Factor-Driven Lead-Lag Effects and Factor Momentum *

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Abstract

This paper shows that the presence of lead-lag effects in the US equity market is a broader phenomenon than previously found in the literature and is associated with the existence of a strong one-day factor momentum. Lead-lag effects are present whenever stocks are exposed to the same common risk factor, holding for almost 100 factors constructed with daily data. This phenomenon is not explained by the previously reported industry, large-cap to small-cap and other lead-lag effects. One-day factor momentum arises as a natural consequence of factor-based stock cross-autocovariance and is present both in the cross-section and the time series. One-day factor momentum is profitable after trading costs and does not present crashes. One-month factor momentum is subsumed by one-day factor momentum with negative alpha in spanning tests. The relevance of the one-day effect is confirmed with machine learning techniques. Short-term reversals in stocks also become stronger after we control for this factor-based cross-autocovariance pattern.

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1 Introduction

The presence of lead-lag effects among stocks is a broad phenomenon in equity markets. It has already been reported widely in the literature. For instance, Lo and MacKinlay [1990] show that returns of large stocks lead smaller stocks returns. Menzly and Ozbas [2006] use upstream and downstream definitions of industries to define cross-industry momentum. Hou [2007] finds evidence that the lead-lag effect between big firms and small firms is predominantly an intra-industry phenomenon. Cohen and Frazzini [2008] report links across customers-suppliers firms. Parsons et al. [2018] document lead-lag effects in stock returns between co-headquartered firms operating in different sectors. Liu and Wu [2018] find "labor momentum", stronger among low analyst coverage, low institutional ownership, and small firms. Lee et al. [2019] shows that technology-linked firms' returns predict local firm returns. And the list goes on.

This paper shows evidence that lead-lag effects in equity markets are a broader phenomenon than previously found and are linked to the existence of one-day factor momentum. While most papers in the literature focus only on one specific economic link across firms at time, we take a more general approach and show that lead-lag effects among stocks occur in multiple dimensions at the same time. Lead-lag effects are determined by common risk exposures or common characteristics, with industry risk being just one particular case. We find evidence for almost 100 factors or characteristics on a daily frequency, from 1963 to 2018, with the cross-autocorrelation between stocks being responsible for 90% of factor return autocorrelation on average. These lead-lag effects are present even for factor portfolios constructed just with large-cap stocks and when we neutralize industry exposure, showing that the previous size and industry effects, reported by Lo and MacKinlay [1990], Hou [2007] and Cohen and Frazzini [2008], are not the causes of this broader pattern that we report.

Short-term one-day factor momentum arises as a natural consequence of this daily lead-lag phenomenon. More precisely, both patterns are closely related as the first would not likely exist without the latter, even though we do not claim that the latter causes the first. These one-day momentum strategies work both in the cross-section and time series. They are profitable even after taking trading costs into account, with a net of costs Sharpe ratio as high as 0.80, and subsume other momentum with longer formation windows, and do not exhibit crashes. Short-term reversals in equities also become stronger when stocks exposure to factors is neutralized, since it is negatively exposed to one-day factor momentum, as reported in our contemporary work Garcia et al. [2020]. This pattern across stocks is possibly driven by slow information diffusion among stocks with similar risks and shows that cross-autocovariance is present in several dimensions among stocks.

To compute stocks lead-lag effects across all characteristic/factor dimensions, we decompose autocorrelation into two different components following Lo and MacKinlay [1990]: one due to individual stock autocorrelation and the other one due to the cross-autocorrelation between stocks, i.e. the lead-lag effect component. For the 103 factors that we analyze, 98 have positive and statistically significant return autocorrelation in the daily frequency, and among these, 94 are due to lead-lag effects. On average, autocorrelation for these 103 factors is 0.098, while the cross-autocorrelation is 0.091. Hence, lead-lags effects within stocks with similar factor exposure, measured by the cross-autocorrelation, are responsible roughly for 90% of factor return autocorrelation.

The presence of lead-lag effect in all characteristic/factor dimensions is not explained by the previously reported industry or size effects. To analyze the potential impact of a industry-driven effect on the factor-driven effects, we construct industry-neutral factor portfolios for all factors that we analyze in this paper. Stock cross-autocorrelation is also present in these industry-neutral factors and is almost as strong as in the regular case. Our new results are also not explained by small stock effects that could be potentially explained by non-synchronized trades or small stocks reacting with a lag to large stocks returns. Factors constructed only with large-cap stocks – whose market equity value is above the NYSE median breakpoint (largest 800 stocks on average) – present the same pattern where positive autocorrelation seem to be due to cross-autocorrelation components, with respective mean values of 0.059 and 0.051.

Previously reported industry-driven lead-lag effects appear to be just a particular case of a broader phenomenon and they are partially explained by the factor-driven lead-lag effects. More than half of industry-driven lead-lag effects is due to factor-driven lead-lag effects that we report in this paper. Industries portfolios have mean positive cross-autocorrelation of 0.07, with this term being responsible for practically all of its autocorrelation. However, when we control industry portfolios for their exposure to other risk factors, both factor autocorrelation and its cross-autocorrelation component decrease at the same time. The cross-autocorrelation for factor-neutral industries decrease by more than half, to 0.03, after controlling for even a limited number of selected factors. This drop becomes even more pronounced when we increase the number of factors that we use to neutralize industries' factor exposures. This finding shows that relevant part of the previously reported industry-driven lead-lag effects is due to factor-driven lead-lag effects that we report in this paper.

Our finding is also not explained by any kind of spurious effects that may occur when we group stocks into portfolios. We construct random factor portfolios and show that they do not present cross-correlation between stocks and neither autocorrelation in returns. We construct random factors using the same time series of returns and market value, but randomly sorting stocks into high, neutral, or low portfolios.

Short-term one-day momentum in factors and industries arises as a natural consequence of the factor-based lead-lag effects that we present here. Nevertheless, we do not claim any causal link between the above effects, just that the phenomena coexist. Despite a high turnover, one-day factor momentum strategies are profitable even after trading costs in both cross-sectional and time-series versions. They present high Sharpe ratios, no crashes, and also subsumes other momentum strategies. For example, one-day time-series factor momentum has a Sharpe ratio of 0.81 after trading costs, with a maximum drawdown of -15%. The high turnover issue can also be improved with predictive models that capture the time-varying strength of factor momentum or with other techniques that are not the focus and not covered by this paper.

Factor momentum based on longer look-back windows, such as the one-month momentum of Gupta and Kelly [2019] and Ehsani and Linnainmaa [2019], are directly related and partially explained by the one-day factor momentum. If we take the one-month factor momentum strategy and neutralize the effect of the first day (one-day momentum), we find a significant decrease in its profitability of around 70%. Alternatively, when we regress it against the one-day factor momentum, the performance of the one-month factor strategy goes from 8.0% to -4.6% (t-statistic of -3.8). Moreover, almost all considered factors are statistically significant at the level of 5% (98 out of 103) in daily frequency, while only 61 are in monthly frequency.

We confirm our findings with Machine Learning techniques and different model selection criteria. Shrinkage models such as Lasso, Elastic Net, or Fused Lasso have very good out-of-sample predictability and lead to the selection of the past one-day factor return (average R^2_{OOS} of 1.9% across factors) and no predictability when we use the data in a monthly frequency (negative R^2_{OOS}). This shows the importance of using factor data on a daily frequency and the particular importance of the past one-day return. The daily model carries more signal than noise about future returns in comparison with the monthly frequency. All models confirm the importance of the last daily return, with the first one-day lag being selected 70% of the time and representing 58% of the selected lags. Performance of factor momentum strategies can also be improved using these models, with net-of-costs Sharpe ratio reaching values as high as 1.08.

Lead-lag effects among stocks are stronger within price-trend factors, such as price momentum, long-term reversal and short-term reversal. Those factors also have the highest out-of-sample predictability in the machine learning models, with values as high as 4.3% in the daily frequency. These results are in line with those of Gu et al. [2020], which found that the most powerful predictors for asset returns are associated with price trends.

Consistent with our findings, short-term reversal becomes stronger after factor exposures are neutralized. In a separate paper, we show that this fact is expected since standard short-term reversals are negatively exposed to the one-day factor momentum [Garcia et al., 2020]. As expected, performance improves as we raise the number of factors used to hedge factor exposures. Short-term reversal return performance goes from 5.7% to 14.2% per year when we neutralize exposure to 16 factors, while also delivering lower volatility, leading to a Sharpe ratio 5 times higher. Short-term reversal is also stronger in the daily frequency rebalance, showing that it is also a fast phenomenon, despite the higher turnover and trading costs.

Most empirical asset pricing papers work with monthly frequency data, probably due to turnover and transaction costs issues. This paper shows that these strategies remain profitable using daily frequency information. Independently of the trading cost, higher frequency data can shed light and help explain anomalies reported in longer frequencies, revealing important patterns of assets covariation.

The rest of the paper is organized as follows. Section 2 covers data and the methodology. Section 3 presents the empirical results for lead-lag effects. Section 4 presents the empirical results for one-day factor momentum. Section 5 presents the setup and results for the Machine Learning models. Section 6 presents the effects of our findings on short-term reversal strategies.

Section 7 discusses additional robustness analysis. Section 8 concludes.

2 Data

We use data from CRSP, Compustat, and I/B/E/S and construct daily returns for 103 risk factors from 1-Jul-1963 to 31-Dec-2018. To compute firm characteristics, we use the code provided by Jeremiah Green[1] and follow all the premises used in Green et al. [2017], as for example including delisting returns as in Shumway and Warther [1999]. We follow Fama and French [1993] and first create value-weighted portfolios, and then long-short factor portfolios. For each characteristic, we sort all stocks into deciles and then build a long-short portfolio (top 30% - bottom 30% or 1-0 dummy difference). We calculate factor returns on a daily frequency, but we compute firms' characteristics to rebalance portfolios every month. All factors portfolios are value-weighted, and the high and low portfolios are chosen to guarantee a positive expected daily returns.

To ensure diversification in factor portfolios, we discard periods in which a factor has less than 30 stocks, since individual reversal effects prevail in more granular portfolios, as shown in Section 6. To form small and large portfolios, we sort stocks using NYSE breakpoints. Most AMEX and NASDAQ stocks are smaller than the NYSE median, so the small group contains a disproportionate number of stocks compared to the large portfolio, with respective averages of 2.970 and 785 stocks over time.

In order to analyze industry effects, we follow Moskowitz and Grinblatt [1999] using 20 industry portfolio. We use the two-digit SIC codes from CRSP to construct value-weighted portfolios, factor-neutral industry portfolios and industry-neutral factors.

For robustness, we also use data from Kenneth French´s public library [2]. Kenneth French´s database is composed of daily returns for 10, 17, 30 and 48 industries portfolios; 7 factors (MKT, SMB, HML, CMA, RMW, UMD, LT REV); 60 deciles style-based portfolios sorted on size, B/M, OP, INV, UMD, LT REV) and 30 double-sorted quintiles. Due to the small availability of Kenneth French's factors on a daily frequency (only 7 factors), we use the SAS code from Jeremiah Green and construct a wide range of 103 factors. Some robustness analysis

[1] https://sites.google.com/site/jeremiahrgreenacctg/home
[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

are done using daily returns from 1930. Results are similar regardless of the data set.

3 Lead-Lag effects

In this section, we show that there are strong factor-driven lead-lag effects and that these effects also hold for industry-neutral factor portfolios. We also present results for industry portfolios and factor-neutral industry portfolios. We show that cross-autocovariance term is relevant in multiple dimensions. Industry is just one particular case of this broader phenomenon, and part of its effect is due to the factor-driven effects that we report in this paper.

3.1 Autocorrelation in factor returns

Persistence in factor returns is a fact already reported by the literature. Among other papers, Gupta and Kelly [2019] reported a mean value of 0.11 for the autoregressive of order one, AR(1), coefficient across 65 factors in monthly returns.

In this paper, we find that factor autocorrelation appears to be stronger with a daily frequency. Out of the 103 factors in our database, 98 are significantly positive at the 5% level with the daily frequency, while only 61 are significantly positive with the monthly frequency, as plotted in Figure 1. The mean value of AR(1) coefficient across our factors is 0.10 for daily returns and 0.08 for monthly returns, which is however quite similar.

3.2 Individual and cross components of autocorrelation

We decompose factor autocovariance into two different components: individual stock autocovariance and cross-autocovariance among stocks, i.e. lead-lag effects.

$$\text{Cov}\left(R_t^{fact}, R_{t-1}^{fact}\right) = \sum_{i=1}^{N} \text{Cov}\left(w^i R_t^i, w^i R_{t-1}^i\right) + \sum_{i=1}^{N} \sum_{j \neq i} \text{Cov}\left(w^i R_t^i, w^j R_{t-1}^j\right) \tag{1}$$

To compute factor return autocorrelation, we divide both sides of the equation by the factor variance. The relative contribution of stocks autocorrelation and stocks cross-autocorrelation will have the same proportion in both autocovariance and autocorrelation.

The first term of equation (1) is composed by the individual stocks autocorrelation and can be computed by the diagonal of the covariance matrix. This contribution to the factor autocorrelation has the same signal of the stock autocorrelation, since the weight w^i becomes positive with squared value. Since stocks have on average negative or null autocorrelation (see Internet Appendix for details), positive autocorrelation in factors must come from the second term of the equation, as is shown in the subsection below.

The second term of equation (1) is composed by the cross-autocorrelation among stocks and can have positive or negative impact on factor autocorrelation. If two stocks are on the same long or short side of factor portfolios, their contribution will have the same sign of their cross-autocorrelation. If they are on different sides of the portfolio (one in short and other in long, or vice-versa), the impact on factor autocorrelation will be in the opposite direction of the stock cross-autocorrelation.

We can also decompose factor autocorrelation into its long and short portfolios contributions. Let R_t^L be the long side portfolio and R_t^S the short side portfolio in period t. The factor return can be expressed as the sum of both long and short side: $R^f = R_t^L + R_t^S$.

$$\mathrm{Cov}\left(R_t^{fact}, R_{t-1}^{fact}\right) = \mathrm{Cov}\left(R_t^L, R_{t-1}^L\right) + \mathrm{Cov}\left(R_t^S, R_{t-1}^S\right) + \mathrm{Cov}\left(R_t^L, R_{t-1}^S\right) + \mathrm{Cov}\left(R_t^S, R_{t-1}^L\right) \quad (2)$$

The first term is the long portfolio autocorrelation, the second term is the short portfolio autocorrelation, and the last two terms are the cross-autocorrelations between them.

3.3 Factor-driven lead-lag effects

Most of the factor return autocorrelation comes from the cross-autocorrelation component, that is, from the lead-lag effects. Figure 2 shows that the cross-component is responsible on average for 90% of the factor return's daily AR(1) coefficients in our broad sample of more than 100 characteristic-based factor portfolios.

Table 1 reports results for a selected subset of 16 factors that are considered more relevant by Kenneth French (the same ones that are reported at a monthly frequency in his database[3]). Except for dividend/price, all factor portfolios present statistically significant and positive AR(1) coefficients, with the cross-component corresponding on average to 93% of this

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

persistence, with mean value of 0.11 across the factors. The price-trend factors are the ones with the strongest lead-lag effects: momentum, long-term reversals and short-term reversals have respectively cross-component values of 0.20, 0.17, and 0.16.

Lead-lag effects come from positive cross-autocorrelation between stocks with similar characteristics, that are on the same long or short portfolios, and not due to negative cross-autocorrelation of stocks in opposite portfolios. Both long and short sides of portfolio present the same pattern of the factor that they compose, with high positive autocorrelation, caused by the cross-component. Table A.1 in the Appendix shows the results for the subsample of 16 factors that we describe above. Mean autocorrelation across these factors is 0.08 in both long and short portfolios, with the cross-component accounting for practically all of this result.

3.3.1 Factor-driven lead-lag effect for industry-neutral factors

Industry-driven lead-lag effects have already been reported by Moskowitz and Grinblatt [1999] and Hou [2007] among others. To show that the phenomenon we report here does not come from this already known industry-based effects, we construct industry-neutral factors. To do that, we first define the factor predictor across each industry and sort stocks into portfolios by this industry-adjusted return predictors; an industry-neutral factor portfolio is so almost equally balanced across industries (Cohen and Polk [1996] and Asness et al. [2000]). We also report a version that takes an offsetting position in each stock's value-weighted industry (Novy-Marx [2013]) to remove the impact of the industry return.

Industry-neutral factors present high first-order autocorrelation due to the cross-autocorrelation among stocks and not due to industry-specific risks. Table 2 shows that both AR(1) coefficient and the cross-component are, on average, as strong as the regular characteristic-based factor portfolios, with average values around 0.11 to 0.12. In the Internet Appendix, we present results for our broad sample of factors and show that momentum is present in industry-neutral factors in both cross-section and time-series dimensions.

Our results are robust to the way we build industry-neutral factor portfolios. In unreported results, we also compute other versions of industry-neutral factors with similar conclusions. For instance, we construct one factor for each industry and then group them according to their industry market value. We also redefine both factor characteristic cut-offs and size breakpoints separately for each industry. All versions are highly correlated.

3.3.2 Factor-driven lead-lag effects for large-cap stocks

Lo and MacKinlay [1990], Hou [2007] and other papers suggest that the relation between small and large stocks returns may be relevant to explain lead-lag effects. Lo and MacKinlay [1990] shows that returns of large stocks lead smaller stock returns, and Hou [2007] finds evidence that this lead-lag effect between big firms and small firms is predominantly an intra-industry phenomenon. To analyze the relevance of firm size on the new phenomena we report, we construct factors only with large caps stocks. We choose stocks whose market value is above the NYSE median breakpoint. These large-stock factors are constructed only with the largest 800 stocks on average.

Factor-driven lead-lag effects are not due to cross effects between small and large-cap stocks. The middle columns of Table 1 report results for factor portfolios constructed only with large stocks. The mean autocorrelation of those factors is 0.08, with factor-driven lead-lags effects corresponding to 84% of the autocorrelation. For factors constructed with all stocks, these numbers are respectively 0.11 and 93%, and for factors only with small stocks (right columns of Table 1), the effect is stronger, with values of 0.15 and 95%. The Internet Appendix presents resuls for all factors and also show that factor momentum is still present in large-cap factors in both cross-sectional and time-series dimensions

3.4 Industry-driven lead-lag effects and factor-neutral versions

Industry momentum and industry-driven lead-lag effects have already been reported at a monthly frequency in the previous literature [Moskowitz and Grinblatt, 1999, Hou, 2007]. We investigate the relevance of risk factors in the industry-driven lead-lag effect. We find that industry is just one particular case of a factor-driven effect. Moreover, we find that part of its effect comes from the different factor exposures of industry portfolios.

We first analyze whether the industry phenomenon holds for the daily frequency, and then if it still holds in factor-neutral versions. We use the same 20 industry definitions of Moskowitz and Grinblatt [1999] and construct factor-neutral industries for two subsets: Fama-French three factors and a broad sample of 16 factors described in Subsection 3.3. To compute betas, we use a one-year rolling window and re-estimate betas every month.

Industry-driven lead-lag effects are also relevant at the daily frequency. Table 3 reports the results for the 20 industry portfolios that we analyze. The mean autocorrelation across then is 0.06, with the cross-stock component corresponding to almost all of the correlation. Despite being significant in most cases, the magnitude of those numbers is lower than in the factor portfolio cases.

When we control industry portfolios' exposure to other risk factors, both autocorrelation and its cross-components decrease. This decrease is larger when we control for more factors, showing that part of the industry lead-lag effect is due to other risk factors rather than industry-specific risks. As reported in Table 3, the cross component decreases from 0.07 to 0.05 when we control industries for the three Fama-French factors, and by more than half, to 0.03, when we control for 16 factors. The mean autocorrelation across industries portfolios also fall in the same proportion. This finding shows that part of the previously reported industry-driven lead-lag effects is due to the factor-driven effects that we report in this paper, rather than be only due to industry-specific risk.

Since there are multiple dimensions of cross-autocovariance among stocks due to multiple factor risk exposures, we have multiple ways to report cross-autocorrelation between stocks. That fact helps to reconciliate the existence of several lead-lags effects already reported in the literature, such as the within industries (Hou [2007] and Moskowitz and Grinblatt [1999]), across industries (Menzly and Ozbas [2006]) or other specific economic links (Cohen and Frazzini [2008], Parsons et al. [2018] and Feng et al. [2019], that can be seen as different ways of express common risk exposures. In the Appendix, we show that the performance of momentum strategies using factor-neutral industries decays by more than half in relation to simple industry momentum, indicating that part of industry momentum comes from factor momentum.

3.5 Random factors

We construct random factors to confirm that the phenomenon we report here come from common risk components and not due to any other spurious effects that may occur when we group stocks into portfolios. For that, we use the time series of stocks returns, market value, and other characteristics information over time, but randomly sort stocks into high, neutral, or low portfolios, to construct factor portfolios.

Random factor returns do not present autocorrelation on average, with mean value of 0.0063 across our 102 factors (not applicable for market factor), with 83 of them being statistically indistinguishable from zero. Figure 3 plots the daily return autocorrelation for all random factors. We keep the same axis scale of regular factors to facilitate the comparison between them.

Lead-lag effects disappear in these random factors. The mean value for cross-autocorrelation across all random factor is -0.0022, while in regular factors this value is 0.09. Figure 4 plots the breakdown composition of autocorrelation into individual and cross-autocorrelation components. This analysis provide further evidence that our finding comes from common risks shared by stocks. As expected, there is no momentum for random factors, as shown in the Internet Appendix.

