific region. However, break-even trading costs of more than 40 (50) bps for the mean return (six-factor alpha) indicate that the strategy should still be profitable after transaction costs.

INSERT TABLE 8 HERE

Third, we further check the robustness of the short-term composite strategy for a sample that we have not examined so far. Emerging markets are attractive for out-of-sample tests in terms of new and independent samples as they are only partially integrated with developed markets. Some of the short-term signals, such as the short-term reversal effect, have also been confirmed for emerging markets (cf., Griffin, Kelly, and Nardari, 2010), while others, such as the same month seasonality effect, could not be confirmed (cf., Li, Zhang, and Zheng, 2018)

Similar to our developed markets sample, the emerging markets sample consists of all constituent stocks of the MSCI Emerging Markets index at each point in time. The sample period starts in December 1995, the earliest date at our disposal, and ends in December 2021. The underlying signals, the construction of the short-term composite, and the portfolio construction are identical to those for developed markets. However, instead of applying regional neutrality, we apply country neutrality, i.e., we rank stocks separately within each county, as it is common for emerging market studies (cf., Van der Hart et al., 2003 or Hanauer and Lauterbach, 2019). The last column in Table 8 shows that the short-term composite strategy has an even higher return in emerging markets than in developed markets. The mean return (six-factor alpha) exceeds 14% (12%) per annum and is highly significant. The associated break-even trading costs that would render the mean return (six-factor alpha) negative slightly exceed 70 (60) bps. Whether this is sufficient to overcome real-life trading costs in emerging markets, which are known to be substantially higher than in developed markets, is a question that we leave open for future research.

3.6 The role of sentiment and limits to arbitrage

So far, our results indicate that the short-term composite strategy generates economically and statistically significant net alphas, at least when efficient trading rules are applied. To further understand the source of return predictability, we investigate the roles of investor sentiment and limits to arbitrage; i.e., investor psychology that allows mispricing to exist and the limits that prevent this mispricing from being resolved.[18] More specifically, we explore the relationship between the performance of the short-term composite and proxies for time-varying market-level sentiment and arbitrage conditions.

Following Jacobs (2015), we use the Baker and Wurgler (2006) market-level investor sentiment index orthogonalized for six macroeconomic variables as a proxy for time-varying investor sentiment. To measure time-varying limits to arbitrage, we construct a composite of the following five time-series by taking the average z-score: (i) the Chicago Board Options Exchange Market Volatility Index (VIX, extended by the VXO before 1990), (ii) the cross-section average idiosyncratic volatility of our global universe, (iii) the Ted spread, which is defined as the difference between the 3-month LIBOR rate and the 3-month U.S. T-bill rate, (iv) the corporate credit spread, which is defined as the difference between the Moody's BAA corporate bond yield and Moody's AAA corporate bond yield, and (v) the aggregate liquidity level (multiplied by -1) from Pástor and Stambaugh (2003). Furthermore, we follow Jacobs (2015) and compute dummy variables that take a value of 1 (0) if investor sentiment or the limits to arbitrage composite was above (below) its median value in the previous month. Next, we regress the return and Fama and French six-factor alpha of the short-term composite on these two dummies using both the 20/20 and 10/50 buy/hold portfolio construction approaches.

INSERT TABLE 9 HERE

Table 9 reports the result of these regressions. The intercept shows the strategy's average annualized return after months classified as low sentiment and low limits-to-arbitrage periods. The coefficients on the sentiment (SENT) and the limits to arbitrage (ARB) dummies show the additional annualized return after high sentiment and limits to arbitrage periods. While we find economically and statistically significant returns after low-sentiment and low limits-to-arbitrage periods, we also document that these returns are significantly higher after high-sentiment periods. This result indicates that sentiment-related mispricing partly explains the return predictability of our short-term composite strategy. Furthermore, the results confirm the findings of Stambaugh, Yu, and Yuan (2012) and Jacobs (2015) for eleven prominent anomalies and a broad range of 100 anomalies, respectively.

We also find that the returns are higher after high limits-to-arbitrage periods. However, compared to the investor sentiment, the additional return is mostly smaller and not significant at the 5% significance level for the raw returns. These results indicate that limits to arbitrage only partially explain the predictability of our short-term composite strategy. Furthermore, limits to arbitrage play only a subordinated role compared to investor sentiment.

[18] We thank William Goetzmann for this suggestion.

4. Conclusions

The relevance of high-turnover signals is questioned in the asset pricing literature because they seemingly do not survive after accounting for market frictions. This paper shows that an economically and statistically highly significant net alpha can be obtained from short-term signals. Our approach consists of combining multiple short-term signals that provide strong diversification benefits, mitigating transaction costs by only trading sufficiently liquid stocks, and using efficient buy-sell rules.

Our short-term composite strategy consists of short-term reversal, short-term momentum, short-term analyst revisions, short-term risk, and monthly seasonality signals. With cost-mitigating buy-sell rules, we find that the break-even transaction costs for a significant mean return and six-factor alpha exceed 55 bps, which is well above the level at which sophisticated investors should be able to trade. Furthermore, a short-term composite strategy that utilizes signals only after their out-of-sample or post-publication periods still exhibits break-even transaction costs above 45 bps. Other market frictions cannot explain the performance either, as the alpha is not disproportionally driven by the short side, and our results remain similarly strong in long-only applications. Also, the alpha is robust to incorporating an implementation lag of one to two days, which is necessary for real-time strategy implementation.