4 One-day factor momentum

A short-term one-day factor momentum arises as a natural consequence of the persistence in risk factor returns, associated with the daily lead-lag effects which we report in this paper. It is present in factor, industry, and style-based portfolios, in both cross-sectional and time-series versions. All these momentum strategies are profitable after trading costs despite a high turnover. The strategies have large Sharpe ratios as high as 0.80 after trading costs, do not present crashes, and subsume other momentum strategies with longer formation windows.

There is also diversification gains in combining one-day factor momentum to other strategies based on longer lookback windows, as the one-month factor momentum, with an increase in Sharpe ratio after trading costs and a reduction in skewness.

We also show that one-month factor momentum is directly related and partially explained by this daily phenomenon, with almost 60% of its performance coming from the influence of one-day momentum.

4.1 Cross-sectional factor momentum

This subsection analyzes cross-sectional momentum (CSMOM) strategies with factor portfolios. We take positions in factors based on the recent performance of factors relative to the cross-section of all factors, buying the top 25% that have recently outperformed and selling the bottom 25% that have underperformed peers. We also consider other cut-off points to select winner or loser factors: 10%, 20%, 30% and 40%. We use daily returns and three different look-back windows for portfolio formation: 1 day – MOM[t-1] – using only the last lagged daily return; 1 month - MOM[t-21:t-1] - using the cumulative return from the last 21 days including the last lagged day; and 1 year – MOM[t-252:t-1] – using the cumulative return of the last 252 days including the last lagged day. The second option delivers strong results with factors as seen in Gupta and Kelly [2019] and Ehsani and Linnainmaa [2019], and with industries (Moskowitz and Grinblatt [1999]). For completeness, we also consider versions that skip one day in those two last methods to isolate the effect of the last day in performance and these are reported later.

We compare two holding periods: one day and 21 days. In the latter, we use the Jegadeesh and Titman [1993]'s approach to address overlapping issues. When the holding period is 21 days, we form the strategy each day and compute the return of this strategy in days $t+1, \ldots, t+21$. In each day, we have returns of 21 strategies formed at different times: each one from one of the last 21 days. The return is the average return of those 21 strategies. One interpretation is that the strategy partially rebalances 1/21 of the portfolio each day.

Performance of CSMOM strategies are not dependent on specific subsets of factors and does not require a large number of factors either. Figure 5 shows the CSMOM$[t-1]$ performance for strategies constructed from random sets of factors. We use the bootstrap method with 50.000 resamples for each set size, from two to 103, and construct a factor momentum strategy with a holding period of 21 days, but similar results hold for one-day holding periods. We plot the average performance from these simulations, and the 95% bootstrapped confidence interval. The performance using our subset of 103 factors is similar to the mean performance using only ten factors. Since results do not depend on particular factors and to reduce computational costs, we report some results only to a subset of 16 factors, the same subset reported in Section 3, composed by the same factors that are present on Kenneth French's database.

4.1.1 Performance and trading costs

Table 4 summarizes results for the CSMOM strategies. We report average annualized returns from Jul-1963 to Dec-2018, annualized Sharpe ratios, maximum drawdown and average daily turnover that also consider the changes in the individual positions of each factor whenever there are changes in factor portfolios. Hence, we consider the changes in each factor's individual stock positions. We also report the break-even trading costs per unit of turnover that would erode the strategy performance.

The version with full daily rebalance (one-day holding period) shows the strength of one-day momentum with an average annualized return of 56.3%, which is more than twice than that of the one-month momentum. As illustrated by Figure 6, this strength is stable over time and continues even after the 2000s, a period in which some anomalies have softened or just disappeared. However, this apparently strong performance disappears when we consider the high turnover associated with this one-day holding period. We assume costs of ten basis points per unit of turnover, based on the estimates in Frazzini et al. [2015].

When we consider a smoother rebalance methodology, with a holding period of 21 days, the CSMOM$[t-1]$ becomes profitable after trading costs. Despite a decrease in absolute returns, this strategy Sharpe ratio is 1.32 (or 0.61 after trading costs), more than twice of CSMOM$[t-21:t-1]$ and CSMOM$[t-252:t-1]$, and with a drawdown of only -10%, compared with -31% and -45% of the 1-month and one-year cases.

One-day momentum also provides diversifications benefits to other momentum strategies. Adding CSMOM$[t-1]$ to CSMOM$[t-21:t-1]$, using a 50% of weight in each strategy, increases the Sharpe ratio from 0.60 to 0.84 (or from 0.31 to 0.51 after trading costs), decreases the drawdown from -31% to -20%, and surprisingly decreases the average turnover from 15% per day to 11%, what leads to a higher breakeven trading cost. These same diversification benefits happen when combining CSMOM$[t-1]$ with CSMOM$[t-252:t-1]$.

4.1.2 Spanning tests

The one-day factor momentum subsumes other factor momentum strategies constructed with longer formation windows, as the one-month and one-year, and is not explained by other traditional factors. Table 5 reports several spanning regressions for CSMOM$[t-1]$ and

CSMOM$[t-21:t-1]$, controlling for each other and for the five Fama-French factors (Fama and French [2015]) plus traditional stock momentum (UMD). We focus on the smooth rebalancing case (holding period of 21 days), which is profitable after trading costs, but results are available for the full rebalancing case as well.

The alpha of CSMOM$[t-1]$ remains high and statistically significant when controlled for CSMOM$[t-21:t-1]$, with an annualized value of 4.0% (t-statistic of 9.1). However, the performance of CSMOM$[t-21:t-1]$ is entirely explained by its leverage exposure to CSMOM$[t-1]$. Surprisingly, its alpha becomes negative and statistically significant (-4.6% with t-statistic of 3.8) once we control for CSMOM$[t-1]$. CSMOM$[t-1]$ has a low exposure to CSMOM$[t-21:t-1]$ at only 0.27, while CSMOM$[t-21:t-1]$ has a leveraged exposure of 2.14 to CSMOM$[t-1]$.

The CSMOM$[t-1]$ is also not explained by five the Fama-French factors plus UMD, presenting an alpha of 6.3% (t-statistic of 9.7), almost the same value of its average annual return. This one-day factor momentum is almost orthogonal to UMD with loading value of 0.03. Adding CSMOM$[t-21:t-1]$ as a control does not change the results with CSMOM$[t-1]$ presenting a alpha of 4.1% (t-statistic of 9.5). As previously reported, the CSMOM$[t-21:t-1]$ is not explained by the five Fama-French factors plus UMD.

CSMOM$[t-252:t-1]$ is also explained by the one-day factor momentum with a high loading of 0.80 and an alpha not different from zero at the 5% level.

4.1.3 Relevance of one-day factor momentum in one-month factor momentum

Besides spanning regressions, we also neutralize the impact of ret$[t-1]$ on the other days by construct double-sorted portfolios. We first sort factors according to their last day return (ret$[t-1]$), grouping them into two groups (High$[t-1]$ and Low$[t-1]$); and then a second conditional sort within each of the two groups, according to their cumulative performance on the remaining days of the month (ret$[t-21:t-2]$), grouping them into three groups (High$[t-21:t-2]$, Mid$[t-21:t-2]$ and Low$[t-21:t-2]$). After that, we create two CSMOM$[t-21:t-1]$ strategies, neutral with respect to CSMOM$[t-1]$, one for factors with low ret$[t-1]$ (MOM$[t-21:t-2]|$Low$[t]$), and other for high ret$[t-1]$ (MOM$[t-21:t-2]|$High$[t]$). This calculation allows us to control for potential effects of last day return on the previous 20 days returns since series with one-day persistence (high AR(1) coefficient) can mechanically create a persistence for longer periods.

The performance of CSMOM$[t-21:t-1]$ decreases by more than 50% on average, when the effect of the last day return is neutralized. Table 6 presents results for two holding periods: 1 day and 21 days. The performance of CSMOM$[t-21:t-1]$ falls by almost 70% in the one-day holding period, from 22% to 6.9% per year, and by more than 40% in the 21-day holding period case, from 8% to 4.7% on average.

Another point to be highlighted is that 5 of the 6 double-sorted factor portfolios with low ret$[t-1]$ have a negative or null annual average return. Only the portfolio Low$[t-1]$ & High$[t-21:t-2]$ (holding period of 21 days) has a positive and statistically significant return of 3.8% (t-statistics of 3.8).

This decline in performance of CSMOM$[t-21:t-1]$ when the effect of the last day return is neutralized, together with the fact that factor return persistence is statistically more robust in daily frequency, shows that this factor momentum is mostly a daily phenomenon.

4.1.4 Other results

The Internet Appendix presents results for a variety of cross-sectional momentum strategies using other subsets: i) all 103 factors, ii) industry-neutral factors, iii) large-cap factors, iv) small-cap factors, v) long side of factors, vi) short side of factors, vii) random factors, viii) 20 industry portfolios and ix) 20 factor-neutral industry portfolios.

4.2 Time-series momentum

This subsection analyzes time-section momentum (TSMOM) strategies with factor portfolios. These strategies are constructed using all factors available at each period. If the cumulative excess return of a factor is positive in a given look-back window, we take a long position in this factor, and if it is negative, we take a short position. The weight in each factor is proportional to its excess performance. The return at each period t is represented by the aggregation of the positions in all factors. Unlike cross-sectional strategies that are always long and short in the same proportion, time-series momentum can be long or short in all factors simultaneously. This is not a problem as all factors are self-financed strategies.

The partial weight of each factor i is given period t by:

$$w^i_{t+1:t+hp} = \min\left(\max\left(\frac{r^i_{t-k:t}}{\sigma^i_{t,1y}}, -2\right), 2\right), \tag{3}$$

where $r^i_{t-k:t}$ is the cumulative return of factor i over the look-back window of k days; $\sigma^i_{t,1y}$ is the factor return volatility over the previous 252 days; hp is the holding period for which the strategy is constructed. We convert returns to z-scores by dividing by factor volatility and limit the leverage to a maximum limit of 2, avoiding extreme positions.

To form TSMOM strategies, we aggregate all factors partial weights into a single portfolio in a way that absolute values of the long and short legs are rescaled to form a unit leverage ($1 long and short) TSMOM portfolio. Hence,

$$\text{TSMOM}_{t+1} = \frac{\sum_{i=1}^{N} w^i_{t+1} r^i_{t+1}}{\sum_{i=1}^{N} |w^i_{t+1}|} \tag{4}$$

Following this approach, we leave the weights between factors more balanced, avoiding excessive weights in some factors when their returns are in the opposite direction of the vast majority of factors.

As in the cross-sectional case, we use three different look-back windows for portfolio formation: 1 day – MOM$[t-1]$ – using only the last lagged daily return; 1 month – $[t-21 : t-1]$ – and one year – MOM$[t-252 : t-1]$ – using the cumulative return of the last 252 days. Moskowitz et al. [2012] reported persistence in returns for one month up to 12 months in equity index, currency, commodity and bond futures. Gupta and Kelly [2019] reports cross-sectional and time-series momentum in equity factors, stronger with one-month look-back window.

4.2.1 Performance and trading costs

Table 4 summarizes results for the TSMOM strategies: average annualized return from Jul-1963 to Dec-2018, annualized Sharpe ratio, maximum drawdown and average daily turnover considering changes in each factor's individual stocks position in addition to the momentum-driven turnover. We also report the break-even trading costs per unit of turnover that would erode the strategy performance.

The average annualized return of one-day momentum is 23.2% with the holding period of

1 day, which is 2.5 higher than in the case of one-month momentum. Figure 7 depicts the evolution of performance over time, which is stable and continues after the 2000s. As in the cross-sectional case, this huge performance disappears when after trading costs, assuming costs of 10 bps per unit of turnover based on the estimates of Frazzini et al. [2015].

Similar to cross-sectional momentum, when we consider a smooth rebalance methodology, with a holding period of 21 days, the TSMOM[$t-1$] turns to be profitable after trading costs. The average return is 11.4% per year, Sharpe ratio is 1.59 (0.81 after trading costs), while the TSMOM[$t-21:t-1$] has an average return of 4.9% per year and Sharpe ratio of 0.78 (0.43 after trading costs). Despite having a larger average return in comparison to other momentum strategies, the maximum drawdown of TSMOM[$t-1$] is only -15%, smaller than the other strategies (-20% for TSMOM[$t-21:t-1$] and -19% for TSMOM[$t-252:t-1$]).

TSMOM[$t-1$] also provides diversification benefits to other momentum strategies. A equally-weighted strategy composed by TSMOM[$t-21:t-1$] and TSMOM[$t-1$] increases the average return of TSMOM[$t-21:t-1$] from 4.9% to 8.0% per year (or from 2.84% to 4.77% after trading costs), increases the Sharpe ratio from 0.75 to 1.27 (or from 0.43 to 0.76 after trading costs), and reduces the maximum drawdown from -20% to -16%. Diversification benefits are stronger for TSMOM[$t-252:t-1$] with Sharpe ratio and average return more than double, both before or after trading costs.

4.2.2 Spanning tests

TSMOM[$t-1$] subsumes other factor momentum strategies constructed with longer formation windows, as the TSMOM[$t-21:t-1$] and TSMOM[$t-252:t-1$], and is not explained by other traditional factors. Table 5 reports several spanning regressions for TSMOM[$t-1$] and TSMOM[$t-21:t-1$], controlling for each other and for the five Fama-French factors (Fama and French [2015]) plus traditional stock momentum (UMD). We focus on the smooth rebalancing case (holding period of 21 days), which presents a better return to turnover relation.

TSMOM[$t-1$] performance remains high when controlled for TSMOM[$t-21:t-1$], with an alpha of 7.2% per year and a t-statistic of 10. However, the opposite does not happen. When controlled for the one-day momentum, TSMOM[$t-21:t-1$] performance becomes negative, with an alpha of -2.1% per year, statistically significant (t-statistic of 3.3).

The TSMOM[$t-1$] is also not explained by the five Fama-French factors plus UMD, presenting an alpha of 11.5% (t-statistic of 11.8), almost the same value of its average annual return. This one-day factor momentum is orthogonal to UMD, with a loading of 0.01. Using the five Fama-French factors and CSMOM[$t-21:t-1$] together as controls does not change the results, with TSMOM[$t-1$] presenting an alpha of 7.6% (t-stat of 10.7). As previously reported, the TSMOM[$t-21:t-1$] is not explained by the five Fama-French factors plus UMD.

4.2.3 One-day factor momentum: cross-sectional or time-series?

Time-series and cross-sectional factor momentum strategies are very similar, with high correlation between them. This correlation is stronger for the one-month look-back window, reaching 0.96. In the 1-day look-back window, this number is lower, but still high: 0.89. One question of interest is: is there any strategy that dominates the other? In spanning tests reported in the Internet Appendix, we confirm that one-day factor momentum in time-series dominates the cross-section case.

4.2.4 Other results

The Internet Appendix present results for a variety of time-series momentum strategies with other subsets that we analyze in section 3: i) all 103 factors, ii) industry-neutral factors, iii) large-cap factors, iv) small-cap factors, v) long side of factors, vi) short side of factors, vii) random factors, viii) 20 industry portfolios and ix) 20 factor-neutral industry portfolios.

5 One-Day Factor Momentum: Machine learning techniques

In this section, we use machine learning techniques to confirm our findings and reinforce that factor momentum is mostly a daily phenomenon. Shrinkage models have excellent out-of-sample predictability for factor return at the daily frequency (average R^2_{OOS} of 1.9% across factors, from 1969 to 2018), but no predictability at the monthly frequency, showing that daily frequency carries more information about future returns than the monthly frequency. Those models also confirm the importance of the last daily return. Of the previous 252 days of returns allowed to be selected, our models select the first lag return 70% of the time, with this lag representing 58% of the selected lags.

The net-of-costs performance of factor momentum can be improved if we use the Machine Learning models that we present in this section. Sharpe ratio net of costs reaches values as high as 1.08 in the cross-sectional case and 0.84 in the time-series case. As shown below, there is some heterogeneity both over time and across factors. Some factors, as the price trend ones, have a stronger daily persistence than others; and there are some periods with higher predictability than others. Take into consideration, it is possible to reduce the turnover and increase the performance after costs.

5.1 Models setup

We choose the following models: *Lasso*, proposed by Tibshirani [1996], *Ridge*, proposed by Hoerl and Kennard [1970], *Elastic Net*, proposed by Zou and Hastie [2005] and *Fused Lasso*, a variant of *Lasso* introduced in Tibshirani et al. [2005]. These models are widely used in the Finance literature, for instance: Kozak et al. [2019] use *Lasso* and *Ridge*, and Gu et al. [2020] use *Lasso*, *Ridge*, *Elastic Net* and other non-linear machine learning methods to measure risk premia. *Fused Lasso* has not been used in the finance literature, to the best of our knowledge.

Lasso encourages sparsity of coefficients and can thus be thought of as a variable selection method. *Ridge* is used for shrinking large regression coefficients in order to reduce overfitting when data suffer from multicollinearity, but does not reduce the number of variables. *Elastic Net* incorporates penalties from both L1 and L2 regularization that are used in *Lasso* and *Ridge* respectively. Fused Lasso is especially useful for analyzing high-dimensional data in which the features exhibit a natural order, that may be relevant when dealing with time series, and it induces the identification of non-zero blocks coefficients around specifics periods, which seems to be the case of momentum.

We estimate univariate predictive regressions for each factor, with the general form:

$$\hat{\mathbf{\Phi}}_{\Omega} = \underset{\Phi}{argmin} \left(\sum_{t=0}^{T} (r_{t+1} - \mu - \sum_{m=0}^{M} \phi_m r_{t-m})^2 + Penalty(\Omega, \Phi) \right), \tag{5}$$

where $\boldsymbol{r_t}$ is the return of period t, $\boldsymbol{\mu}$ is the intercept, $\boldsymbol{\Phi}$ is the vector of coefficient lags ranging from $\boldsymbol{\phi_1}$ to $\boldsymbol{\phi_M}$, $\boldsymbol{M}$ is the number of lags considered, $\boldsymbol{T}$ is the estimation sample size, $\boldsymbol{\Omega}$ is the hyperparameters for which $\boldsymbol{\Phi}$ is minimized.

For *Lasso* the penalty term is the L1 norm from the lags coefficients:

$$Penalty(\alpha) = \alpha \sum_{m=0}^{M} |\phi_m| \tag{6}$$

For *Ridge*, the penalty term is the L2 norm:

$$Penalty(\gamma) = \gamma \sum_{m=0}^{M} \phi_m^2 \tag{7}$$

Elastic Net uses a combination of L1 and L2 norms:

$$Penalty(\gamma, \alpha) = \gamma \left(\frac{(1-\alpha)}{2} \sum_{m=0}^{M} \phi_m^2 + \alpha \sum_{m=0}^{M} |\phi_m| \right) \tag{8}$$

For *Fused Lasso*, it is the following penalization:

$$Penalty(\alpha, \varepsilon) = \left(\alpha \sum_{m=0}^{M} |\phi_m| + \varepsilon \sum_{m=1}^{M} |\phi_m - \phi_{m-1}| \right) \tag{9}$$

The models are estimated with one year of lags (252 days or 12 months) and a rolling window of 5 years, plus the one year of lags. After each estimation, we forecast returns for the next 252 days (or 12 months) with the estimated parameters fixed and then re-estimate the model with rolling estimation windows. We estimate all models with an intercept but sometimes use only the lags, to avoid any reversals effects that may be captured by the intercept, since the estimation window is larger than five years.[4]

Since we are working with time series, we use the Bayesian Information Criterion (BIC) for tuning the hyperparameters. In the *Ridge* case, we use the trace of the H matrix ($\widehat{y} = Hy$) to define the degrees of freedom. The results are very similar if we use cross-validation techniques.

To evaluate predictive performance, we calculate for every factor, the out-of-sample R^2 using two benchmarks:

[4]For *Lasso*, *Ridge* and *Elastic Net*, we use Matlab´s functions (https://www.mathworks.com/). For Fused Lasso, we use the minimization package of Gurobi in Matlab.

$$\mathbf{R}^2_{OOS,i} = 1 - \frac{\sum_t (r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_t (r_{i,t+1} - r^{benchmark}_{i,t+1})^2} \tag{10}$$

$$r^{benchmark}_{i,t+1} = \begin{cases} \overline{r}_{i,5y}, \\ 0, \end{cases}$$

where $\overline{r}_{i,5y}$ represents the previous 5-years average return of the factor i.

5.1.1 Factor return predictability

Table 7 shows that machine learning models have excellent predictability for factor returns in the daily frequency, but negative performance for the monthly frequency. We report results for Elastic Net and Lasso. Despite the theoretical motivation, Fused Lasso performance is very similar to Lasso. Ridge has poor performance, revealing that there are a small number of significant parameters, with most of parameters close to zero. To investigate potential reversal effects captured by the intercept, we analyse three different cases for Lasso and Elastic Net: model without the intercept used in the estimation, only with the lag structure; regular intercept estimated in the 5 year rolling window; and with the intercept changed to the current one-year average return, a sample used to capture momentum. We also report in Table 7 results based on OLS and other historical means of returns.

Panel A of Table 7 presents the daily frequency results, using zero as the benchmark to compute R^2_{OOS}. Of the 16 factors we analyzed, 15 have positive out-of-sample predictability for the machine learning models, for the period from 1969 to 2018. The forecasts without the use of intercept are a little better, with an average R^2_{OOS} mean across factors of 1.8%. Use the one-year prevailing mean as intercept makes the results worse. Predictability results are even better if we use the prevailing mean factor returns as the benchmark to compute R^2_{OOS}. As expected, OLS and historical means have poor performance.

The highest predictability occurs for price trend factors: momentum, long-term reversals, and short-term reversals, with respective values of 4.3%, 3.7%, and 2.5%. These results are in line with those of Gu et al. [2020], which found that the most powerful predictors for asset returns are associated with price trends and include return reversal and momentum. Another similarity is that SMB, the factor that reflects small and less liquid stocks effects, have less predictive power since they have comparatively low signal to noise ratios.

Predictability results are poor at the monthly frequency. The mean R^2_{OOS} across factors is negative for all models that we tested. The best model at the monthly frequency is Lasso, without the use of intercept, with a mean value of -1.0%. The price trend factors, which have the best performance at daily frequency, have the poorest performance at the monthly frequency. Another interesting point is that daily factor return carries more signal to noise ratio than the monthly return, which is supposed to have less noise. One possible explanation is that news or information shocks regarding factors are not completely incorporated into stock price in one day but is fully incorporated in one month.

This finding is somewhat related to the relevance of the first lag return in the one-month factor momentum, presented on subsection 4.1.3, and reinforce that factor momentum is mostly a daily phenomenon.

5.1.2 Lags selected by ML models

After we confirm that the models do a good job in capturing the signal in daily factor returns, we turn to see which days are selected. Since Lasso and Elastic Net have similar results, we choose only one to report results: Elastic Net. Out of the 103 factors we analyzed, the first lag and the first week (first 5 lags) represents respectively 60% and 72% of the total selected lags by the model. The remaining 247 represents only 28% of the selected lags. Apart from being more selected, the lag(t-1) is the one with largest magnitude, with average value of 0.053 across the 103 factors.

Besides no predictability power at a monthly frequency, the first lag(t-1) represents only 22% of the selected lags, and is active only 28% of the time with Elastic Net at the monthly frequency.

Figure 8 depicts the evolution of the lag(t-1) over time for AR(1), Elastic Net and Lasso models, in both daily and monthly frequency. The first fact to point out is the smooth pattern of AR(1) lag in the daily frequency case, showing that monthly factor returns have much more noise than the daily factor returns. This is also reflected in the value and frequency of lag(t-1) selected by the shrinkage methods we use, much lower than the AR(1) coefficient. The second fact to point out is that lag(t-1) of Lasso and Elastic Net follow much closer the time pattern of the AR(1) lag at the daily frequency, what is one more evidence in favor of our thesis that this is a daily phenomenon.

5.1.3 Performance of machine learning strategies

The performance after costs of both time-series and cross-sectional momentum can be improved if we use the return forecasts of the Machine Learning techniques we present above. This increase in performance comes from the fact that we take into account the heterogeneity that occurs both across factors and over time. Some factors, as the price trend ones, have a stronger daily persistence and predictability than the others; and there are periods with higher predictability than others.

We construct factor momentum using return forecasts of Elastic Net and Lasso models. For the cross-sectional case, we use the factor return forecasts to rank all factors, and then buy the top winners and sell the bottom loser factors to form cross-sectional momentum. The long position is formed with the highest ranked factors, while the short position selects the lowest factors (4 of 16 factors for each leg), with equal weight across factor portfolios. For the time-series strategies, if the factor return forecast is positive, we take a long position, and if it is negative, we take a short position in the factor. In both cases, we use only the autocorrelation structure to construct the factor return forecasts, ignoring the intercept from estimation.

Elastic Net and Lasso reduce the daily turnover from CSMOM[t-1] from 13% of 8%, increasing the break-even trading cost from 0.18% to 0.27%. If we assume costs of 10 bps per unit of turnover, based on the estimates in Frazzini et al. [2015], net-of-costs Sharpe ratio increases from 0.61 in the CSMOM[t-1] case to 1.08 in the Lasso model. For the time-series case, there is also a benefit in using estimates from Lasso and Elastic Net. The average annual excess return raises from 11.4% in the TSMOM[t-1] to 12.8%, and the net-of-costs Sharpe ratio goes from 0.81 to 0.84 using Elastic Net model. Detailed results are available in the Internet Appendix.

6 Stocks short-term reversals and factor momentum

In this section, we focus on the connection between two patterns in asset prices: stock short-term reversals and factor momentum. Standard stock short-term reversals are by construction exposed negatively to factor momentum. Somehow, by aggregating stocks into portfolios, the idiosyncratic effects of stocks that lead to negative autocorrelation at the stock level is dissipated by the positive effect that comes from risk factors, as we explain with more detail in Garcia et al. [2020]. These effects occur on frequencies from one day to one month.

Short-term reversal becomes stronger after we neutralize stock exposure to factors. As expected, this increase in performance is larger as we control for more factors. Since factors have positive autocorrelation, short-term reversal is indirectly positively exposed to factors with recent worst performance and negatively exposed to factors with better performance. To be clear, the procedure used to form short-term reversal strategies indirectly creates a negative exposure to factor momentum, since short-term reversals sells stocks with better performance over the previous week (month), which are on average those with positive exposure to factor with better performance over the same period; and buy loser stocks, which are those on average exposed to factors with worse performance. This fact is reflected in the negative loadings of short-term reversal to factor momentum, which ranges from -0.51 in CSMOM[t-21:t-1] to -1.14 in CSMOM[t-1], in time-series regressions.

To mitigate this dragging effect on STREV (Short-term reversal) performance, we construct a strategy where we hedge factor exposures. We hedge each stock of the winner and loser portfolio individually, using betas computed every month with an one-year rolling window of daily returns. Instead of using residuals to form winners and losers stocks portfolios, as in Blitz et al. [2013], we chose to hedge stock factors exposure and continue to rank winners and losers portfolios by recent raw return. Our procedure proved to be more efficient, not only in a improving performance but also in creating a strategy that is orthogonal to factor momentum. In Garcia et al. [2020], we go deeper into the reasons why this happens and also present other empirical facts, such as different look-back windows, rankings according to stock residuals, volatility adjustments, among other things.

Table 8 presents results for short-term reversals hedged for a variety of factors (Hedged

STREV). The first point to emphasize is the huge performance difference when we depart the original case (STREV) and consider the short-term reversal which is neutral to 16 factors (the same we focus on previous sections): annualized average return increases more than 2.5 times, from 5.7% to 14.2%; Sharpe ratio rises from 0.59 to 3.12; and the maximum drawdown is reduced from -33% to -11%, showing that this strategy is crash-free. Other important aspect is that performance after costs increase as we hedge the strategy. We also account for the effect of the hedging costs. The increase in performance is larger than the increase in turnover due to hedging, as reflected in the column break-even trading costs. The net-of-costs annualized return of regular STREV is 1.2% and statistically not different from zero, while net-of-costs annualized return of the fully Hedged STREV is 7.9% and statistically significant.

Another point to be emphasized is the monotonic increase in performance that happens when we increase the number of factors used to neutralize stocks exposure. As we consider variations from the 3 Fama-French factors to our 16 factors subsample, we find that average annual return rises from 10.1% to 14.2%; Sharpe ratio goes from 1.58 to 3.12; maximum drawdown goes from -22% to -11%. The Hedged STREV strategies are also not explained by the 5 Fama-French factors plus UMD and CSMOM[t-1].

The loadings of CSMOM[t-1] also reinforce our points. STREV has a negative loading of -1.14 to CSMOM[t-1], evidencing that buying recent losers and selling recent winner stocks indirectly creates a negative exposure to factor momentum. This loading decreases significantly to -0.30 when we use the 3 Fama-French factors to Hedged STREV, and goes to almost zero when we use more factors, like 9, 12 or 16 factors. Similar alphas of regular STREV and STREV hedged to 16 factors demonstrate that our approach is successful to neutralize single stocks reversals to their exposure to one-day factor momentum.

7 Robustness

In this section, we briefly describe some additional robustness tests we do in this paper.

7.1 Factor momentum strategies

In the cross-sectional factor momentum case, we consider a variety of other cut-off point to select factors: 10%, 20%, and 40%. One-day momentum is present in all cases, and in general, the smaller the cut-off point, the higher the performance and the turnover.

We also consider other holding periods rather than 1 and 21 days. In general, there is a smooth pattern as we increase the holding period between 1 to 21 days, without any kind of sharp effect.

We consider other ways to construct time-series portfolios: i) not scaling the strategy weight by factor current volatility, ii) scaling by volatility but not by the magnitude of cumulative performance on the look-back window, iii) rescale both long and short sides to form a unit-leverage TSMOM portfolio ($1 long and $1 short together), as done in Gupta and Kelly [2019].Conclusions do no change in these alternative approaches.

7.2 Kenneth French's database and longer sample windows

Factor momentum also holds for the factors in the Kenneth French's database[5]: factors, industries and style-based portfolios. Since this database only provides the already constructed time-series of returns, and do not give information about stocks position in each portfolio, it is impossible to repeat the turnover calculations and the breakdown of individual and cross components of return autocorrelation. Results for factor and style-based portfolios (both CSMOM and TSMOM) are presented in Table A5 of Appendix. Results for industry portfolios are present in Figures A.5 and **??** in the Appendix.

We can expand our sample window and compute factor momentum from 1930 to 2018, but with only a few available factors. Results are also present in Table A5 of Appendix.

8 Conclusion

This paper has two major contributions. The first is documenting that lead-lag effects in equity markets are a broader phenomenon than previously found, being present on a daily basis for almost a 100 factors, from 1963 to 2018. The second is presenting short-term strategies

[5] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

that exploit this pattern and are profitable after trading costs, and subsumes other strategies constructed with monthly frequency, as the one-month factor momentum.

Differently from most of the papers in the literature, we do not focus on only one specific link across stocks at a time. Wee take a more general approach and show evidence that lead-lag effects occur in multiple dimensions at the same time. This cross-autocovariance is responsible on average for 90% of factor return autocorrelation at a daily frequency.

Industry-driven lead-lag effects appear to be just one particular case of this wider phenomenon. Industry-neutral factors still present cross-autocovariance as strong as the the case with regular factors. However, when we neutralize the factor exposure of industries, industry-driven lead-lags fall by 60% on average, showing that this cross-autocovariance pattern across stocks is mostly due to factors, and part of the industry lead-lags come from factor effects.

These effects are also not due to small stock effects, such as non-synchronized trades or small stocks reacting with a lag to large stocks returns. Factors constructed only with large-cap stocks, whose market equity value is above the NYSE median breakpoint (largest 800 stocks on average), also have positive autocorrelation due to cross-autocorrelation components, with respective mean values of 0.059 and 0.051.

One-day factor momentum arises as a consequence of the factor autocorrelation that is linked to the lead-lags effects that we discuss here. These short-term momentum strategies work both in the cross-section and the time series. Strategies are profitable after trading costs, present high Sharpe ratios, no crashes, and also subsumes other momentum strategies. We also show that factor momentum in longer look-back windows, such as the one-month reported by Gupta and Kelly [2019] and Ehsani and Linnainmaa [2019], are directly related and partially explained by the one-day factor momentum, with almost 60% of its performance coming from the influence of one-day momentum.

Our finding is also used to improve stock short-term reversals, that is indirectly negative exposed to one-day factor momentum by construction. Short-term reversal performance goes from 5.7% per year to 14.2% per year when we neutralize stock exposure to 16 factors, besides a lower volatility, leading to a Sharpe ratio five times higher.

References

C. S. Asness, R. B. Porter, and R. L. Stevens. Predicting stock returns using industry-relative firm characteristics. *Available at SSRN 213872*, 2000.

D. Blitz, J. Huij, S. Lansdorp, and M. Verbeek. Short-term residual reversal. *Journal of Financial Markets*, 16(3):477–504, 2013.

L. Cohen and A. Frazzini. Economic links and predictable returns. *The Journal of Finance*, 63(4):1977–2011, 2008.

R. B. Cohen and C. Polk. An investigation of the impact of industry factors in asset-pricing tests. *WP96-002*, 1996.

S. Ehsani and J. T. Linnainmaa. Factor momentum and the momentum factor. Technical report, National Bureau of Economic Research, 2019.

E. F. Fama and K. R. French. Common risk factors in the returns on stocks and bonds. *Journal of*, 1993.

E. F. Fama and K. R. French. A five-factor asset pricing model. *Journal of financial economics*, 116(1):1–22, 2015.

G. Feng, S. Giglio, and D. Xiu. Taming the factor zoo: A test of new factors. Technical report, National Bureau of Economic Research, 2019.

A. Frazzini, R. Israel, and T. J. Moskowitz. Trading costs of asset pricing anomalies. *working paper, AQR*, 2015.

C. Garcia, R. Ribeiro, and M. C. Medeiros. Short-term reversals: The impact of factor momentum. *working paper*, 2020.

J. Green, J. R. Hand, and X. F. Zhang. The characteristics that provide independent information about average us monthly stock returns. *The Review of Financial Studies*, 30(12): 4389–4436, 2017.

S. Gu, B. Kelly, and D. Xiu. Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5):2223–2273, 2020.

T. Gupta and B. Kelly. Factor momentum everywhere. *The Journal of Portfolio Management*, 45(3):13–36, 2019.

A. E. Hoerl and R. W. Kennard. Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, 12(1):55–67, 1970.

K. Hou. Industry information diffusion and the lead-lag effect in stock returns. *The review of financial studies*, 20(4):1113–1138, 2007.

N. Jegadeesh and S. Titman. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, 48(1):65–91, 1993.

S. Kozak, S. Nagel, and S. Santosh. Shrinking the cross-section. *Journal of Financial Economics*, 2019.

C. M. Lee, S. T. Sun, R. Wang, and R. Zhang. Technological links and predictable returns. *Journal of Financial Economics*, 132(3):76–96, 2019.

Y. Liu and X. Wu. Labor links and shock transmissions. In *Paris December 2018 Finance Meeting EUROFIDAI-AFFI*, 2018.

A. W. Lo and A. C. MacKinlay. When are contrarian profits due to stock market overreaction? *The review of financial studies*, 3(2):175–205, 1990.

L. Menzly and O. Ozbas. Cross-industry momentum. In *AFA 2005 Philadelphia meetings*, 2006.

T. J. Moskowitz and M. Grinblatt. Do industries explain momentum? *The Journal of finance*, 54(4):1249–1290, 1999.

T. J. Moskowitz, Y. H. Ooi, and L. H. Pedersen. Time series momentum. *Journal of financial economics*, 104(2):228–250, 2012.

R. Novy-Marx. The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1):1–28, 2013.

C. A. Parsons, R. Sabbatucci, and S. Titman. Geographic lead-lag effects. *Available at SSRN 2780139*, 2018.

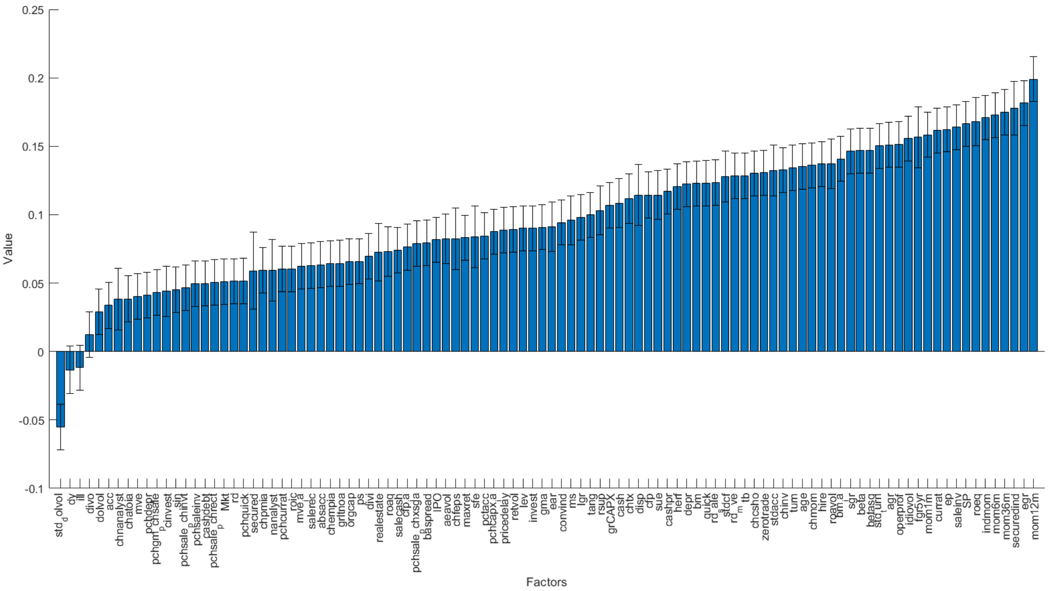
T. Shumway and V. A. Warther. The delisting bias in crsp's nasdaq data and its implications for the size effect. *The Journal of Finance*, 54(6):2361–2379, 1999.

R. Tibshirani. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1):267–288, 1996.

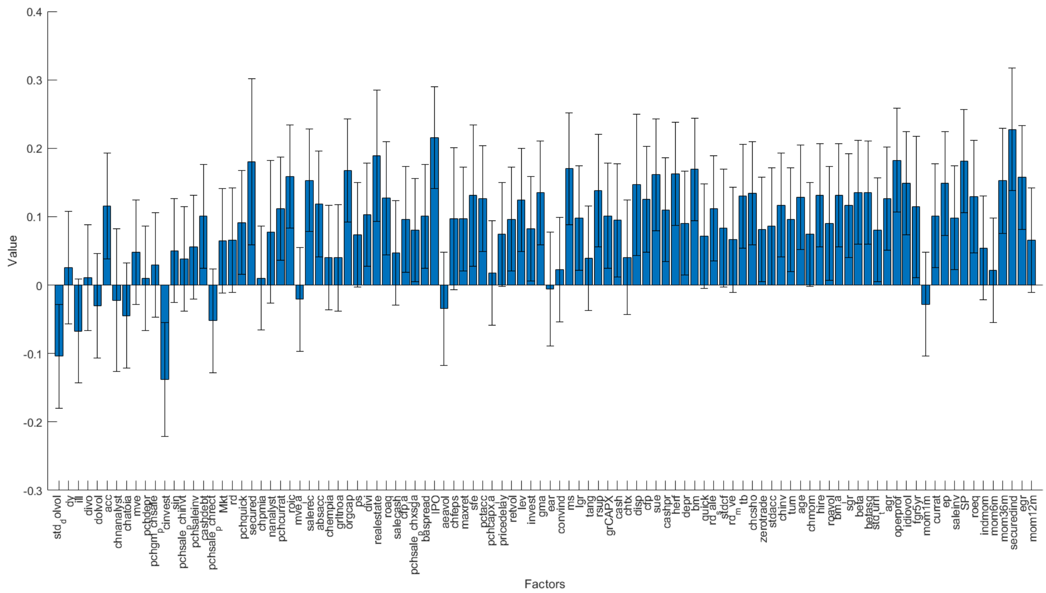
R. Tibshirani, M. Saunders, S. Rosset, J. Zhu, and K. Knight. Sparsity and smoothness via the fused lasso. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 67(1):91–108, 2005.

H. Zou and T. Hastie. Regularization and variable selection via the elastic net. *Journal of the royal statistical society: series B (statistical methodology)*, 67(2):301–320, 2005.

Figure 1: Factors autocorrelation.



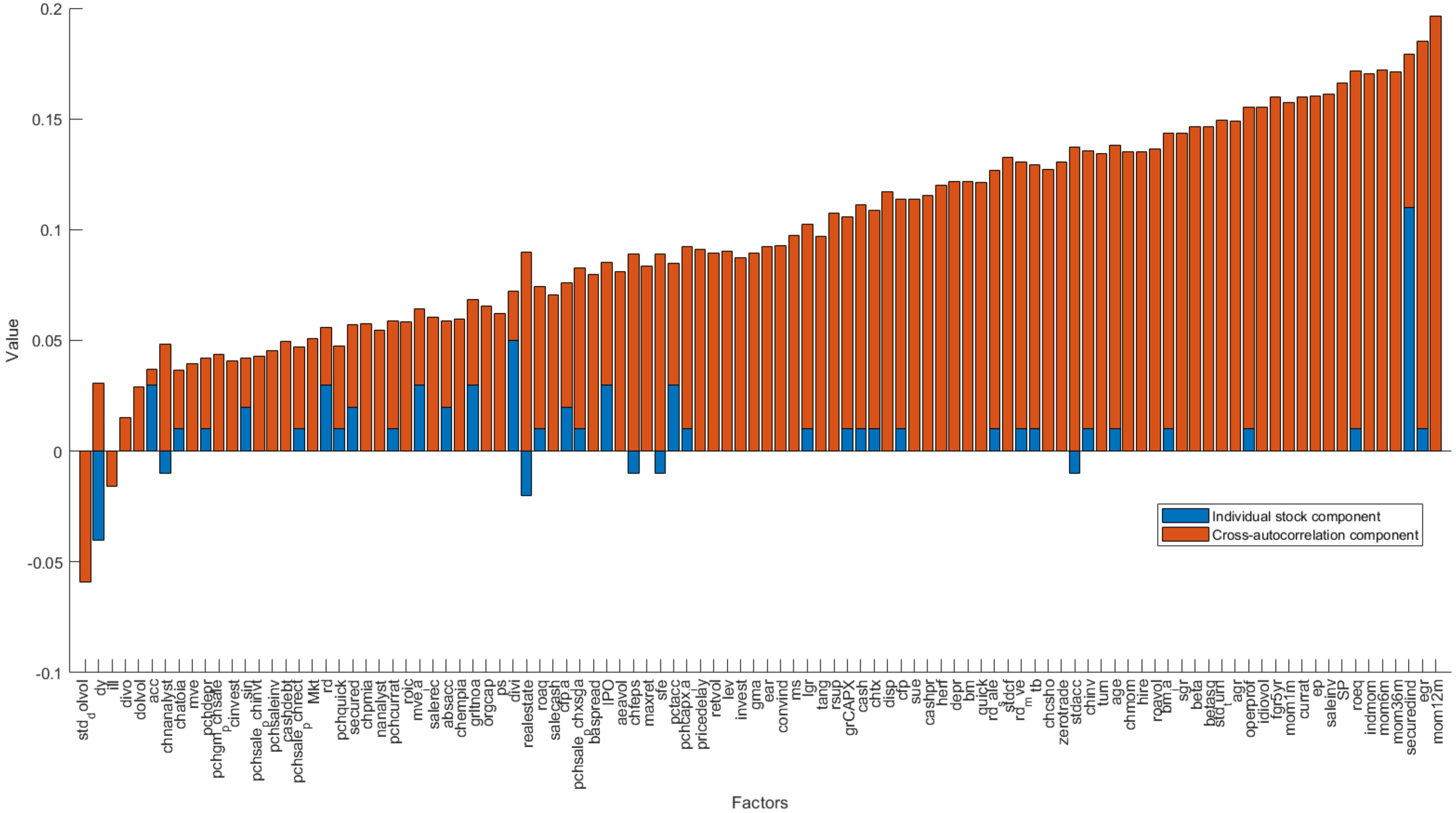
Panel (a) daily frequency.