Further robustness tests show that the alpha is present within the separate North America, Europe, and Pacific & Japan regions, and also carries over to Emerging Markets. Although the performance of the short-term composite strategy has diminished over time, it remains profitable after costs in the out-of-sample or post-publication periods for the various signals. Finally, we provide evidence consistent with the hypothesis that sentiment-related mispricing partly explains the return predictability, as we find significantly higher returns after high-sentiment periods. Although we also find that the returns are higher after high limits-to-arbitrage periods, limits to arbitrage play only a subordinated role compared to investor sentiment.

The alpha from short-term signals seems out of reach for investors such as index providers with low rebalancing frequencies and sizable implementation lags (i.e., the gap between the announcement and effective date of index changes). Other investors might also be hampered by investment barriers that prevent them from capturing the alpha opportunity offered by short-term signals. Such investment barriers include having limited access to the necessary data, missing infrastructure to process the data, and the inability to execute the resulting signals in a timely and efficient manner. But for those investors who meet all the required conditions, short-term signals present a genuine opportunity to earn alpha beyond the common Fama-French factors.

Figure 1: Fama-French alphas of short-term signals

This figure plots the gross and net Fama-French six-factor model alpha of short-term signals. The first two bars show the alphas for the average individual short-term signal applying standard top-minus-bottom quintile (20/20) sorts. The third and fourth bars show the alphas for the short-term composite comprising the five individual signals and common top-minus-bottom quintile (20/20) sorts. Finally, the last two bars show the alphas for the short-term composite when applying more advanced buy and sell rules (10/50). I.e., every month, the long (short) portfolio consists of the stocks that currently belong to the top (bottom) 10% plus the stocks selected in previous months that are still among the top (bottom) 50% of stocks. For the calculation of net alphas, we assume average trading costs of 25 bps. The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

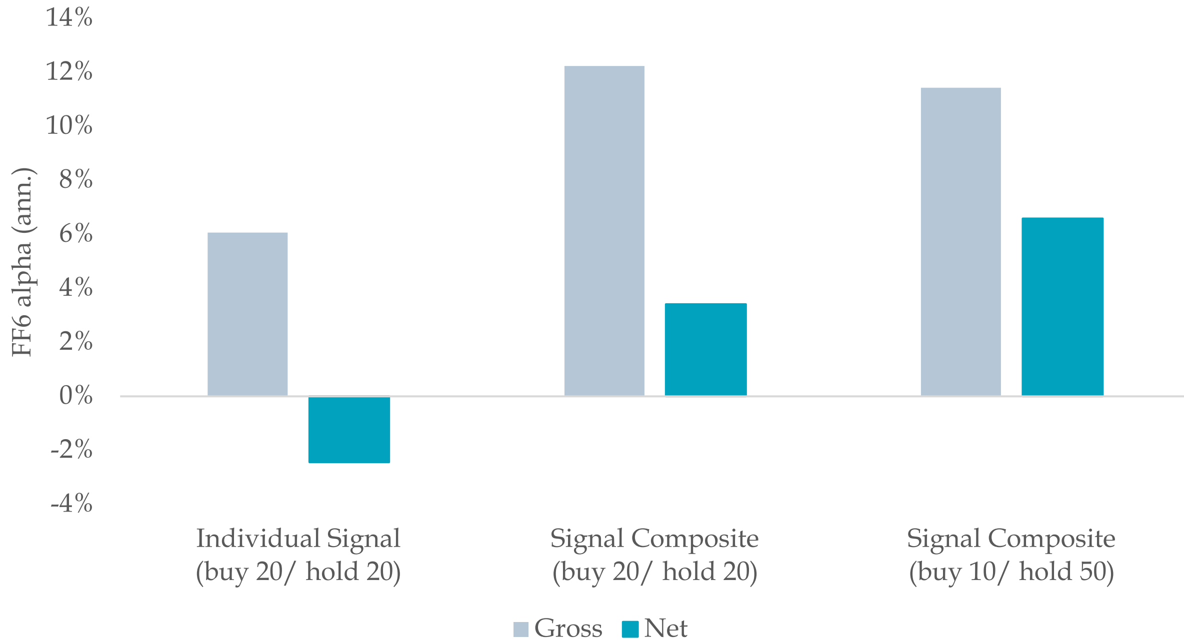

Figure 2: Cumulative performance for the multi-signal strategy

This figure plots the cumulative performance of the top-minus-bottom (T-B) quintile portfolio of the multi-signal strategy and its CAPM and Fama-French six-factor model (FF6) alpha. The short-term composite is computed by first normalizing each of the five short-term metrics (short-term reversal, short-term momentum, short-term analyst revisions, short-term risk, and monthly seasonality) cross-sectionally using standard robust z-scores, capped at plus and minus 3, and then averaging these scores. The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