Panel (b) monthly frequency

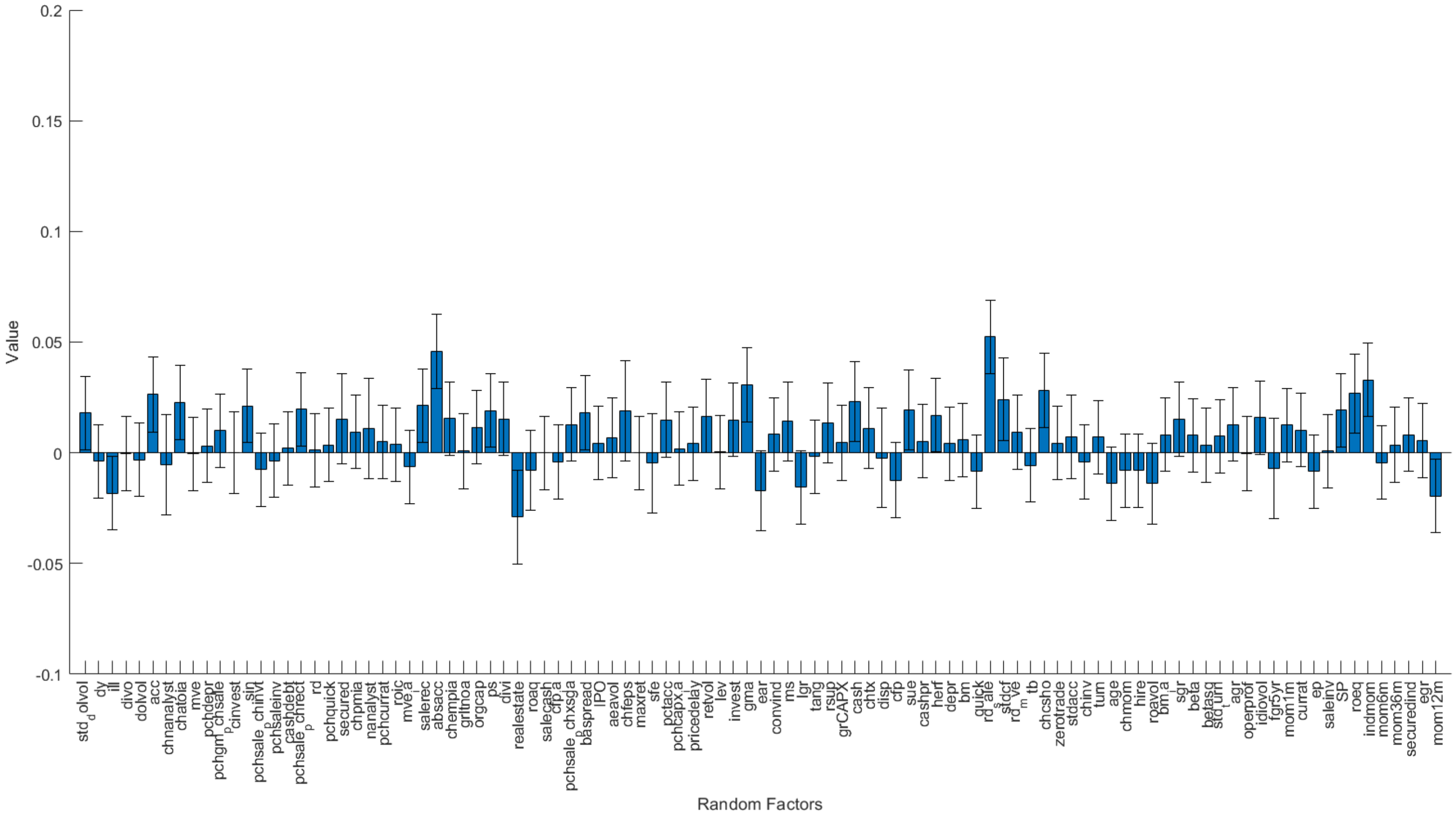
Notes: This figure reports the return autocorrelation for our sample of 103 factors along with 95% confidence intervals. This first order autocorrelation is computed using all factors returns available from Jul/1/1963 to Dec/31/2018. Panel A reports results for daily frequency and Panel B for monthly frequency. Factor are constructed stocks characteristics provided in Green et al. [2017] (and the Jeremiah Green SAS code available in *https : //sites.google.com/site/jeremiahrgreenacctg/home*). Section 2 gives more details about factors construction.

Figure 2: Factor autocorrelation: individual and cross components (daily frequency)



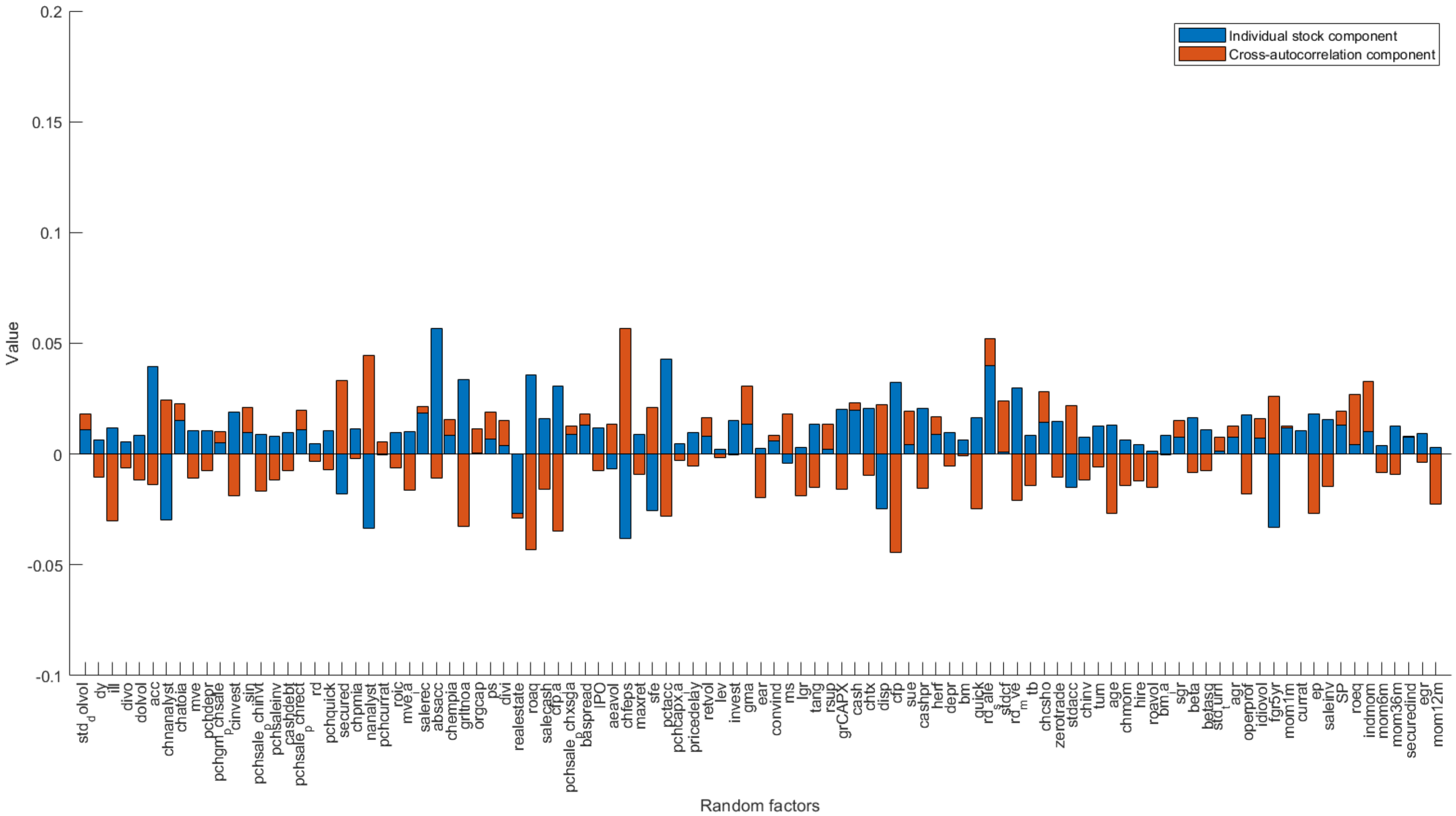
Notes: This figure reports the breakdown of factor returns autocorrelation into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the 103 factors of our database, the same ones described in Section 2 and Figure 1. Individual stocks component is the contribution of stocks autocorrelation for factor autocorrelation and the cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation. Subsection 3.2 describes with more details how each of the component is computed.

Figure 3: Random factor autocorrelation (daily frequency)



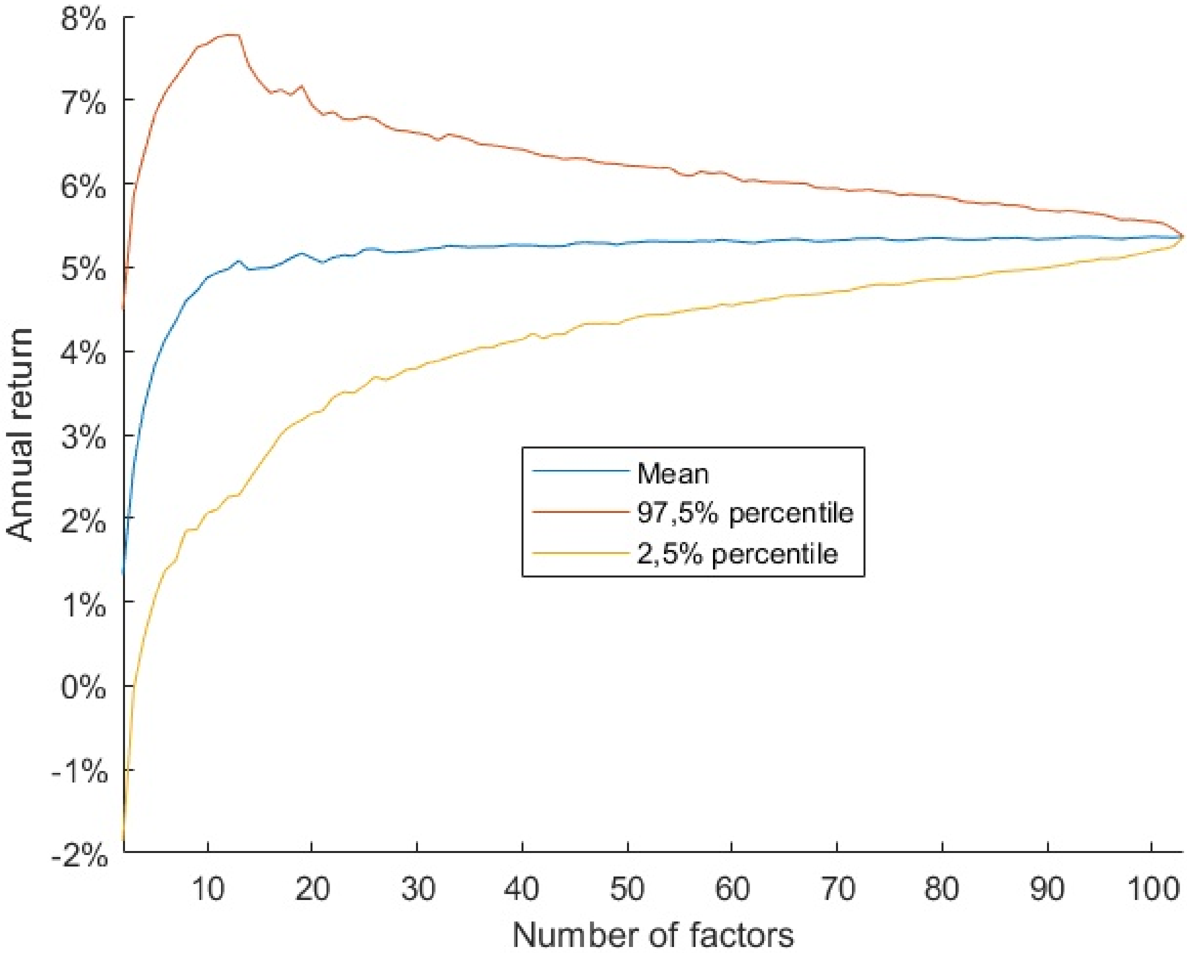
Notes: This figure reports the daily return autocorrelation for the 102 random factors that we construct using the same time-series of stocks returns, market value, and availability of characteristics from Jul/1/1963 to Dec/31/2018, but randomly sort stocks into high, neutral, or low portfolios to construct factors. Subsection 3.5 - Random factors describes with more details how the factors are constructed. We keep the same axis scale of Figures 1 and 2 to facilitate the comparison between the values.

Figure 4: Random factor autocorrelation: individual and cross components (daily frequency)



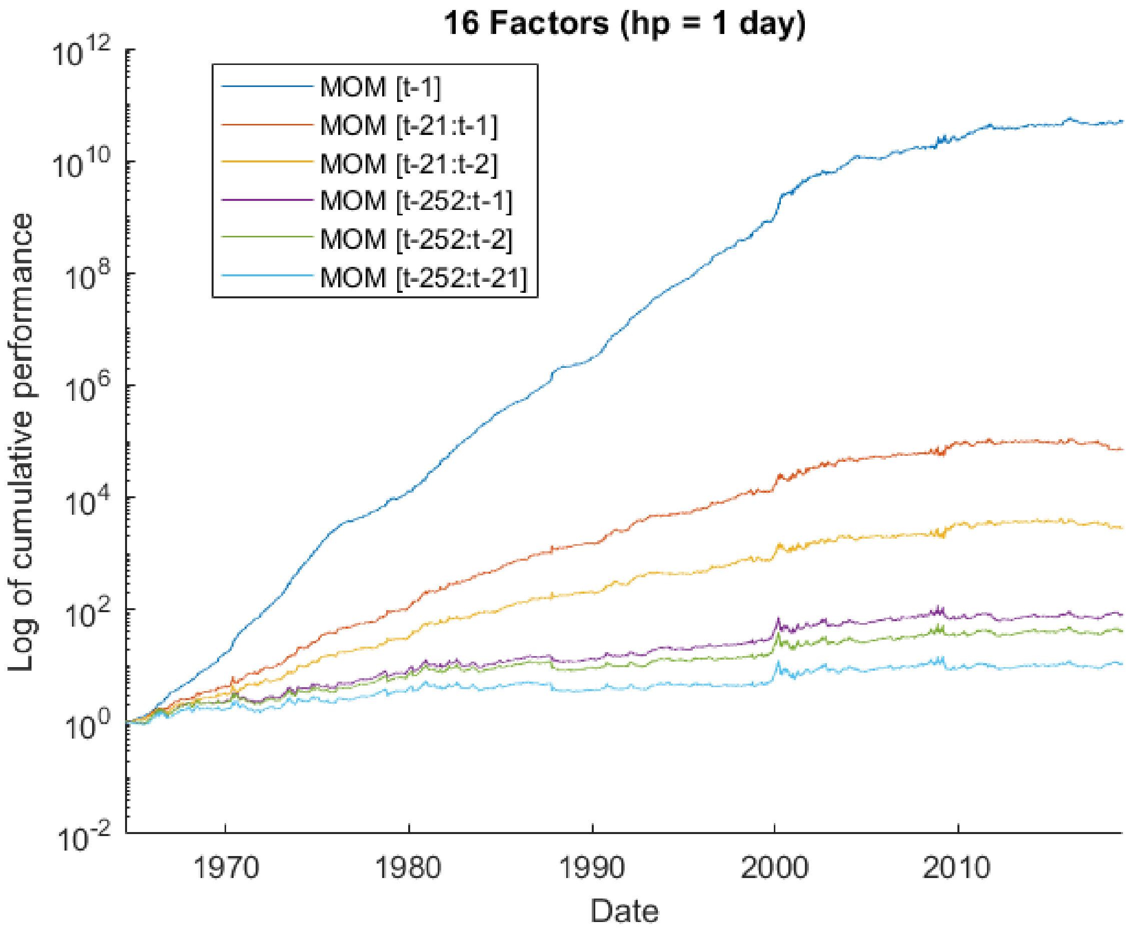
Notes: This figure reports the breakdown of the random factor returns autocorrelation into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the 102 random factors that we construct, the same ones described in Subsection 3.5 and Figure 3. Individual stocks component is the contribution of stocks autocorrelation for factor autocorrelation and the cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation. Subsection 3.2 describes with more details how each of the component is computed.

Figure 5: One-day Factor Momentum: Performance for random subsets



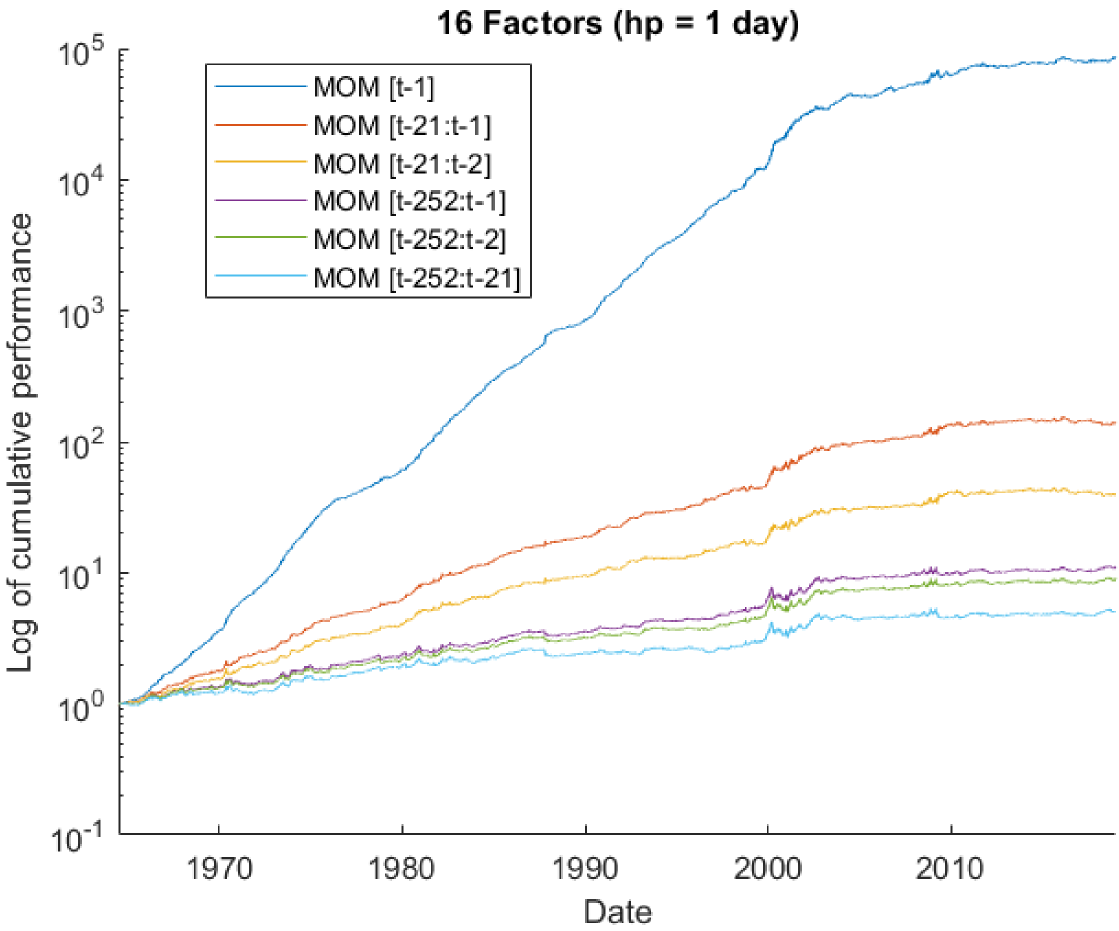
Notes: This figure plots the results for one-day momentum strategies constructed with random sets of factors, from sets of 2 to all 103 available factors. We use the bootstrap method with 50.000 simulations for each set size, from 2 to 103, and construct a factor momentum strategy. Blue line represents the average performance of the 50.000 simulations and the red lines represent the 95% bootstrapped confidence interval. To construct one-day factor momentum strategies we take positions in factors based on its recent performance relative to the cross-section of all factors, buying the top 15% that have recently outperformed and selling the bottom 15% that have underperformed peers on the last day. We keep the position for 21 days, using the same approach of Jegadeesh and Titman [1993]. We use factors daily returns from Jul/1963 to Dec/2018. Subsection 4.1 presents more details about how the construction of cross-section momentum.