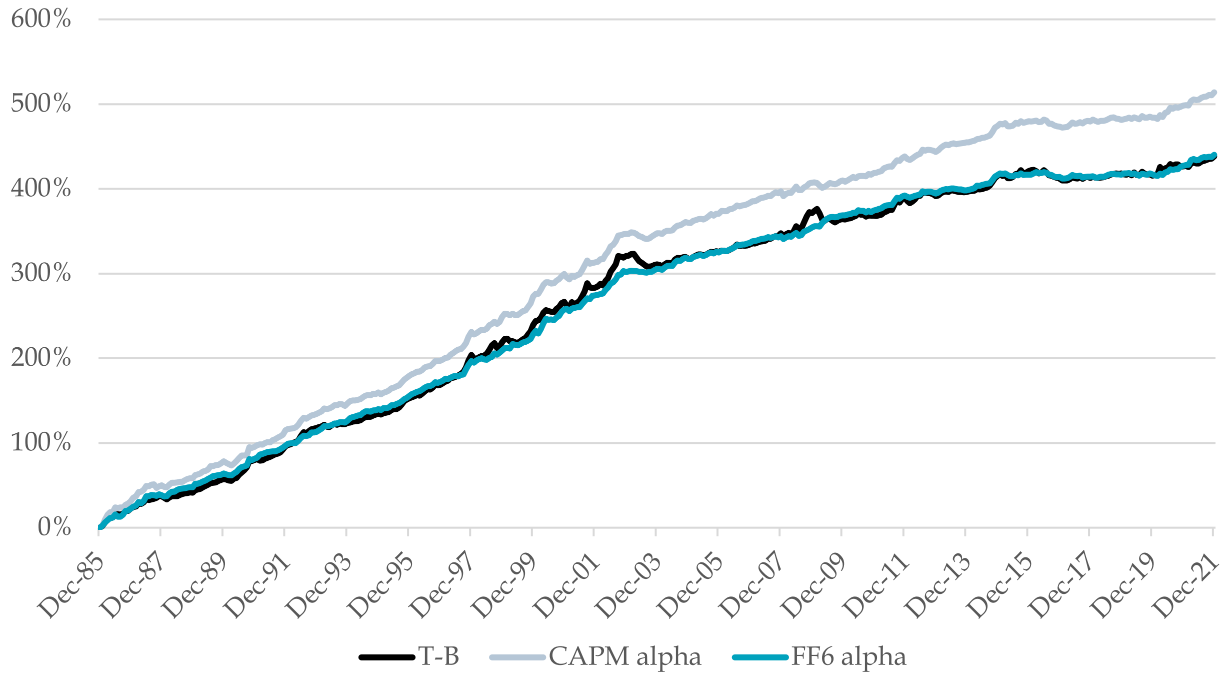

Figure 3: Net Fama-French alpha relative to assumed costs per trade

This figure plots the annualized Fama-French six-factor net alpha of the short-term composite for a continuous range of transaction costs. Each line presents one of the four portfolio construction approaches (X/Y). Every month the long (short) portfolio consists of the stocks that currently belong to the top (bottom) X% plus the stocks selected in previous months that have not deteriorated beyond the top (bottom) Y%. The first dot at the top left of each marks the gross six-factor alpha of the strategy. When following the line to the bottom right, the next two dots mark the net alpha and transaction cost levels when the strategies become insignificant at the 1% and 5% significant levels. The last dot for each strategy show at which trading cost level the net alpha becomes negative. The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

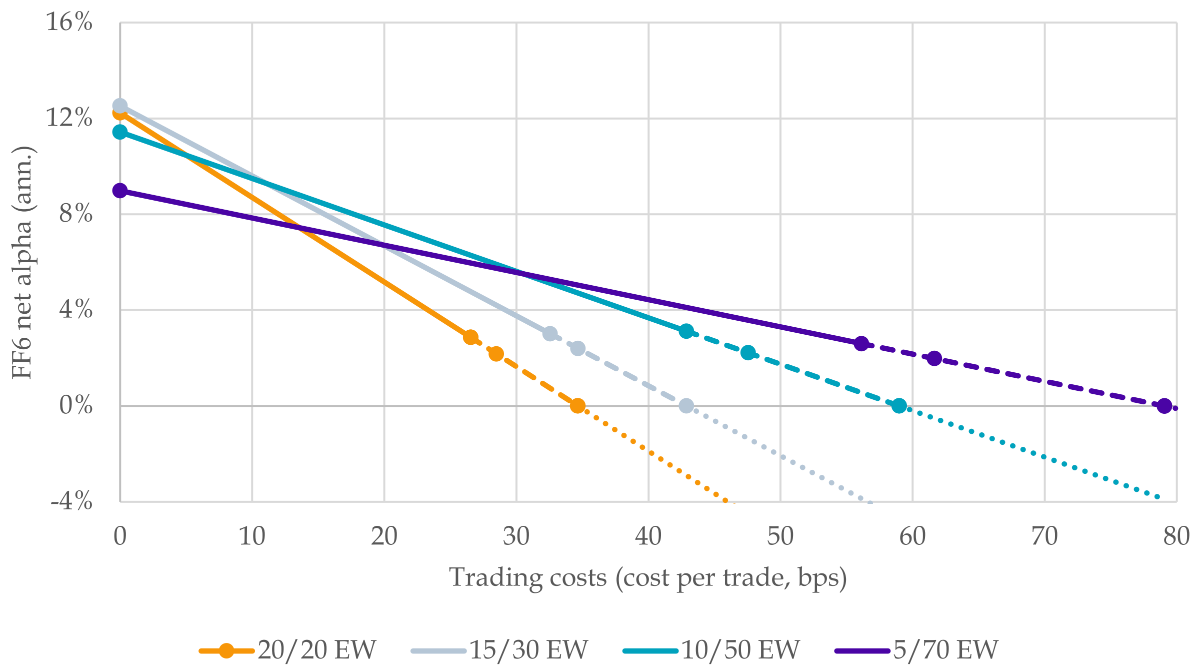

Figure 4: Alpha and associated break-even trading cost for different implementation lags