Figure 6: Cross-section Factor Momentum: Performance



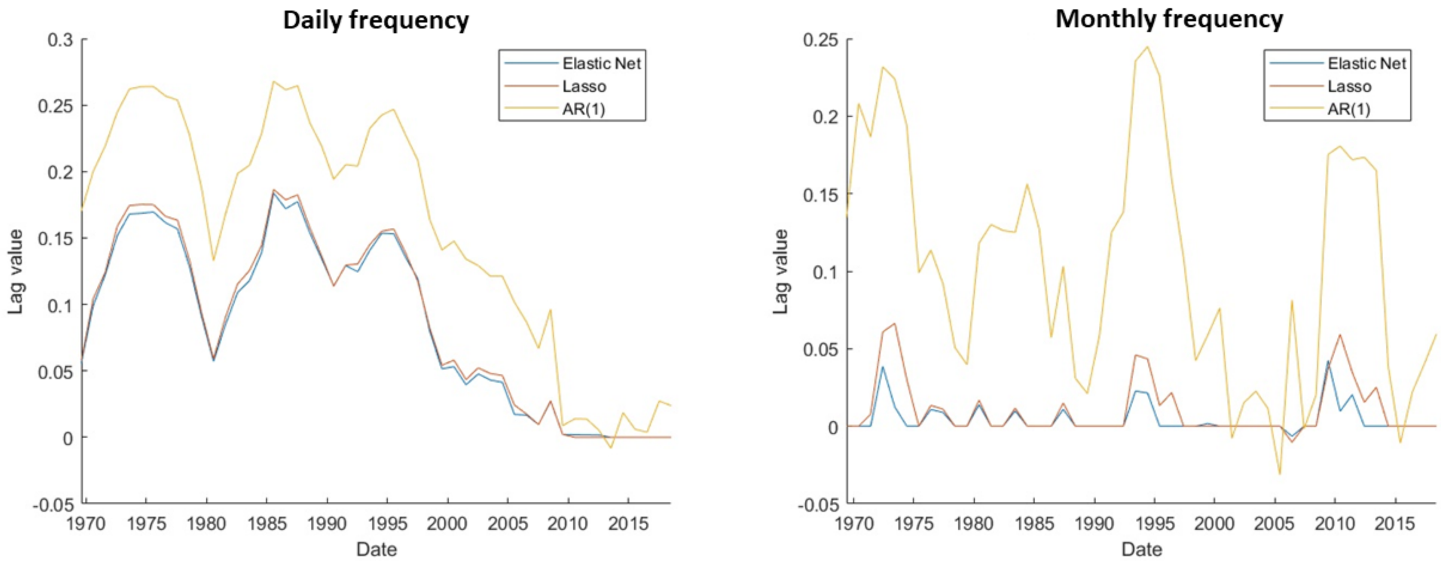
Notes: This figure plots the cumulative performance of cross-section factor momentum strategies, from 1963 to 2018, for several look-back windows: 1 day, 21 days (skipping and not 1 day) and 252 days (skipping and not 1 and 21 days) and a holding period of 1 day. To construct factor momentum strategies we take positions in factors based on its recent performance relative to the cross-section of selected subset of 16 factor, buying the top 25% that have recently outperformed and selling the bottom 25% that have underperformed peers. We use factors daily returns from Jul/1963 to Dec/2018. Subsection 4.1 presents more details about how the construction of cross-section momentum.

Figure 7: Time-series Factor Momentum: Performance



Notes: This figure plots the cumulative performance of time-series factor momentum strategies, from 1963 to 2018, for several look-back windows: 1 day, 21 days (skipping and not 1 day) and 252 days (skipping and not 1 and 21 days) and a holding period of 1 day. Time-series momentum consider absolute performance to define winners and losers factors. If the cumulative excess return of a factor is positive in a given look-back window, we take a long position in this factor, and if it is negative, we take a short position. The weight in each factor is proportional to its excess performance. The return at each period is represented by the aggregation of the position in all 16 factors of our subsample. Subsection 4.2 presents more details about how the construction of time-series momentum. We use factors daily from Jul/1963 to Dec/2018.

Figure 8: Lag(t-1) - mean value between 16 factors



Notes: This figure plots the mean value of coefficients of lag(t-1) between the 16 factors, from 1969 to 2018, for Elastic Net, Lasso and AR(1) models. Left figure plots for the models using factors daily returns and right figure for factors monthly returns. Each year we estimate univariate predictive regressions for each factor, with 252 daily (12 monthly) lags and Elastic Net or Lasso penalization methods. We use rolling 6-year estimation windows and re-estimate the models every year using BIC (Bayesian Information Criterion) to tune the hyperparameters. We also plot the time evolution of the first-order autoregressive coefficients - AR(1) - using rolling 6-year estimation window. Section 5 - Machine Learning Models - describes with more details the models setup and estimation methods.

Table 1: Factors: Individual and cross components from autocorrelation in daily frequency

Factors	Regular factors (Large and Small)				Large portfolios of factor				Small portfolios of factor			
	Auto correlation	Components			Auto correlation	Components			Auto correlation	Components		
		Individual	Cross	% of Cross		Individual	Cross	% of Cross		Individual	Cross	% of Cross
MKT	0.05	0.00	0.05	100%	0.04	0.00	0.04	100%	0.11	0.00	0.11	100%
t-stat	6.0	0.0	6.0		4.6	0.0	4.6		12.7	0.0	12.7	
INV	0.09	0.00	0.09	97%	0.06	0.00	0.05	92%	0.11	0.00	0.11	98%
t-stat	10.7	0.3	10.4		6.6	0.5	6.1		13.2	0.2	13.0	
OP	0.15	0.01	0.15	96%	0.09	0.01	0.08	89%	0.18	0.00	0.18	97%
t-stat	17.9	0.7	17.2		10.5	1.1	9.4		21.7	0.6	21.1	
B/M	0.12	0.00	0.12	99%	0.07	0.00	0.07	98%	0.19	0.00	0.19	99%
t-stat	14.6	0.1	14.5		8.0	0.1	7.8		23.0	0.3	22.7	
SIZE	0.04	0.00	0.04	98%	0.04	0.00	0.04	100%	0.11	0.00	0.11	100%
t-stat	4.8	0.1	4.7		4.5	0.0	4.5		13.1	0.0	13.1	
E/P	0.16	0.00	0.16	99%	0.11	0.00	0.11	97%	0.20	0.00	0.20	99%
t-stat	19.4	0.2	19.2		13.0	0.4	12.6		24.2	0.2	23.9	
CF/P	0.11	0.01	0.10	91%	0.07	0.02	0.05	78%	0.14	0.01	0.12	90%
t-stat	13.4	1.2	12.1		8.2	1.8	6.4		16.3	1.7	14.6	
D/P	-0.01	-0.04	0.03	-	0.07	0.00	0.07	97%	-0.03	-0.05	0.02	-
t-stat	-1.2	-4.7	3.5		7.7	0.2	7.5		-3.8	-5.8	2.0	
Accruals (ACC)	0.03	0.03	0.01	20%	0.02	0.03	-0.02	-88%	0.07	0.03	0.03	50%
t-stat	3.9	3.1	0.8		2.0	3.7	-1.8		7.7	3.8	3.9	
Market Beta (BETA)	0.15	0.00	0.15	100%	0.10	0.00	0.10	99%	0.18	0.00	0.18	100%
t-stat	17.6	0.0	17.5		12.4	0.1	12.3		21.8	0.0	21.8	
Net Share Issues (CHCSHO)	0.13	0.00	0.13	98%	0.06	0.01	0.06	92%	0.15	0.00	0.15	98%
t-stat	15.5	0.3	15.2		7.6	0.6	7.0		18.4	0.3	18.0	
Daily Var. (RETVOL)	0.09	0.00	0.09	100%	0.05	0.00	0.05	103%	0.13	0.00	0.13	100%
t-stat	10.6	0.0	10.6		6.2	-0.2	6.4		15.4	0.1	15.4	
Daily residual var. (IDIOVOL)	0.16	0.00	0.16	100%	0.10	0.00	0.09	99%	0.21	0.00	0.21	100%
t-stat	18.6	0.0	18.6		11.4	0.2	11.2		24.9	-0.1	25.0	
MOM	0.20	0.00	0.20	99%	0.15	0.01	0.15	96%	0.24	0.00	0.24	99%
t-stat	24.0	0.3	23.7		17.9	0.6	17.3		28.9	0.1	28.7	
ST REV	0.16	0.00	0.16	99%	0.12	0.00	0.12	99%	0.20	0.00	0.20	99%
t-stat	19.0	0.1	18.8		13.8	0.1	13.7		23.9	0.3	23.5	
LT REV	0.18	0.00	0.17	98%	0.14	0.00	0.13	97%	0.18	0.01	0.17	96%
t-stat	20.5	0.4	20.1		15.8	0.5	15.3		20.7	0.8	19.9	
Mean	0.11	0.00	0.11	93%	0.08	0.01	0.07	84%	0.15	0.00	0.15	95%

Notes: This table reports the daily autocorrelation for our subsample of 16 factors and its breakdown into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the 16 factors of our subsample. Individual stocks component is the contribution of stocks autocorrelation for factor autocorrelation and the cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation. Section 2 gives more details about the factors construction and subsection 3.2 describes with more details how each of the component is computed. The left panel reports results for factors using Fama & French definition, using both large and small portfolios. The middle panel reports results for factors constructed only with large portfolios, that is, using only stocks with market cap above the NYSE median. The right panel reports results for factors constructed only with small portfolios, that is, using only stocks with market cap below the NYSE median. The bottom line presents the mean value for the 16 factors of each component.

Table 2: Industry-neutral Factors: Individual and cross components from autocorrelation in daily frequency

Factors	Regular				Industry-neutral				Industry-neutral hedged			
	Auto correlation	Components			Auto correlation	Components			Auto correlation	Components		
		Individual	Cross	% of Cross		Individual	Cross	% of Cross		Individual	Cross	% of Cross
INV	**0.09**	0.00	**0.09**	97%	**0.12**	0.01	**0.11**	94%	**0.11**	0.01	**0.10**	94%
t-stat	**10.7**	0.3	**10.4**		**13.8**	0.8	**12.9**		**13.0**	0.8	**12.2**	
OP	**0.15**	0.01	**0.15**	96%	**0.12**	0.01	**0.11**	92%	**0.10**	0.01	**0.09**	94%
t-stat	**17.9**	0.7	**17.2**		**14.0**	1.1	**12.9**		**11.8**	0.7	**11.1**	
B/M	**0.12**	0.00	**0.12**	99%	**0.11**	0.00	**0.11**	99%	**0.12**	0.00	**0.11**	99%
t-stat	**14.6**	0.1	**14.5**		**13.4**	0.2	**13.3**		**13.8**	0.2	**13.6**	
SIZE	**0.04**	0.00	**0.04**	98%	**0.04**	0.00	**0.04**	98%	**0.03**	0.00	**0.03**	98%
t-stat	**4.8**	0.1	**4.7**		**5.2**	0.1	**5.1**		**3.8**	0.1	**3.8**	
E/P	**0.16**	0.00	**0.16**	99%	**0.15**	0.00	**0.15**	99%	**0.16**	0.00	**0.15**	98%
t-stat	**19.4**	0.2	**19.2**		**17.7**	0.2	**17.5**		**18.6**	0.3	**18.3**	
CF/P	**0.11**	0.01	**0.10**	91%	**0.11**	**0.02**	**0.09**	82%	**0.12**	**0.02**	**0.09**	82%
t-stat	**13.4**	1.2	**12.1**		**12.8**	**2.3**	**10.4**		**13.4**	**2.4**	**11.0**	
D/P	-0.01	**-0.04**	**0.03**	-	**0.14**	0.00	**0.15**	102%	**0.17**	0.00	**0.17**	102%
t-stat	-1.2	**-4.7**	**3.5**		**17.2**	-0.3	**17.6**		**20.1**	-0.4	**20.5**	
Accruals (ACC)	**0.03**	**0.03**	0.01	20%	**0.04**	**0.03**	0.01	25%	**0.04**	**0.03**	0.01	18%
t-stat	**3.9**	**3.1**	0.8		**4.4**	**3.3**	1.1		**4.3**	**3.5**	0.8	
Market Beta (BETA)	**0.15**	0.00	**0.15**	100%	**0.14**	0.00	**0.14**	100%	**0.15**	0.00	**0.15**	100%
t-stat	**17.6**	0.0	**17.5**		**17.1**	0.0	**17.0**		**17.4**	0.0	**17.3**	
Net Share Issues (CHCSHO)	**0.13**	0.00	**0.13**	98%	**0.11**	0.00	**0.11**	98%	**0.12**	0.00	**0.12**	99%
t-stat	**15.5**	0.3	**15.2**		**13.4**	0.3	**13.1**		**14.0**	0.2	**13.8**	
Daily Var. (RETVOL)	**0.09**	0.00	**0.09**	100%	**0.10**	0.00	**0.10**	100%	**0.10**	0.00	**0.10**	100%
t-stat	**10.6**	0.0	**10.6**		**11.6**	-0.1	**11.6**		**11.3**	0.0	**11.3**	
Daily residual var. (IDIOVOL)	**0.16**	0.00	**0.16**	100%	**0.16**	0.00	**0.16**	100%	**0.16**	0.00	**0.16**	100%
t-stat	**18.6**	0.0	**18.6**		**19.7**	0.1	**19.6**		**19.6**	0.1	**19.5**	
MOM	**0.20**	0.00	**0.20**	99%	**0.21**	0.01	**0.20**	98%	**0.21**	0.00	**0.20**	98%
t-stat	**24.0**	0.3	**23.7**		**25.0**	0.6	**24.4**		**24.9**	0.6	**24.3**	
ST REV	**0.16**	0.00	**0.16**	99%	**0.15**	0.00	**0.15**	100%	**0.16**	0.00	**0.16**	100%
t-stat	**19.0**	0.1	**18.8**		**17.8**	-0.1	**17.8**		**18.7**	0.0	**18.7**	
LT REV	**0.18**	0.00	**0.17**	98%	**0.17**	0.00	**0.16**	98%	**0.18**	0.00	**0.18**	98%
t-stat	**20.5**	0.4	**20.1**		**19.5**	0.3	**19.2**		**21.4**	0.4	**20.9**	
Mean	**0.12**	**0.00**	**0.12**	**92%**	**0.12**	**0.01**	**0.12**	**92%**	**0.13**	**0.01**	**0.12**	**92%**

Notes: This table reports the daily autocorrelation for our subsample of 16 factors and its breakdown into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the 16 factors of our subsample. Individual stocks component is the contribution of stocks autocorrelation for factor autocorrelation and the cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation. Section 2 gives more details about the factors construction, subsection 3.2 describes with more details how each of the component is computed and subsection 3.3.1 explains how we construct industry-neutral factors. The left panel reports results for regular factors using Fama & French definition. The middle panel reports results for industry-neutral factors, in which the factor predictor is defined across each industry. The right panel reports results for another version of industry-neutral factors, in which we also take an offsetting position in each stock's value-weighted industry (Novy-Marx [2013]) to remove industry return shocks. The bottom line presents the mean value for the 16 factors of each component.

Table 3: Factor-neutral Industries: Individual and cross components from autocorrelation in daily frequency

Industries	Regular				Factor neutral (3 factors)				Factor neutral (16 factors)			
	Auto correlation	Components			Auto correlation	Components			Auto correlation	Components		
		Individual	Cross	% of Cross		Individual	Cross	% of Cross		Individual	Cross	% of Cross
Mining	**0.07**	0.00	**0.06**	98%	**0.08**	0.00	**0.08**	96%	**0.06**	0.00	**0.05**	93%
t-stat	**7.9**	0.2	**7.6**		**9.4**	0.3	**9.0**		**6.8**	0.3	**6.4**	
Food	**0.07**	0.00	**0.07**	99%	**0.07**	0.00	**0.06**	97%	**0.05**	0.00	**0.05**	102%
t-stat	**8.2**	0.1	**8.0**		**7.6**	0.2	**7.4**		**5.3**	0.0	**5.4**	
Apparel	**0.11**	0.00	**0.11**	98%	**0.06**	0.01	**0.05**	86%	**0.04**	0.01	**0.03**	86%
t-stat	**13.2**	0.3	**12.8**		**6.5**	0.9	**5.6**		**4.2**	0.7	**3.6**	
Paper	**0.07**	0.00	**0.07**	97%	**0.02**	0.01	0.01	61%	**0.02**	0.01	0.01	46%
t-stat	**8.1**	0.3	**7.8**		**2.8**	0.7	1.7		**2.0**	0.7	0.9	
Chemical	**0.08**	0.00	**0.08**	97%	**0.08**	0.01	**0.07**	85%	**0.06**	0.01	**0.04**	69%
t-stat	**9.6**	0.3	**9.2**		**9.5**	1.0	**8.1**		**6.5**	1.6	**4.5**	
Petroleum	0.00	**-0.02**	**0.02**	745%	**0.07**	**-0.04**	**0.11**	164%	**0.03**	-0.05	**0.08**	239%
t-stat	0.4	**-2.5**	**2.9**		**7.9**	**-4.9**	**12.9**		**4.0**	-5.5	**9.7**	
Construction	**0.09**	**0.02**	**0.07**	75%	**0.03**	**0.06**	**-0.03**	-97%	**0.03**	0.06	**-0.03**	-96%
t-stat	**11.2**	**2.8**	**8.3**		**3.8**	**7.6**	**-3.7**		**3.6**	7.3	**-3.5**	
Prim. Metals	**0.08**	0.00	**0.08**	97%	**0.08**	0.01	**0.07**	89%	**0.05**	0.01	**0.04**	80%
t-stat	**9.4**	0.3	**9.0**		**8.9**	0.7	**7.9**		**5.6**	0.9	**4.5**	
Fab. Metals	**0.09**	0.00	**0.09**	95%	**0.05**	0.02	**0.04**	66%	**0.03**	0.02	0.01	32%
t-stat	**10.8**	0.5	**10.2**		**6.4**	1.9	**4.2**		**3.5**	2.1	1.1	
Machinery	**0.05**	0.00	**0.04**	95%	**0.08**	0.01	**0.07**	89%	**0.06**	0.01	**0.05**	86%
t-stat	**5.5**	0.2	**5.2**		**9.0**	1.0	**8.0**		**7.3**	1.1	**6.3**	
Electrical Eq	**0.05**	0.00	**0.05**	101%	**0.07**	0.00	**0.06**	94%	**0.03**	0.00	**0.03**	79%
t-stat	**5.4**	-0.1	**5.4**		**7.8**	-0.1	**7.4**		**4.1**	0.3	**3.2**	
Transport Eq	**0.06**	0.01	**0.05**	91%	**0.07**	**0.02**	**0.05**	74%	**0.05**	0.01	**0.04**	76%
t-stat	**7.1**	0.6	**6.4**		**8.5**	**2.1**	**6.3**		**6.3**	1.5	**4.8**	
Manufacturing	**0.07**	0.01	**0.07**	93%	**0.03**	**0.02**	0.01	21%	**0.02**	**0.02**	0.00	5%
t-stat	**8.9**	0.6	**8.2**		**3.4**	**2.8**	0.7		**2.3**	**2.4**	0.1	
Railroads	**0.05**	0.01	**0.04**	88%	0.01	0.01	0.00	-15%	0.01	0.01	0.00	-22%
t-stat	**6.0**	0.7	**5.2**		**1.2**	1.5	-0.2		**1.0**	1.3	-0.2	
Other transportations	**0.11**	0.00	**0.11**	96%	**0.09**	0.01	**0.08**	84%	**0.07**	0.02	**0.06**	79%
t-stat	**13.6**	0.6	**12.9**		**10.5**	1.7	**8.8**		**8.3**	1.9	**6.5**	
Utilities	**0.07**	0.00	**0.07**	100%	**0.11**	0.00	**0.11**	100%	**0.07**	0.00	**0.07**	107%
t-stat	**8.3**	0.0	**8.2**		**13.3**	0.0	**13.3**		**7.7**	-0.4	**8.2**	
Dept. stores	**0.08**	0.01	**0.07**	93%	**0.06**	0.01	**0.05**	82%	**0.04**	0.01	**0.02**	63%
t-stat	**8.9**	0.7	**8.2**		**7.3**	1.3	**6.0**		**4.3**	1.5	**2.7**	
Retail	**0.13**	0.00	**0.12**	97%	**0.07**	**0.02**	**0.06**	78%	**0.04**	**0.02**	**0.02**	63%
t-stat	**14.9**	0.4	**14.4**		**8.6**	**2.2**	**6.7**		**4.5**	**2.2**	**2.8**	
Financial	**0.05**	0.00	**0.04**	98%	**0.10**	0.01	**0.05**	52%	**0.10**	0.00	**0.05**	48%
t-stat	**5.4**	0.1	**5.3**		**11.6**	1.0	**6.0**		**12.0**	0.2	**5.8**	
Other	**-0.04**	**-0.06**	**0.02**	-	**-0.09**	**-0.07**	-0.02	17%	**-0.09**	**-0.07**	**-0.02**	22%
t-stat	**-5.0**	**-7.5**	**2.7**		**-10.5**	**-8.5**	-1.8		**-10.6**	**-8.1**	**-2.3**	
Mean	**0.07**	**0.00**	**0.07**	**129%**	**0.06**	**0.01**	**0.05**	**66%**	**0.04**	**0.01**	**0.03**	**63%**

Notes: This table reports the daily autocorrelation for industries portfolios and its breakdown into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each the 20 industries defined in Moskowitz and Grinblatt [1999]. Subsection 3.2 describes with more details how each of the component is computed and subsection 3.4 explains how we construct factor-neutral industries portfolios. The left panel reports results for regular industries. The middle panel reports results for factor-neutral industries hedged for the Fama-French 3 factors. The right panel reports reports results for factor-neutral industries hedged for our subsample of 16 factors.