This figure plots the performance of the multi-signal composite for implementation lags ranging from zero to ten trading days. Every month the long (short) portfolio consists of the stocks that currently belong to the top (bottom) 10% plus the stocks selected in previous months that have not deteriorated beyond the top (bottom) 50%. The upper panel shows the annualized Fama-French six-factor alpha. The lower panel shows the associated break-even trading cost (i.e., the average trading costs at which the Fama-French six-factor alpha becomes zero). The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

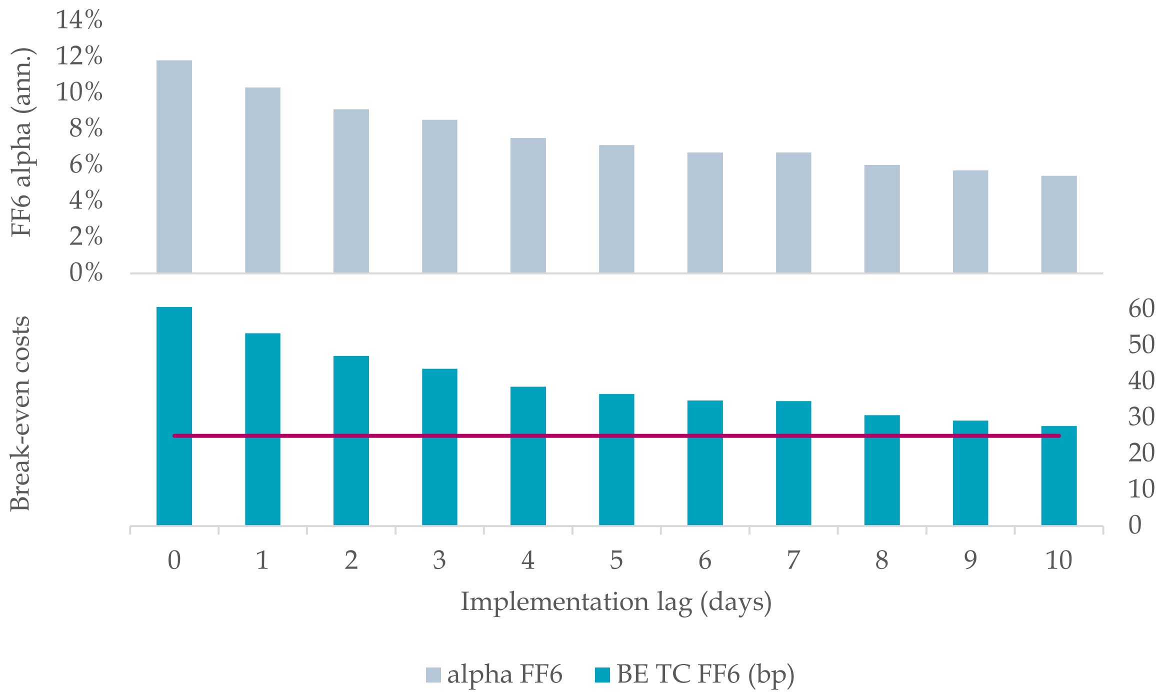

Figure 5: Break-even costs for different combinations of short-term signals

This figure plots the average break-even trading cost that would render the Fama-French six-factor alpha to zero for short-term composites comprising one to five signals. For each n-signal composite, we calculate the break-even costs for all possible combinations ($\binom{5}{n}$) and compute the average. Every month the long (short) portfolio consists of the stocks that currently belong to the top (bottom) 10% plus the stocks selected in previous months that have not deteriorated beyond the top (bottom) 50%. The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

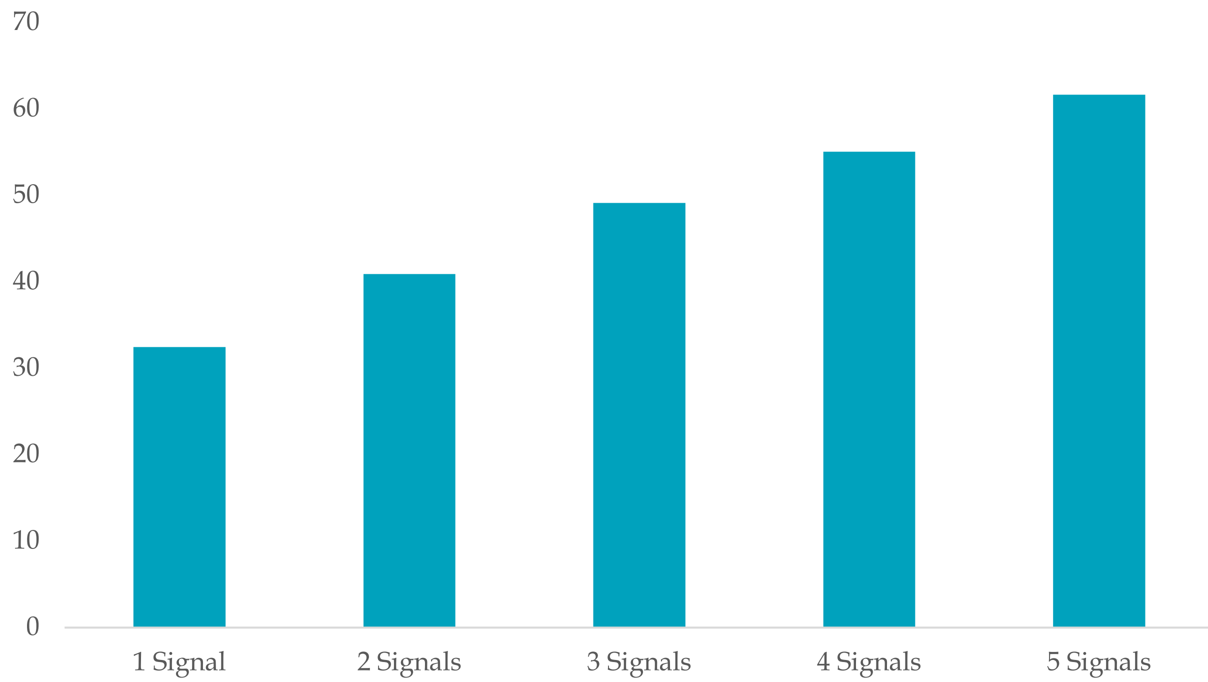

Table 1: The short-term signals

This table presents an overview of the short-term signals used in this study. Column 1 shows the abbreviation, Column 2 the full name, Column 3 the relevant reference, Column 4 the sample period of the original study, and Column 5 the publication month of the original study.

Abbreviation	Full name	Reference	Sample period	Publication
STR	industry relative reversal	Da, Liu, and Schaumburg (2014)	Jan-82 - Mar-09	Mar-14
IND_MOM	industry momentum	Moskowitz and Grinblatt (1999)	Jan-73 - Jul-95	Aug-99
REV30D	analyst earnings revisions	Van der Hart, Slagter, and van Dijk (2003)	Jan-85 - May-99	Feb-03
SEA_SAME	return seasonality	Heston and Sadka (2008)	Jan-63 - Dec-02	Feb-08
iVOL	idiosyncratic volatility	Ang, Hodrick, Xing, and Zhang (2006)	Jan-86 - Dec-00	Feb-06

Table 2: Short-term signal statistics

The table shows the annualized mean return, CAPM alpha, Fama-French six-factor alpha, and associated t-statistics for equally-weighted top-minus-bottom quintile portfolios. Furthermore, the table reports the regression coefficients for the Fama-French six-factor model, the average number of stocks in the portfolios, and the average annualized one-way turnover. Finally, the last two rows show break-even trading cost levels, defined as the average trading costs at which the mean return and Fama-French six-factor alpha become zero. The five signals are described in Table 1 and the sample consists of global large-cap stocks over the period from December 1985 to December 2021.

	STR	**IND_MOM**	**REV30D**	**SEA_SAME**	**iVOL**
Mean (ann. %)	7.82	5.44	7.63	6.49	2.14
t-value	(6.24)	(3.25)	(6.25)	(5.74)	(0.98)
CAPM alpha (ann. %)	6.24	6.81	9.14	6.08	6.42
CAPM t-value	(4.83)	(3.97)	(7.93)	(4.64)	(3.80)
FF6 alpha (ann. %)	6.32	7.37	6.90	7.33	2.43
FF6 t-value	(4.09)	(3.92)	(7.29)	(5.42)	(1.68)
RMRF	0.14	-0.11	-0.04	0.04	-0.36
SMB	0.12	-0.14	-0.07	0.03	-0.42
HML	0.06	-0.17	-0.09	-0.11	0.33
RMW	0.13	-0.07	-0.01	0.05	0.05
CMA	-0.05	0.13	0.07	-0.29	0.28
WML	-0.07	-0.04	0.27	-0.08	0.34
# Stocks	691	691	646	690	697
Ann. one-way turnover(%)	1930	1866	1524	1887	1306
Break-even TC (mean, bps)	20.26	14.59	25.04	17.19	8.20
Break-even TC (alpha, bps)	16.36	19.75	22.65	19.43	9.32

Table 3: Short-term signal return correlations

This table presents the correlation matrix for the top-minus-bottom quintile portfolio returns of the individual short-term signals. The five signals are described in Table 1 and the sample consists of global large-cap stocks over the period from December 1985 to December 2021.

	STR	IND_MOM	REV30D	SEA_SAME	iVOL
STR	1.00	-0.58	-0.36	0.13	-0.39
IND_MOM	-0.58	1.00	0.26	0.09	0.16
REV30D	-0.36	0.26	1.00	-0.06	0.51
SEA_SAME	0.13	0.09	-0.06	1.00	-0.28
iVOL	-0.39	0.16	0.51	-0.28	1.00

Table 4: Multi-signal strategy statistics

This table presents results for equally-weighted quintile portfolios of the short-term composite and the top-minus-bottom quintile portfolio. For each portfolio, the table shows the annualized outperformance over the market and the associated CAPM alpha, Fama-French six-factor alpha, and t-statistics. Furthermore, the table reports the regression coefficients for the Fama-French six-factor model, the average number of stocks in the portfolios, and the average annualized one-way turnover. Finally, the last two rows show break-even trading cost levels, defined as the average trading costs at which the mean return and Fama-French six-factor alpha become zero. The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