Table 4: Factor Momentum: Performance and Turnover

Panel A	16 Factors									
Cross-Section Momentum	**Holding period = 1 day**					**Holding period = 21 days**				
	Excess return	**Sharpe ratio**	**Max DD**	**Daily turnover**	**Breakeven trade cost**	**Excess return**	**Sharpe ratio**	**Max DD**	**Daily turnover**	**Breakeven trade cost**
MOM [t-1]	**56.3%**	**3.46**	**-30%**	**239%**	**0.07%**	**6.3%**	**1.32**	**-10%**	**13%**	**0.18%**
t-stat	**21.1**					**9.7**				
MOM [t-21:t-1]	**22.1%**	**1.33**	**-33%**	**71%**	**0.11%**	**8.0%**	**0.60**	**-31%**	**15%**	**0.20%**
t-stat	**9.5**					**4.8**				
MOM [t-21:t-1] + [t-1]	**38.8%**	**2.99**	**-23%**	**134%**	**0.10%**	**7.3%**	**0.84**	**-20%**	**11%**	**0.24%**
t-stat	**19.3**					**6.4**				
MOM [t-252:t-1]	**8.4%**	**0.55**	**-45%**	**27%**	**0.12%**	**5.5%**	**0.37**	**-45%**	**9%**	**0.23%**
t-stat	**4.5**					**3.2**				
MOM [t-252:t-1] + [t-1]	**30.9%**	**2.79**	**-23%**	**124%**	**0.09%**	**6.1%**	**0.74**	**-27%**	**9%**	**0.26%**
t-stat	**18.5**					**5.7**				

Panel B	16 Factors									
Time-series Momentum	**Holding period = 1 day**					**Holding period = 21 days**				
	Excess return	**Sharpe ratio**	**Max DD**	**Daily turnover**	**Breakeven trade cost**	**Excess return**	**Sharpe ratio**	**Max DD**	**Daily turnover**	**Breakeven trade cost**
MOM [t-1]	**23.2%**	**3.32**	**-14%**	**108%**	**0.08%**	**11.4%**	**1.59**	**-15%**	**22.0%**	**0.19%**
t-stat	**22.3**					**11.3**				
MOM [t-21:t-1]	**9.3%**	**1.46**	**-14%**	**23%**	**0.16%**	**4.9%**	**0.75**	**-20%**	**8.2%**	**0.23%**
t-stat	**10.6**					**5.7**				
MOM [t-21:t-1] + [t-1]	**15.9%**	**3.02**	**-8%**	**59%**	**0.10%**	**8.0%**	**1.27**	**-16%**	**12.9%**	**0.24%**
t-stat	**21.1**					**9.3**				
MOM [t-252:t-1]	**4.5%**	**0.80**	**-20%**	**8%**	**0.21%**	**3.5%**	**0.61**	**-19%**	**3.8%**	**0.36%**
t-stat	**6.0**					**4.7**				
MOM [t-252:t-1] + [t-1]	**13.3%**	**2.94**	**-9%**	**55%**	**0.09%**	**7.3%**	**1.47**	**-12%**	**11.6%**	**0.24%**
t-stat	**20.7**					**10.7**				

Notes: This table reports the performance of the cross section and time-series factor momentum. Every day we rank all factors based in their cumulative performance over several periods (1 day, 21 days, 21 days excluding last day, 252 days, 252 days excluding last day and last 21 days). Panel A reports the cross-section case, in which we form long-short strategies with the winners and losers factors. The long position is formed with the highest ranked factors, and the short position with the lowest factors (4 of 16 factors for each leg), with equal weight across factor portfolios. Panel B reports the time-series case, in which we take a long position if the factor absolute performance is positive, or a short position, if it is negative. We use daily returns from Jul/1/1963 to Dec/31/2018 and two different holding periods: 1 day and 21 days, using the same methodology as Jegadeesh and Titman [1993]. Section 4 explains with more details how factor momentum are constructed in both cross section and time-series. It´s reported the annualized excess return, Sharpe ratio, maximum drawdown in 3 months, average daily turnover of both long and short legs, and the break even trading cost, that is, the cost per unit of turnover that would erode all the performance.

Table 5: Factor Momentum: Spanning Tests

Panel A

Cross-Section case	Regressor variables								
Hp = 21 days	**Alpha**	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**UMD**	**MOM[t-1]**	**MOM(21-days)**
MOM (1 day)	**4.0%**								**0.27**
t-stat	**9.1**								**46.7**
	6.3%	**-0.06**	**-0.05**	**0.11**	0.01	0.00	**0.03**		
	9.7	**-9.1**	**-6.2**	**6.5**	0.8	-0.2	**2.6**		
	4.1%	**-0.02**	**-0.02**	**0.04**	-0.01	0.00			**0.26**
	9.5	**-4.4**	**-3.3**	**3.9**	-0.6	-0.2			**48.9**
MOM (1 month)	**-4.6%**							**2.14**	
t-stat	**-3.8**							**59.7**	
	7.7%	**-0.15**	**-0.12**	**0.28**	0.06	-0.01	**0.17**		
	4.2	**-8.5**	**-4.7**	**6.1**	1.4	-0.2	**5.2**		
	-4.4%	**-0.03**	-0.02	0.03	**0.06**	0.00		**2.11**	
	-3.6	**-2.7**	-1.0	0.9	**2.0**	0.2		**59.5**	
MOM (1 year)	1.5%	-0.01	0.05	**-0.13**	**0.24**	**-0.09**		**0.80**	
t-stat	0.7	-0.5	1.4	**-2.5**	**4.6**	**-2.0**		**10.2**	

Time-Series case	Regressor variables								
Hp = 21 days	**Alpha**	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**UMD**	**MOM[t-1]**	**MOM(21-days)**
MOM (1-day)	**7.2%**								**0.77**
t-stat	**10.0**								**41.3**
	11.5%	**-0.11**	**-0.09**	**0.15**	**0.06**	0.04	0.01		
	11.8	**-12.3**	**-7.3**	**6.4**	**2.8**	1.6	0.4		
	7.6%	**-0.05**	**-0.04**	**0.06**	0.02	0.02			**0.72**
	10.7	**-6.7**	**-4.1**	**3.4**	1.1	1.5			**37.9**
MOM (1-month)	**-2.1%**							**0.65**	
t-stat	**-3.3**							**38.3**	
	4.3%	**-0.08**	**-0.05**	**0.15**	**0.04**	0.02	**0.09**		
	4.9	**-9.3**	**-4.6**	**6.7**	**2.1**	0.8	**5.8**		
	-2.0%	-0.01	-0.01	0.03	0.02	0.00		**0.64**	
	-3.1	-1.7	-0.7	1.8	1.6	-0.1		**35.9**	
MOM (1-year)	**1.8%**	**-0.02**	0.00	-0.01	**0.07**	0.00		**0.16**	
t-stat	**2.2**	**-2.2**	0.1	-0.6	**3.3**	0.2		**7.4**	

This table reports spanning regressions in which the dependent variable is one factor momentum strategy and the right-hand-side variables are the returns of the Fama-French five factor (Fama and French [2015] - MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD), and other factor momentum strategy with a different look-back window. We use daily returns from Jul/1/1963 to Dec/31/2018 and a holding period of 21 days, with the same methodology of Jegadeesh and Titman [1993]. The alpha is annualized and reported in excess of the risk free rate. The first three rows reports results for the one-day factor momentum as the dependent variable, the next three ones use the one-month (or 21 days) factor momentum, and the last line uses the one-year factor momentum. Panel A reports results for the cross-section case and Panel B for the time-series case. Subsections 4.1.2 and 4.2.2 preset more details.

Table 6: Relevance of One-day factor Momentum: Double-sorted portfolios

Double-sorted portfolios	16 Factors							
	Holding period = 1 day				Holding period = 21 days			
	Excess return	Sharpe ratio	MOM[t-21:t-1] alpha	Loading	Excess return	Sharpe ratio	MOM[t-21:t-1] alpha	Loading
MOM[t-21:t-1]	**22.1%**	**1.33**			**8.0%**	**0.60**		
t-stat	**9.5**				**4.8**			
MOM [t-21:t-2] | Low[t-1]	**6.9%**	**0.52**	**-4.6%**	**0.57**	**5.1%**	**0.63**	0.4%	**0.57**
t-stat	**4.3**		**-3.7**	**45.9**	**4.8**		1.0	**108.9**
MOM [t-21:t-2] | High[t-1]	**6.9%**	**0.54**	**-4.0%**	**0.54**	**4.2%**	**0.53**	-0.3%	**0.56**
t-stat	**4.4**		**-3.2**	**42.7**	**4.1**		-0.8	**90.3**
Low [t-1] & Low [t-21:t-2]	**-16.8%**	**-1.66**	**-9.9%**	**-0.35**	-1.6%	**-0.26**	**1.7%**	**-0.36**
t-stat	**-13.2**		**-9.2**	**-28.2**	-1.7		**3.0**	**-43.8**
Low [t-1] & Mid [t-21:t-2]	**-14.8%**	**-1.74**	**-13.4%**	**-0.06**	0.3%	**0.07**	1.1%	**-0.08**
t-stat	**-13.6**		**-12.1**	**-4.7**	0.7		1.8	**-9.8**
Low [t-1] & High [t-21:t-2]	**-10.3%**	**-1.04**	**-14.0%**	**0.22**	**3.8%**	**0.78**	**2.1%**	**0.21**
t-stat	**-7.8**		**-11.5**	**16.8**	**5.9**		**3.8**	**28.0**
High [t-1] & Low [t-21:t-2]	**18.2%**	**1.79**	**22.6%**	**-0.14**	**3.6%**	**0.72**	**5.1%**	**-0.15**
t-stat	**12.6**		**14.4**	**-8.8**	**5.4**		**7.7**	**-15.1**
High [t-1] & Mid [t-21:t-2]	**24.9%**	**2.68**	**21.6%**	**0.15**	**6.3%**	**1.26**	**5.0%**	**0.16**
t-stat	**18.2**		**15.5**	**10.0**	**9.3**		**7.8**	**17.5**
High [t-1] & High [t-21:t-2]	**27.4%**	**2.57**	**17.7%**	**0.40**	**8.3%**	**1.18**	**4.8%**	**0.41**
t-stat	**17.3**		**13.7**	**31.6**	**8.7**		**8.0**	**46.3**

This table reports the performance of portfolios constructed from factors using a double-sort and the resulting one-month factor momentum strategy, neutral for the one-day factor momentum. To construct double-sorted portfolios, we first sort our subsample of 16 factors according to their last day return, grouping them into two groups (High[t-1] and Low[t-1]); and then a second sort within each of the two groups, according to their cumulative performance on the remaining days of the month (ret[t-21:t-2]), grouping them into three groups (High [t-21:t-2], Mid [t-21:t-2] and Low [t-21:t-2]). After that, we create two MOM[t-21:t-1] strategies neutral for the MOM[t-1]: one for factors with low ret[t-1] (MOM [t-21:t-2] | Low[t-1]), and other for high ret[t-1] (MOM [t-21:t-2] | High[t-1]). We use daily returns from Jul/1/1963 to Dec/31/2018 and two holding periods of 1 and 21 days, using the same methodology of Jegadeesh and Titman [1993]. For each strategy, we report its annualized excess return and Sharpe ratio, as also the annualized alpha of the regression against the regular cross-section MOM[t-21:t-1], reported on the first row. Subsection 4.1.3 presents more details about this table.

Table 7: Predictability of factor returns - R^2_{OOS}

Panel A

16 Factors	**Elastic Net**			**Lasso**			**OLS & historical mean**			
Daily frequency	**regular**	**without**	**1 year**	**regular**	**without**	**1 year**	**OLS**	**252 d**	**21 d**	**1 day**
Accruals (ACC)	-0.1%	-0.1%	-0.4%	-0.2%	-0.2%	-0.4%	-40%	0%	-4%	-94%
Market Beta (BETA)	2.2%	2.3%	1.7%	2.3%	2.4%	1.8%	-34%	0%	-4%	-71%
B/M	2.1%	2.2%	1.4%	2.2%	2.3%	1.4%	-46%	0%	-3%	-75%
CF/P	1.1%	1.1%	0.0%	1.1%	1.1%	0.0%	-29%	0%	-3%	-74%
Net Share Issues (CHCSHO)	1.0%	1.0%	0.5%	1.0%	1.0%	0.5%	-28%	0%	-4%	-73%
D/P	0.5%	0.6%	0.4%	0.5%	0.6%	0.5%	-2%	-1%	-5%	-103%
E/P	1.9%	2.0%	0.9%	2.0%	2.1%	1.0%	-31%	0%	-3%	-67%
Daily residual var. (IDIOVOL)	1.9%	2.1%	1.4%	2.1%	2.2%	1.5%	-27%	0%	-3%	-69%
INV	1.1%	1.2%	0.7%	1.1%	1.2%	0.7%	-43%	0%	-4%	-82%
MOM	4.3%	4.3%	3.4%	4.4%	4.4%	3.5%	-45%	0%	-3%	-59%
ST REV	2.7%	2.6%	2.4%	2.6%	2.5%	2.4%	-44%	0%	-5%	-69%
LT REV	3.2%	3.4%	2.9%	3.3%	3.5%	2.9%	-26%	0%	-3%	-65%
SIZE	0.8%	1.0%	0.6%	0.8%	1.0%	0.5%	-25%	0%	-3%	-94%
OP	2.7%	2.7%	2.0%	2.7%	2.7%	2.0%	-25%	0%	-3%	-73%
Daily Var. (RETVOL)	0.7%	0.7%	0.2%	0.7%	0.8%	0.3%	-44%	0%	-4%	-83%
MKT	1.3%	1.3%	1.0%	1.3%	1.4%	1.0%	-30%	0%	-5%	-91%
Mean	**1.7%**	**1.8%**	**1.2%**	**1.7%**	**1.8%**	**1.2%**	**-32%**	**-0.2%**	**-3.8%**	**-77%**

Table 7: - continued from previous page

Panel B

16 Factors	**Elastic Net**			**Lasso**			**OLS & historical mean**		
Monthly frequency	**Regular**	**WI**	**1y IC**	**Regular**	**WI**	**1y IC**	**OLS**	**12m**	**1 m**
Accruals (ACC)	-0.1%	-0.3%	-7.2%	-0.1%	-0.4%	-7.2%	-36%	0%	-3%
Market Beta (BETA)	-2.3%	0.0%	-10.5%	-2.5%	-0.1%	-10.8%	-47%	-2%	-8%
B/M	-2.5%	-1.1%	-11.3%	-0.9%	0.4%	-9.8%	-42%	-1%	-3%
CF/P	-1.4%	-0.1%	-13.8%	-1.7%	-0.4%	-14.3%	-55%	-1%	-7%
Net Share Issues (CHCSHO)	0.2%	0.0%	-5.6%	0.2%	-0.5%	-4.1%	-48%	0%	-5%
D/P	-0.5%	0.0%	-2.5%	-0.7%	-0.1%	-2.6%	-5%	-1%	-9%
E/P	-2.4%	-0.4%	-14.6%	-3.3%	-1.3%	-15.3%	-51%	-2%	-7%
Daily residual var. (IDIOVOL)	-2.9%	-0.1%	-11.3%	-4.1%	-1.3%	-12.9%	-37%	-3%	-9%
INV	-1.1%	-0.3%	-6.9%	-3.0%	-2.1%	-9.0%	-33%	-1%	-2%
MOM	-16.3%	-16.3%	-26.8%	-2.6%	-2.6%	-14.0%	-82%	0%	-7%
ST REV	-0.6%	-2.4%	-3.8%	-1.6%	-3.4%	-4.7%	-75%	2%	-5%
LT REV	-3.5%	-0.4%	-4.2%	-4.2%	-1.1%	-5.1%	-34%	-3%	-4%
SIZE	-4.0%	-0.8%	-9.0%	-5.5%	-2.3%	-10.7%	-30%	-3%	-6%
OP	0.8%	0.9%	-11.9%	1.4%	1.4%	-11.4%	-22%	0%	-5%
Daily Var. (RETVOL)	-2.5%	-0.4%	-8.8%	-3.0%	-0.9%	-9.3%	-40%	-2%	-8%
MKT	-1.1%	0.0%	-8.4%	-2.0%	-0.8%	-9.4%	-35%	-1%	-7%
Mean	**-2.5%**	**-1.3%**	**-9.8%**	**-2.1%**	**-1.0%**	**-9.4%**	**-42%**	**-1.1%**	**-6%**

Notes: This table reports the predictability of factor returns for Elastic Net, Lasso, OLS and factor returns historical means. We plot the mean out-of-sample R^2 values for each of the 16 factors that we focus for the period from 1969 to 2018, using zero as the benchmark. Panel A reports results for the models using factors daily returns and Panel B for monthly frequency. Each year we estimate univariate predictive regressions for each factor, using 6-year rolling windows, 252 daily (12 monthly) lags, with Elastic Net or Lasso penalization methods and BIC (Bayesian Information Criterion) to tune the hyperparameters. Section 5 gives more details about models setup and estimation. We estimate both Elastic Net and Lasso with intercept but report predictability results for more two different variations: one forecast only with the autoregressive structure and not using intercept (middle column - "without"); and the other one with the intercept changed to the prevailing one-year mean return of the factor (right column - "1 year").

Table 8: Hedged Short-term reversal

Short-term reversals 1-month	Excess return	Sharpe ratio	Max DD	Daily Turnover	Break-even trading cost	Alpha 3 factors	Alpha 6f + CSMOM	Loading to Fact mom Univariate	Loading to Fact mom Plus 6 factors
Regular	5.7%	0.59	-32.8%	17%	0.13%	5.0%	14.8%	-1.14	-1.07
t-stat	4.6					3.9	12.8	-31.8	-30.7
Hedged to Mkt	6.5%	0.86	-25.3%	18%	0.14%	6.0%	12.0%	-0.59	-0.57
t-stat	6.4					5.8	12.0	-18.7	-19.2
Hedged to FF3F	10.1%	1.58	-22.3%	19%	0.20%	9.5%	13.5%	-0.30	-0.29
t-stat	11.3					10.5	15.2	-10.3	-11.9
Hedged to 6 factors	12.6%	2.25	-20.6%	20%	0.23%	12.0%	14.7%	-0.18	-0.15
t-stat	15.8					15.1	18.6	-6.9	-7.4
Hedged to 9 factors	12.9%	2.69	-12.7%	21%	0.23%	12.4%	14.1%	-0.05	-0.02
t-stat	18.8					18.1	20.9	-2.4	-1.1
Hedged to 12 factors	13.2%	2.87	-11.1%	22%	0.23%	12.8%	14.0%	-0.01	0.01
t-stat	20.0					19.5	21.4	-0.7	0.9
Hedged to 16 factors	14.2%	3.12	-10.5%	23%	0.23%	13.9%	14.6%	0.04	0.07
t-stat	21.7					21.2	22.3	2.1	3.9

Notes: This table reports the performance of several stock short-term reversal strategies (STREV). The row present results for regular STREV, constructed using one-month look-back window do define winners and losers stocks that will be respectively sold and bought in the next month. The next columns report results for STREV neutral for distinct subsets of risk-factors, beggining only with market factor, and then from 3 to 16 factors (the same group we focus on previous tables and sections). To compute these STREV neutral strategies we hedge each stock of the winner and loser portfolio individually, using betas computed every month with one-year rolling windows of daily returns. These strategies are rebalanced every month, and use daily returns from Jul/1/1963 to Dec/31/2018. We report annualized excess return, Sharpe ratio, maximum drawdown in 3 months, average daily turnover of both long and short legs, break-even trading cost, that is, the cost per unit of turnover that would erode all the performance, annualized alphas of time-series regressions against Fama-French 3 factors (Fama and French [1993]) and 5 Fama-French factors (FF5F - Fama and French [2015]) plus stock momentum (UMD) and plus cross-section one-day momentum (CSMOM[t-1]). Subsection 6.1 gives more details about how we construct these strategies.

A Internet Appendix

A.1 Individual and cross components of autocorrelation

Figure A.1 shows that stocks have on average negative or null autocorrelation.

A.2 Factor-driven lead-Lag effect for industry-neutral factors

Figure A.2 plots the results for our broad sample of factors and Tables A.2 and A3 in the Appendix show that momentum is present in industry-neutral factors in both cross-section and time-series dimensions.

A.3 Factor-driven lead-lag effects for large-cap stocks

Figures A.3 and A.4 in the Appendix plot results for all factors. Tables A.2 and A3 show that factor momentum is still present in large-cap factors in both cross-sectional and time-series dimensions.

A.4 Industry-driven lead-lag effects and factor-neutral versions

Tables A.2 and A3 show that the performance of momentum strategies using factor-neutral industries decays by more than half in relation to simple industry momentum, indicating that part of industry momentum comes from factor momentum.

A.4.1 Other cases of cross-sectional momentum: industry-neutral, large-cap, long and short sides of factors

Table A.2 in the Appendix presents results for a variety of cross-sectional momentum strategies using other subsets: i) all 103 factors, ii) industry-neutral factors, iii) large-cap factors, iv) small-cap factors, v) long side of factors, vi) short side of factors, vii) random factors, viii) 20 industry portfolios and ix) 20 factor-neutral industry portfolios.

One-day momentum is still present in industry-neutral factors and in factors constructed only with large-cap stocks. These results are in line with those of Section 3. Styled based portfolios also present one-day momentum, expressed as both long and short sides of factors.

A.5 Random factors

Tables A.2 and A3 show that there is no momentum for random factors, since there is neither cross-autocorrelation nor autocorrelation structure. Momentum for factor-neutral industries decay by more than half in relation to standard industry momentum, indicating that part of industry momentum comes from factor momentum.

A.5.1 Other cases of time-series momentum: Industry-neutral, large-cap, long and short sides of factors

Table A4 presents results for a variety of time-series momentum strategies with other subsets that we analyze in section 3: i) all 103 factors, ii) industry-neutral factors, iii) large-cap factors, iv) small-cap factors, v) long side of factors, vi) short side of factors, vii) random factors, viii) 20 industry portfolios and ix) 20 factor-neutral industry portfolios.

As in the case of cross-sectional momentum, one-day momentum is still present in industry-neutral factors and in factors constructed only with large-cap stocks. These results are in line with those of Section 3. We also find that style-based portfolios present one-day momentum, in this case, expressed in both long and short sides of factors. Despite a higher average return, strategies constructed only with one leg of factors present large drawdowns. Once again, random factors do not present momentum in the time-series, as expected since there is no cross-autocorrelation within them and null autocorrelation. Performance of factor-neutral industry momentum decays by almost 75% in relation to standar industry momentum, implying that most of industry momentum comes indirectly from factor momentum.

A.5.2 One-day factor momentum: cross-sectional or time-series?

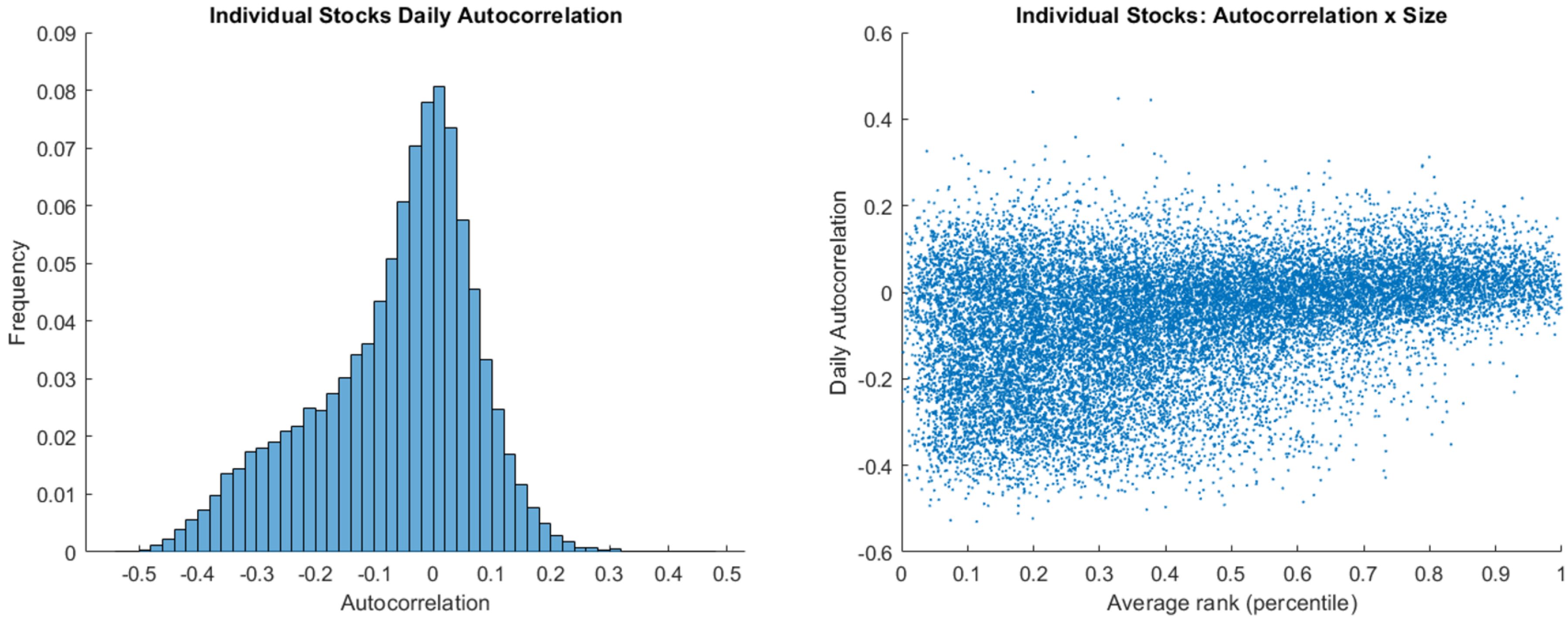
Time-series and cross-sectional factor momentum strategies are very similar, with high correlation between them. This correlation is stronger for the one-month look-back window, reaching 0.96. In the 1-day look-back window, this number is lower, but still high: 0.89. One question of interest is: is there any strategy that dominates the other?

In spanning tests, we confirm that one-day factor momentum in time-series dominates the cross-section case. Table A3 of Appendix reports that performance of TSMOM$[t-1]$ remains positive and statistically significant after controlled for CSMOM$[t-1]$. Despite the high loading of 1.33 with respect to CSMOM[$t-1$], TSMOM[$t-1$] has a alpha of 2.6% per year (t-statistic of 5.5). Results do not change if we include the five Fama-French factors. However, CSMOM[$t-1$] is subsumed by TSMOM[$t-1$], presenting an alpha statistically not distinguishable from zero. The same pattern holds for the one-month factor momentum, with time-series strategies subsuming cross-section, as already reported by Gupta and Kelly [2019].

A.5.3 Performance of machine learning strategies

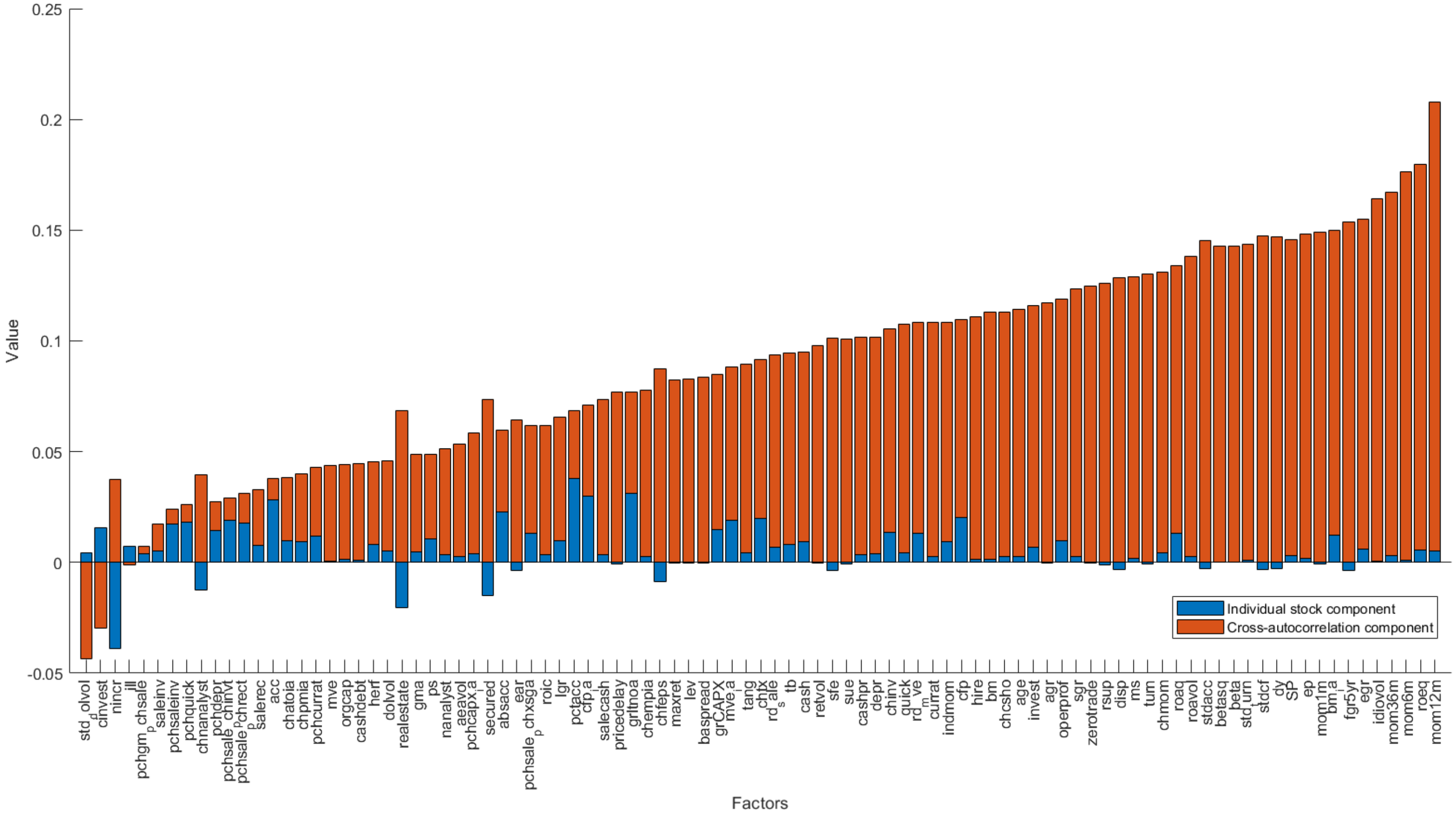
As shown in Table A6, Elastic Net and Lasso reduce the daily turnover from CSMOM[t-1] from 13% of 8%, increasing the break-even trading cost from 0.18% to 0.27%. If we assume costs of 10 bps per unit of turnover, based on the estimates in Frazzini et al. [2015], net-of-costs Sharpe ratio increases from 0.61 in the CSMOM[t-1] case to 1.08 in the Lasso model. For the time-series case, there is also a benefit in using estimates from Lasso and Elastic Net. The average annual excess return raises from 11.4% in the TSMOM[t-1] to 12.8%, and the net-of-costs Sharpe ratio goes from 0.81 to 0.84 using Elastic Net model.

Figure A.1: Stocks daily autocorrelation



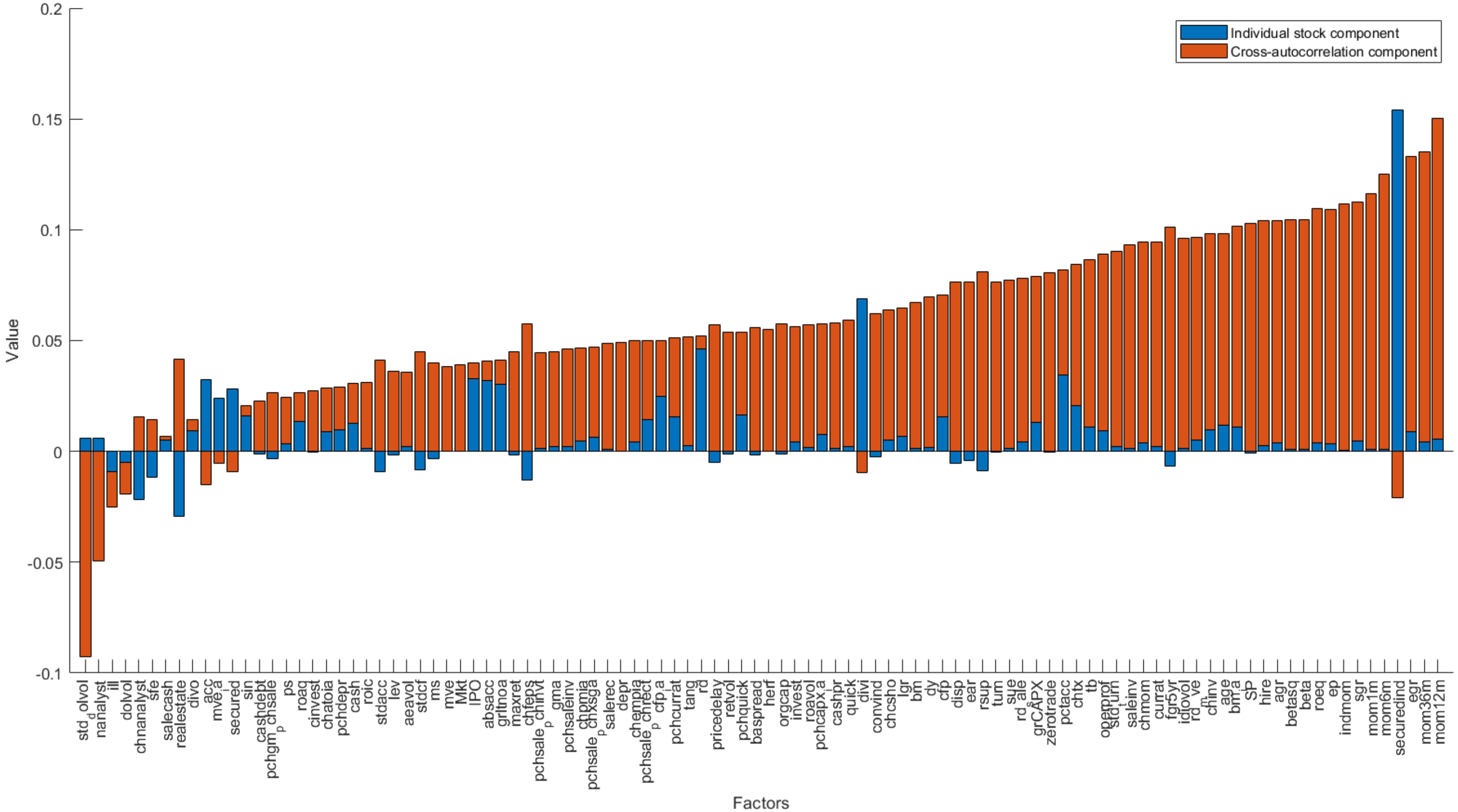
Notes: This figures plot the daily autocorrelation of individual stocks returns. Sample is composed by daily returns from Jul/1/1963 to Dec/31/2018 and 19.996 stocks. In the left is plotted the histogram of stocks autocorrelation and on the right a scatter plot of stocks autocorrelation and its size rank, where 1.00 is the largest 1% stocks.

Figure A.2: Industry-neutral factor portfolios: individual and cross components (daily frequency)



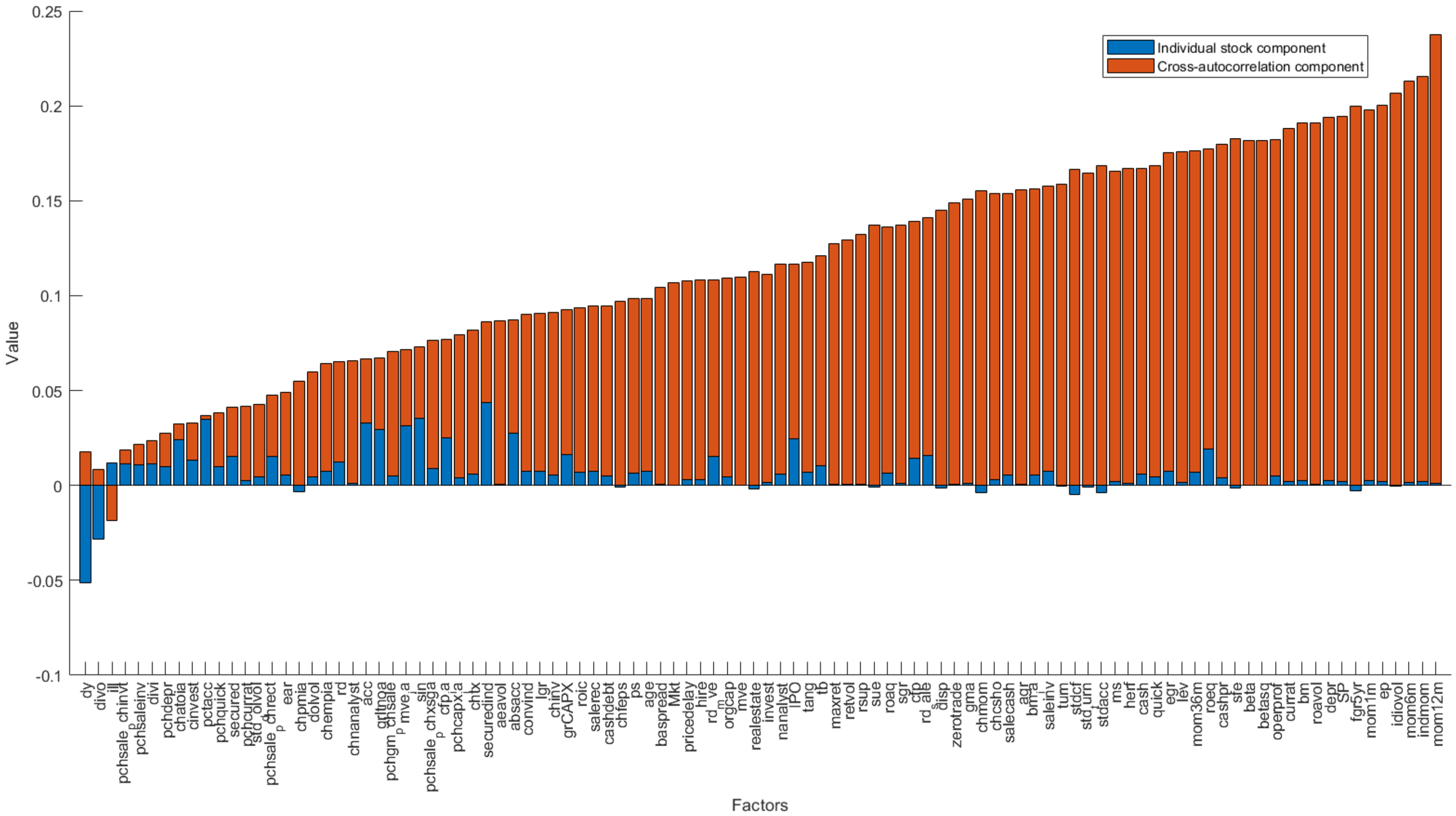
Notes: This figure reports the breakdown of industry-neutral factor autocorrelation into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the 102 factors of our database (we exclude the Market factor). Individual stocks component is the contribution of stocks autocorrelation for factor autocorrelation and the cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation. Subsection 3.2 describes with more details how each of the component is computed. To construct industry-neutral factors, we define factor predictor across each industry. Subsection 3.3.1 gives more details on how industry-neutral factors is constructed.