	Top	2	3	4	Bottom	Top-Bottom
Outperformance (ann. %)	5.88	2.47	0.11	-2.18	-6.29	12.17
t-value	(9.42)	(5.83)	(0.37)	(-6.00)	(-7.72)	(8.98)
CAPM alpha (ann. %)	6.71	3.10	0.30	-2.57	-7.56	14.27
CAPM t-value	(9.95)	(7.74)	(1.00)	(-6.49)	(-10.08)	(10.81)
FF6 alpha (ann. %)	6.02	2.68	0.02	-2.52	-6.21	12.23
FF6 t-value	(9.80)	(6.96)	(0.06)	(-6.45)	(-10.26)	(11.02)
RMRF	-0.05	-0.05	-0.01	0.03	0.07	-0.13
SMB	-0.05	-0.04	-0.06	0.00	0.16	-0.21
HML	-0.02	-0.01	0.02	0.04	-0.04	0.02
RMW	0.03	0.01	0.01	0.00	-0.04	0.07
CMA	-0.01	0.05	0.04	0.01	-0.09	0.07
WML	0.08	0.04	0.02	-0.01	-0.12	0.20
# Stocks	349	351	351	351	349	697
Ann. one-way turnover(%)	906	942	954	952	858	1764
Break-even TC (mean, bps)	32.46	13.10	0.58	-11.44	-36.66	34.50
Break-even TC (alpha, bps)	33.22	14.24	0.09	-13.26	-36.15	34.65

Table 5: Efficient portfolio construction for top-minus-bottom portfolios

This table presents results for different buy/hold portfolio construction approaches of equally-weighted top-minus-bottom portfolios sorted on the short-term composite. Every month the long (short) portfolio consists of the stocks that currently belong to the top (bottom) X% plus the stocks selected in previous months that have not deteriorated beyond the top (bottom) Y%. The first number of the column row names presents X, while the second number presents Y. For each approach, the table shows the annualized mean return, CAPM alpha, Fama-French six-factor alpha, and associated t-statistics. Furthermore, the table reports the regression coefficients for the Fama-French six-factor model, the average number of stocks in the portfolios, and the average annualized one-way turnover. Finally, the last two rows show break-even trading cost levels, defined as the average trading costs at which the mean return and Fama-French six-factor alpha become zero. The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

	20/20 EW	**15/30 EW**	**10/50 EW**	**5/70 EW**
Mean (ann. %)	12.17	12.49	11.30	8.95
t-value	(8.98)	(8.13)	(6.81)	(4.97)
CAPM alpha (ann. %)	14.27	15.03	14.19	12.11
CAPM t-value	(10.81)	(10.47)	(9.77)	(7.94)
FF6 alpha (ann. %)	12.23	12.52	11.43	8.98
FF6 t-value	(11.02)	(10.71)	(10.12)	(8.90)
RMRF	-0.13	-0.16	-0.18	-0.20
SMB	-0.21	-0.21	-0.21	-0.23
HML	0.02	0.02	0.02	0.05
RMW	0.07	0.09	0.08	0.07
CMA	0.07	0.07	0.03	-0.05
WML	0.20	0.25	0.30	0.36
# Stocks	697	640	636	571
Ann. one-way turnover(%)	1764	1460	969	568
Break-even TC (mean, bps)	34.50	42.79	58.30	78.77
Break-even TC (alpha, bps)	34.65	42.88	58.98	79.07

Table 6: In-sample (pre-publication) versus out-of-sample (post-publication) performance

This table presents results for the in-sample, out-of-sample, pre-publication, and post-publication performance of equally-weighted top-minus-bottom portfolios sorted on the short-term composite. The in-sample and pre-publication performance of the short-term composite strategy starts as a composite of all five signals in December 1985. Subsequently, we remove signal by signal when their in-sample and pre-publication samples end (cf., Table 1). The out-of-sample (post-publication) performance starts in August 1995 (September 1999) when the out-of-sample (post-publication) period for industry momentum begins. Subsequently, we add signal by signal after their in-sample and pre-publication samples end. 20/20 and 10/50 indicate buy/hold portfolio construction approaches as described in Table 5. For each strategy, the table shows the gross annualized mean return, gross Fama-French six-factor alpha, and associated t-statistics. Furthermore, the table reports the net Fama-French six-factor alpha when assuming average trading costs of 25 bps and break-even trading cost levels, defined as the average trading costs at which the gross mean return and Fama-French six-factor alpha become zero.

		In-sample	Out-of-sample	Pre-publication	Post-publication
	Sample start	Jan-86	Aug-95	Jan-86	Sep-99
	Sample end	Mar-09	Dec-21	Mar-14	Dec-21
20/20 EW	**Mean (ann. %)**	13.36	8.89	12.63	7.74
	t-value	(6.48)	(4.26)	(7.14)	(3.19)
	FF6 alpha (ann. %)	14.59	9.64	12.81	9.64
	FF6 t-value	(7.74)	(6.11)	(6.85)	(5.63)
	Net FF6 alpha (ann. %)	4.79	0.99	4.06	1.02
	Net FF6 t-value	(2.96)	(0.63)	(2.17)	(0.60)
	Break-even TC (mean, bps)	34.50	38.12	25.61	35.97
	Break-even TC (alpha, bps)	34.65	38.73	27.85	36.59
10/50 EW	**Mean (ann. %)**	11.68	8.25	11.55	8.40
	t-value	(5.14)	(3.30)	(5.71)	(3.03)
	FF6 alpha (ann. %)	11.00	8.66	11.67	9.52
	FF6 t-value	(5.93)	(5.71)	(5.98)	(5.54)
	Net FF6 alpha (ann. %)	5.97	3.94	6.76	4.86
	Net FF6 t-value	(3.22)	(2.60)	(3.46)	(2.83)
	Break-even TC (mean, bps)	58.30	57.89	43.55	58.61
	Break-even TC (alpha, bps)	58.98	54.69	45.88	59.39

Table 7: Efficient portfolio construction for long-only portfolios

This table presents results for different buy/hold portfolio construction approaches of equally-weighted top portfolios sorted on the short-term composite. Every month the long portfolio consists of the stocks that currently belong to the top X% plus the stocks selected in previous months that have not deteriorated beyond the top Y%. The first number of the column row names presents X, while the second number presents Y. For each approach, the table shows the annualized outperformance over the market and the associated CAPM alpha, Fama-French six-factor alpha, and t-statistics. Furthermore, the table reports the regression coefficients for the Fama-French six-factor model, the average number of stocks in the portfolios, and the average annualized one-way turnover. Finally, the last two rows show break-even trading cost levels, defined as the average trading costs at which the mean return and Fama-French six-factor alpha become zero. The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

	20/20 EW (long-only)	**15/30 EW (long-only)**	**10/50 EW (long-only)**	**5/70 EW (long-only)**
Outperformance (ann. %)	5.88	6.00	5.37	4.03
t-value	(9.42)	(8.85)	(7.57)	(5.61)
CAPM alpha (ann. %)	6.71	6.96	6.50	5.19
CAPM t-value	(9.95)	(9.81)	(9.60)	(7.94)
FF6 alpha (ann. %)	6.02	6.14	5.56	4.03
FF6 t-value	(9.80)	(9.45)	(9.65)	(8.09)
RMRF	-0.05	-0.06	-0.07	-0.08
SMB	-0.05	-0.04	-0.04	-0.05
HML	-0.02	-0.02	-0.02	0.03
RMW	0.03	0.03	0.02	0.03
CMA	-0.01	-0.02	-0.04	-0.10
WML	0.08	0.10	0.12	0.15
# Stocks	349	319	323	302
Ann. one-way turnover(%)	906	756	497	277
Break-even TC (mean, bps)	32.46	39.67	54.07	72.95
Break-even TC (alpha, bps)	33.22	40.65	56.02	72.79

Table 8: Regional results for the 10/50 multi-signal strategy

This table presents the results of the 10/50 multi-signal strategy in different regions. The first three columns show the developed market subregions North America, Europe, and Japan& Pacific, while the fourth column shows emerging markets (EM). Every month the long (short) portfolio consists of the stocks that currently belong to the top (bottom) 10% plus the stocks selected in previous months that have not deteriorated beyond the top (bottom) 50%. For each region, the table shows the annualized mean return, CAPM alpha, Fama-French six-factor alpha, and associated t-statistics. Furthermore, the table reports the regression coefficients for the Fama-French six-factor model, the average number of stocks in the portfolios, and the average annualized one-way turnover. Finally, the last two rows show break-even trading cost levels, defined as the average trading costs at which the mean return and Fama-French six-factor alpha become zero. The sample period is from December 1985 to December 2021 for the three developed market subregions and December 1995 to December 2021 for EM, respectively.

	North America	**Europe**	**Japan & Pacific**	**EM**
Mean (ann. %)	10.11	14.72	8.95	14.67
t-value	(4.41)	(7.49)	(4.11)	(8.42)
CAPM alpha (ann. %)	14.11	17.45	11.18	16.34
CAPM t-value	(7.19)	(9.29)	(5.99)	(10.12)
FF6 alpha (ann. %)	10.62	14.23	10.55	12.60
FF6 t-value	(6.93)	(9.03)	(6.24)	(8.30)
RMRF	-0.17	-0.19	-0.21	-0.18
SMB	-0.36	-0.12	-0.01	0.01
HML	0.08	-0.06	-0.05	0.03
RMW	-0.06	0.02	0.13	0.06
CMA	0.00	-0.08	-0.10	0.02
WML	0.32	0.27	0.27	0.21
# Stocks	237	208	190	278
Ann. One-way turnover(%)	953	949	1032	1033
Break-even TC (mean, bps)	53.05	77.58	43.35	71.02
Break-even TC (alpha, bps)	55.77	74.97	51.13	61.01

Table 9: The role of sentiment and limits to arbitrage

This table presents coefficients from regressions of the short-term composite return and its Fama and French six-factor alpha on dummies that take a value of 1 (0) if investor sentiment (SENT) or the limits to arbitrage composite (ARB) was above (below) its median value in the previous month. The top-minus-bottom return coefficients are annualized (%), and the t-statistics are in parentheses. We use the Baker and Wurgler (2006) market-level investor sentiment index orthogonalized for six macroeconomic variables as a proxy for time-varying investor sentiment. To measure time-varying limits to arbitrage, we construct a composite of the following five time-series: (i) the Chicago Board Options Exchange Market Volatility Index (VIX, extended by the VXO before 1990), (ii) the cross-section average idiosyncratic volatility of our global universe, (iii) the Ted spread, (iv) the corporate credit spread, and (v) the aggregate liquidity level (multiplied by -1) from Pástor and Stambaugh (2003). The sample consists of global large-cap stocks over the period from December 1985 to December 2021.

	Top-Bottom Return			Top-Bottom FF6 alpha		
	Intercept	**SENT**	**ARB**	**Intercept**	**SENT**	**ARB**
20/20 EW	8.94	6.51		9.52	5.44	
	(3.92)	(2.27)		(6.73)	(2.80)	
	9.81		4.73	9.45		5.55
	(6.42)		(1.69)	(7.71)		(2.82)
	6.21	6.82	5.14	6.39	5.80	5.90
	(2.76)	(2.41)	(1.88)	(3.68)	(3.04)	(3.02)
	Intercept	**SENT**	**ARB**	**Intercept**	**SENT**	**ARB**
10/50 EW	7.70	7.23		8.96	6.02	
	(2.74)	(2.03)		(6.81)	(2.92)	
	9.67		3.26	9.92		4.07
	(5.38)		(0.97)	(7.82)		(2.01)
	5.73	7.45	3.71	6.60	6.29	4.45
	(2.13)	(2.11)	(1.12)	(3.68)	(3.05)	(2.19)

Appendix

Table A1: Additional tests

This table presents the results of equally-weighted top-minus-bottom portfolios sorted on the multi-signal strategy for different specifications. The first column is our base case, as shown in Table 5, while the second column replaces the industry relative reversal signal with the raw short-term reversal signal. The third column represents our base case but starts only in July 1990 to make it comparable to the last column, in which we replace our self-calculated Fama-French factors with control factors from Kenneth French's website. Every month the long (short) portfolio consists of the stocks that currently belong to the top (bottom) 10% plus the stocks selected in previous months that have not deteriorated beyond the top (bottom) 50%. For each specification, the table shows the annualized mean return, CAPM alpha, Fama-French six-factor alpha, and associated t-statistics. Furthermore, the table reports the regression coefficients for the Fama-French six-factor model, the average number of stocks in the portfolios, and the average annualized one-way turnover. Finally, the last two rows show break-even trading cost levels, defined as the average trading costs at which the mean return and Fama-French six-factor alpha become zero. The sample period is from December 1985 to December 2021 for the first two columns and June 1990 to December 2021 for the last two columns.

	10/50 EW			
Source FF factors	**own**	**own**	**own**	**KF**
STR	**ind.-adj.**	**raw**	**ind.-adj.**	**ind.-adj.**
Start	**Jan-86**	**Jan-86**	**Jul-90**	**Jul-90**
Mean (ann. %)	11.30	10.79	11.12	11.12
t-value	(6.81)	(6.50)	(5.99)	(5.99)
CAPM alpha (ann. %)	14.19	13.68	13.94	13.94
CAPM t-value	(9.77)	(9.56)	(9.27)	(9.27)
FF6 alpha (ann. %)	11.43	10.79	11.55	9.58
FF6 t-value	(10.12)	(9.42)	(9.25)	(8.00)
RMRF	-0.18	-0.18	-0.19	-0.21
SMB	-0.21	-0.21	-0.25	-0.29
HML	0.02	0.05	-0.04	-0.09
RMW	0.08	0.08	0.00	0.39
CMA	0.03	0.00	0.09	-0.19
WML	0.30	0.31	0.28	0.33
# Stocks	636	649	634	634
Ann. One-way turnover(%)	969	926	956	956
Break-even TC (mean, bps)	58.30	58.28	58.13	58.13
Break-even TC (alpha, bps)	58.98	58.28	60.40	50.12

Table A2: Regional results after trading costs for the 10/50 multi-signal strategy post-2003

This table presents regional results of the 10/50 multi-signal strategy after trading costs post-2003. The columns show global developed markets, the US, international markets (global developed markets excluding the US), and emerging markets. Every month the long (short) portfolio consists of the stocks that currently belong to the top (bottom) 10% plus the stocks selected in previous months that have not deteriorated beyond the top (bottom) 50%. For each region, the table shows the annualized gross and net mean return, net CAPM alpha, net Fama-French six-factor alpha, and associated t-statistics, after applying 25 bp costs per trade (for global, US and international) or 35 bp costs per trade (for EM). Furthermore, the table reports the regression coefficients for the CAPM and the Fama-French six-factor model, and the average annualized one-way turnover. The sample period is from January 2004 to December 2021.

	Global	US	International	EM
Gross mean (ann. %)	7.42	4.21	9.00	11.93
t-value	(3.24)	(1.45)	(3.99)	(6.98)
Net mean (ann. %)	2.60	-0.69	4.18	4.78
t-value	(1.13)	(-0.24)	(1.84)	(2.79)
Net CAPM alpha (ann. %)	5.82	3.59	6.69	6.29
CAPM t-value	(3.52)	(1.78)	(3.78)	(3.66)
CAPM beta	-0.38	-0.42	-0.35	-0.16
Net FF6 alpha (ann. %)	2.96	0.94	4.12	3.20
FF6 t-value	(1.95)	(0.47)	(2.62)	(1.68)
RMRF	-0.15	-0.14	-0.15	-0.10
SMB	-0.22	-0.30	-0.10	0.04
HML	-0.24	0.00	-0.24	0.03
RMW	-0.04	-0.01	0.01	0.04
CMA	0.18	-0.02	0.10	0.11
WML	0.22	0.30	0.22	0.20
Ann. one-way turnover(%)	964	981	964	1021

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