Figure A.3: Large stocks factor portfolios: individual and cross components (daily frequency)



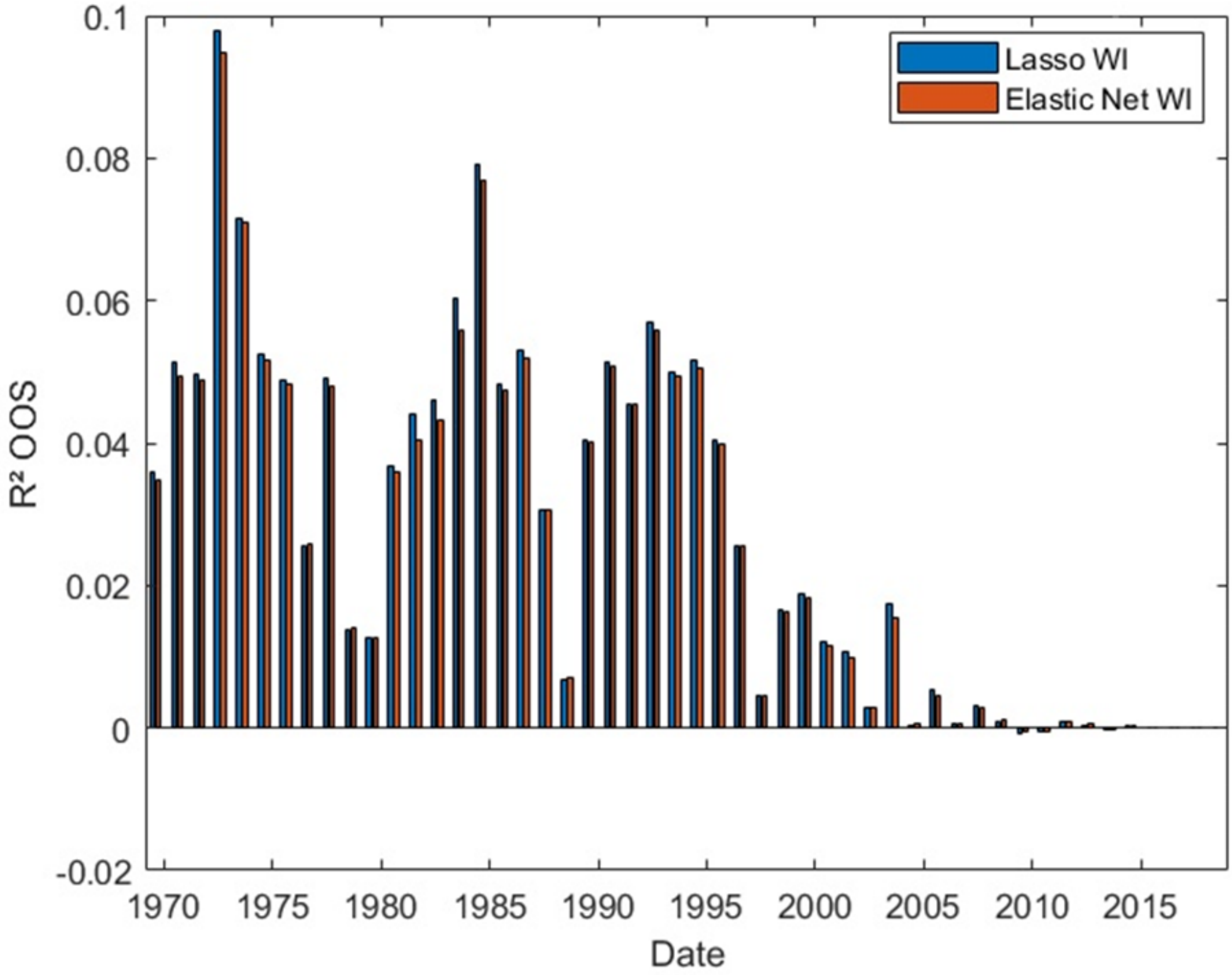
Notes: This figure reports the breakdown of large-cap factors autocorrelation into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the 103 factors of our database. Individual stocks component is the contribution of stocks autocorrelation for factor autocorrelation and the cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation. Subsection 3.2 describes with more details how each of the component is computed. The large-cap factors are constructed only with stocks which market cap is above the NYSE median. Subsection 3.3.2 gives more details on how these factors are constructed.

Figure A.4: Small stocks factor portfolios: individual and cross components (daily frequency)



Notes: This figure reports the breakdown of small-cap factors autocorrelation into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the 103 factors of our database. Individual stocks component is the contribution of stocks autocorrelation for factor autocorrelation and the cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation. Subsection 3.2 describes with more details how each of the component is computed. These factors are constructed only with stocks which market cap is below the NYSE median. Subsection 3.3.2 gives more details on how these factors are constructed

Figure A.5: Out-of-Sample R^2 over time - 16 factors



Notes: This figure reports the out-of-sample predictive R^2 for the factors daily returns, using zero as the benchmark. Each bar represents the mean R^2 value in the current year across the 16 factors of our subsample, with no overlapping, from 1969 to 2018. We plot the results for the return forecast of Lasso and Elastic Net models, using only the autoregressive structure, without the intercept. Models are estimated every year using 6-year rolling windows and BIC (Bayesian Information Criterion) to tune the hyperparameters. Section 5 gives more details about models setup and estimation.

Table A.1: Factors: Individual and cross components from Long and Short portfolios (daily frequency)

Factors	Factor				Long side of factor				Short side of factor			
	Auto correlation	Components			Auto correlation	Components			Auto correlation	Components		
		Individual	Cross	% of Cross		Individual	Cross	% of Cross		Individual	Cross	% of Cross
MKT	**0.05**	0.00	**0.05**	100%	**0.05**	0.00	**0.05**	100%				
t-stat	**6.0**	0.0	**6.0**		**6.0**	0.0	**6.0**					
INV	**0.09**	0.00	**0.09**	97%	**0.06**	0.00	**0.06**	100%	**0.10**	0.00	**0.10**	100%
t-stat	**10.7**	0.3	**10.4**		**7.3**	0.0	**7.3**		**12.0**	0.0	**11.9**	
OP	**0.15**	0.01	**0.15**	96%	**0.10**	0.00	**0.10**	100%	**0.06**	0.00	**0.06**	99%
t-stat	**17.9**	0.7	**17.2**		**12.2**	0.1	**12.2**		**7.5**	0.0	**7.4**	
B/M	**0.12**	0.00	**0.12**	99%	**0.06**	0.00	**0.06**	100%	**0.10**	0.00	**0.10**	100%
t-stat	**14.6**	0.1	**14.5**		**7.4**	0.0	**7.4**		**12.2**	0.0	**12.1**	
SIZE	**0.04**	0.00	**0.04**	98%	**0.11**	0.00	**0.11**	100%	**0.04**	0.00	**0.04**	100%
t-stat	**4.8**	0.1	**4.7**		**12.6**	0.0	**12.6**		**4.6**	0.0	**4.6**	
E/P	**0.16**	0.00	**0.16**	99%	**0.06**	0.00	**0.06**	100%	**0.10**	0.00	**0.10**	100%
t-stat	**19.4**	0.2	**19.2**		**6.9**	0.0	**6.9**		**12.1**	0.0	**12.0**	
CF/P	**0.11**	0.01	**0.10**	91%	**0.07**	0.00	**0.07**	98%	**0.10**	0.00	**0.10**	99%
t-stat	**13.4**	1.2	**12.1**		**8.4**	0.1	**8.3**		**11.5**	0.1	**11.3**	
D/P	-0.01	**-0.04**	**0.03**	-	**0.12**	0.00	**0.12**	99%	**0.04**	**-0.03**	**0.07**	178%
t-stat	-1.2	**-4.7**	**3.5**		**14.0**	0.2	**13.9**		**4.3**	**-3.3**	**7.7**	
Accruals (ACC)	**0.03**	**0.03**	0.01	20%	**0.08**	0.00	**0.08**	99%	**0.08**	0.00	**0.07**	97%
t-stat	**3.9**	**3.1**	0.8		**9.3**	0.1	**9.2**		**8.8**	0.3	**8.5**	
Market Beta (BETA)	**0.15**	0.00	**0.15**	100%	**0.05**	0.00	**0.05**	100%	**0.10**	0.00	**0.10**	100%
t-stat	**17.6**	0.0	**17.5**		**5.7**	0.0	**5.7**		**11.8**	0.0	**11.8**	
Net Share Issues (CHCSHO)	**0.13**	0.00	**0.13**	98%	**0.06**	0.00	**0.06**	100%	**0.09**	0.00	**0.09**	100%
t-stat	**15.5**	0.3	**15.2**		**7.1**	0.0	**7.1**		**10.4**	0.0	**10.3**	
Daily Var. (RETVOL)	**0.09**	0.00	**0.09**	100%	**0.07**	0.00	**0.07**	99%	**0.07**	0.00	**0.07**	100%
t-stat	**10.6**	0.0	**10.6**		**8.7**	0.1	**8.6**		**8.7**	0.0	**8.7**	
Daily residual var. (IDIOVOL)	**0.16**	0.00	**0.16**	100%	**0.03**	0.00	**0.03**	101%	**0.10**	0.00	**0.10**	100%
t-stat	**18.6**	0.0	**18.6**		**3.9**	0.0	**3.9**		**11.9**	0.0	**11.8**	
MOM	**0.20**	0.00	**0.20**	99%	**0.10**	0.00	**0.10**	100%	**0.09**	0.00	**0.09**	99%
t-stat	**24.0**	0.3	**23.7**		**11.7**	0.0	**11.7**		**11.2**	0.1	**11.2**	
ST REV	**0.16**	0.00	**0.16**	99%	**0.10**	0.00	**0.10**	100%	**0.07**	0.00	**0.07**	100%
t-stat	**19.0**	0.1	**18.8**		**12.4**	0.0	**12.3**		**8.4**	0.0	**8.4**	
LT REV	**0.18**	0.00	**0.17**	98%	**0.08**	0.00	**0.08**	100%	**0.09**	0.00	**0.09**	99%
t-stat	**20.5**	0.4	**20.1**		**9.7**	0.0	**9.6**		**10.7**	0.1	**10.6**	
Mean	**0.11**	**0.00**	**0.11**	**93%**	**0.08**	**0.00**	**0.08**	**100%**	**0.08**	**0.00**	**0.08**	**105%**

Notes: This table reports the daily autocorrelation for both long and short sides from our sample of 16 factors, and its breakdown into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the 16 factors of our subsample. Individual stocks component is the contribution of stocks autocorrelation for factor autocorrelation and the cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation. Section 2 gives more details about the factors construction and subsection 3.2 describes with more details how each of the component is computed. The left panel reports results for factors using the regular Fama & French methodology. The middle panel reports results for the long side of the factors (both small and large portfolios), and the right panel reports results for the short side of factors.

Table A.2: Cross-sectional Momentum: other cases

Panel A	**103 Factors**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	35.0%	3.41	-21%	36.7%	4.1%	1.32	-9%	3.9%
t-stat	22.2			22.0	9.7			9.2
MOM [t-21:t-1]	15.2%	1.40	-26%	16.0%	6.4%	0.71	-26%	5.3%
t-stat	10.1			10.3	5.5			4.3
MOM [t-21:t-1] + [t-1]	25.0%	2.96	-13%	26.0%	5.3%	0.92	-16%	4.6%
t-stat	20.0			20.3	6.9			5.9
MOM [t-252:t-1]	6.4%	0.64	-39%	0.9%	4.6%	0.47	-39%	-1.0%
t-stat	5.0			1.0	3.8			-1.1
MOM [t-252:t-1] + [t-1]	20.1%	2.79	-14%	17.7%	4.4%	0.81	-23%	1.5%
t-stat	19.2			17.9	6.1			2.7

Panel B	**15 Industry-neutral Factors**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	35.5%	3.32	-21%	37.5%	4.5%	1.40	-8%	4.5%
t-stat	21.5			21.7	10.3			10.2
MOM [t-21:t-1]	16.3%	1.44	-22%	17.8%	6.0%	0.67	-27%	5.5%
t-stat	10.4			11.0	5.2			4.4
MOM [t-21:t-1] + [t-1]	25.8%	2.98	-15%	27.4%	5.3%	0.92	-17%	5.0%
t-stat	20.1			20.9	6.9			6.3
MOM [t-252:t-1]	7.6%	0.74	-43%	3.2%	5.5%	0.55	-43%	0.9%
t-stat	5.7			2.8	4.3			0.9
MOM [t-252:t-1] + [t-1]	21.0%	2.88	-14%	19.4%	5.1%	0.92	-25%	2.7%
t-stat	19.7			18.6	6.9			4.5

Table A2: - continued from previous page

Panel C	**16 Large-cap Factors**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**57.3%**	**2.76**	**-54%**	**63.7%**	**4.0%**	**0.73**	**-13%**	**4.2%**
t-stat	**17.0**			**17.3**	**5.5**			**5.8**
MOM [t-21:t-1]	**16.0%**	**0.75**	**-44%**	**21.0%**	**5.3%**	**0.32**	**-36%**	**5.6%**
t-stat	**6.0**			**6.7**	**2.9**			**2.4**
MOM [t-21:t-1] + [t-1]	**36.3%**	**2.20**	**-33%**	**40.8%**	**4.9%**	**0.46**	**-25%**	**4.9%**
t-stat	**14.6**			**15.4**	**3.8**			**3.4**
MOM [t-252:t-1]	**9.4%**	**0.47**	**-52%**	1.5%	**6.7%**	**0.33**	**-51%**	-1.7%
t-stat	**4.0**			0.7	**3.1**			-0.9
MOM [t-252:t-1] + [t-1]	**32.5%**	**2.26**	**-45%**	**29.2%**	**5.7%**	**0.53**	**-31%**	1.3%
t-stat	**15.1**			**14.0**	**4.3**			1.1

Panel D	**16 Small-cap Factors**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**85.6%**	**3.74**	**-48%**	**96.0%**	**11.2%**	**1.63**	**-14%**	**11.3%**
t-stat	**21.0**			**21.4**	**11.7**			**11.7**
MOM [t-21:t-1]	**36.4%**	**1.58**	**-44%**	**44.1%**	**11.6%**	**0.63**	**-38%**	**12.7%**
t-stat	**10.9**			**12.0**	**5.1**			**4.8**
MOM [t-21:t-1] + [t-1]	**60.7%**	**3.34**	**-38%**	**68.2%**	**11.7%**	**0.98**	**-24%**	**12.0%**
t-stat	**20.1**			**21.5**	**7.4**			**7.1**
MOM [t-252:t-1]	**10.9%**	**0.52**	**-48%**	2.0%	**6.2%**	**0.30**	**-49%**	-3.4%
t-stat	**4.4**			0.8	**2.9**			-1.5
MOM [t-252:t-1] + [t-1]	**45.1%**	**2.94**	**-34%**	**41.9%**	**9.1%**	**0.81**	**-27%**	**3.9%**
t-stat	**18.7**			**17.4**	**6.2**			**2.9**

Table A2: - continued from previous page

Panel E	**15 Long side of Factors**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**23.5%**	**3.41**	**-15%**	**24.5%**	**3.3%**	**1.57**	**-5%**	**3.2%**
t-stat	**23.1**			**23.1**	**11.6**			**11.4**
MOM [t-21:t-1]	**11.2%**	**1.57**	**-16%**	**12.0%**	**4.2%**	**0.72**	**-17%**	**3.9%**
t-stat	**11.3**			**12.2**	**5.5**			**4.9**
MOM [t-21:t-1] + [t-1]	**17.3%**	**3.10**	**-11%**	**18.1%**	**3.8%**	**1.00**	**-10%**	**3.5%**
t-stat	**21.5**			**22.5**	**7.4**			**7.0**
MOM [t-252:t-1]	**4.2%**	**0.62**	**-25%**	1.0%	**2.9%**	**0.44**	**-25%**	-0.5%
t-stat	**4.7**			1.4	**3.4**			-0.9
MOM [t-252:t-1] + [t-1]	**13.5%**	**2.79**	**-12%**	**12.2%**	**3.1%**	**0.85**	**-14%**	**1.3%**
t-stat	**19.7**			**19.0**	**6.3**			**3.6**

Panel F	**15 Short side of Factors**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**21.2%**	**2.45**	**-17%**	**22.5%**	**2.8%**	**1.19**	**-5%**	**2.8%**
t-stat	**16.9**			**17.1**	**8.8**			**8.8**
MOM [t-21:t-1]	**9.9%**	**1.13**	**-18%**	**10.8%**	**4.3%**	**0.64**	**-16%**	**4.0%**
t-stat	**8.4**			**8.9**	**4.9**			**4.3**
MOM [t-21:t-1] + [t-1]	**15.6%**	**2.31**	**-11%**	**16.6%**	**3.6%**	**0.84**	**-10%**	**3.4%**
t-stat	**16.3**			**16.9**	**6.3**			**5.8**
MOM [t-252:t-1]	**4.7%**	**0.60**	**-25%**	1.2%	**3.3%**	**0.44**	**-26%**	-0.4%
t-stat	**4.6**			1.4	**3.5**			-0.5
MOM [t-252:t-1] + [t-1]	**12.8%**	**2.19**	**-11%**	**11.5%**	**3.1%**	**0.74**	**-14%**	**1.3%**
t-stat	**15.6**			**13.9**	**5.6**			**2.6**

Table A2: - continued from previous page

Panel G	**15 Random factors**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**1.7%**	**0.58**	**-7%**	**1.8%**	**-0.2%**	**-0.36**	**-2%**	**-0.2%**
t-stat	**4.4**			**4.6**	**-2.6**			**-2.2**
MOM [t-21:t-1]	**-1.2%**	**-0.43**	**-8%**	**-0.9%**	-0.2%	**-0.14**	**-4%**	-0.2%
t-stat	**-3.1**			**-2.6**	-1.0			-0.7
MOM [t-21:t-1] + [t-1]	0.3%	**0.11**	**-7%**	0.4%	-0.2%	**-0.20**	**-3%**	-0.2%
t-stat	0.9			1.4	-1.5			-1.2
MOM [t-252:t-1]	-0.1%	**-0.03**	**-4%**	0.1%	0.2%	**0.11**	**-4%**	0.4%
t-stat	-0.2			0.2	0.9			1.2
MOM [t-252:t-1] + [t-1]	**0.8%**	**0.43**	**-5%**	**0.9%**	0.0%	**0.02**	**-3%**	0.1%
t-stat	**3.2**			**3.6**	0.2			0.6

Panel H	**20 Industries portfolio**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**33.2%**	**2.96**	**-22%**	**34.3%**	**3.1%**	**1.11**	**-7%**	**2.9%**
t-stat	**19.5**			**19.3**	**8.2**			**7.5**
MOM [t-21:t-1]	**12.2%**	**1.04**	**-31%**	**12.2%**	**5.4%**	**0.59**	**-19%**	**4.3%**
t-stat	**7.8**			**7.4**	**4.6**			**3.5**
MOM [t-21:t-1] + [t-1]	**22.5%**	**2.48**	**-20%**	**22.8%**	**4.3%**	**0.77**	**-13%**	**3.6%**
t-stat	**17.0**			**16.7**	**5.8**			**4.8**
MOM [t-252:t-1]	**5.1%**	**0.42**	**-36%**	0.0%	**3.9%**	**0.34**	**-36%**	-1.1%
t-stat	**3.5**			0.0	**2.9**			-1.0
MOM [t-252:t-1] + [t-1]	**18.7%**	**2.24**	**-22%**	**15.9%**	**3.7%**	**0.58**	**-19%**	0.9%
t-stat	**15.6**			**14.1**	**4.5**			1.3

Table A2: - continued from previous page

Panel I	**20 Factor-neutral Industries portfolio**							
Cross-Section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**17.8%**	**2.08**	**-21%**	**18.3%**	**1.5%**	**0.69**	**-8%**	**1.5%**
t-stat	**14.4**			**14.3**	**5.1**			**5.0**
MOM [t-21:t-1]	**5.6%**	**0.68**	**-20%**	**5.9%**	**3.1%**	**0.50**	**-14%**	**3.4%**
t-stat	**5.2**			**5.1**	**3.9**			**4.0**
MOM [t-21:t-1] + [t-1]	**11.7%**	**1.74**	**-19%**	**11.9%**	**2.3%**	**0.61**	**-9%**	**2.4%**
t-stat	**12.4**			**12.3**	**4.6**			**4.6**
MOM [t-252:t-1]	**3.7%**	**0.46**	**-32%**	**4.1%**	**3.5%**	**0.47**	**-17%**	**3.9%**
t-stat	**3.6**			**3.6**	**3.7**			**3.7**
MOM [t-252:t-1] + [t-1]	**10.7%**	**1.75**	**-22%**	**10.8%**	**2.5%**	**0.62**	**-10%**	**2.7%**
t-stat	**12.5**			**12.2**	**4.7**			**4.6**

Notes: This table reports the performance of cross section momentum for several cases: 103 factor portfolios (Panel A), 15 industry-neutral factors (Panel B), 16 large-cap factors (Panel C), 16 small-cap factors (Panel D), 15 Long side of factors (Panel E), 15 Short side of factors (Panel F), 15 Random Factors (Panel G), 20 Industries portfolios (Panel H), 20 Factor-neutral Industries portfolios (Panel I). Every day we rank all factors/portfolios based in their cumulative performance over several periods (1 day, 21 days, 21 days excluding last day, 252 days, 252 days excluding last day and last 21 days). After that it is formed long-short strategies with the winners and losers factors. The long position is formed with the highest ranked factors, and the short position with the lowest factors (top and bottom max[round(0.30 x N,1]), with equal weight across factor/portfolios. We use daily returns from Jul/1/1963 to Dec/31/2018 and two different holding periods: 1 day and 21 days, using the same methodology as Jegadeesh and Titman [1993]. Subsection 4.2 gives more details on how these strategies are constructed. It´s reported the annualized excess return, Sharpe ratio, maximum drawdown in 3 months, average daily turnover of both long and short legs, and the break even trading cost, that is, the cost per unit of turnover that would erode all the performance.

Table A3: Factor Momentum: spanning regressions of CSMOM and TSMOM

Panel A	**16 Factors**							
Hp = 21 days	**Alpha**	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**CSMOM[t-1]**	**TSMOM[t-1]**
CSMOM[t-1]	-0.2%							**0.59**
t-stat	-0.6							**64.3**
CSMOM[t-1]	-0.2%	0.01	0.00	0.01	**-0.02**	**-0.03**		**0.60**
t-stat	-0.5	1.6	-0.5	1.5	**-2.6**	**-3.5**		**66.5**
TSMOM (1-day)	**2.6%**						**1.33**	
t-stat	**5.5**						**80.0**	
TSMOM (1-day)	**2.8%**	**-0.03**	**-0.02**	0.02	**0.04**	**0.04**	**1.30**	
t-stat	**6.0**	**-7.2**	**-3.3**	1.9	**4.0**	**4.5**	**79.1**	

Panel B	**16 Factors**							
Hp = 21 days	**Alpha**	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**CSMOM(21-d)**	**TSMOM(21-d)**
CSMOM(21-days)	**-1.2%**							**1.97**
t-stat	**-2.4**							**157.9**
CSMOM(21-days)	-0.9%	0.00	-0.01	-0.01	**-0.03**	**-0.05**		**1.98**
t-stat	-1.9	0.1	-1.2	-1.2	**-2.6**	**-4.5**		**157.7**
TSMOM (21-days)	**0.9%**						**0.47**	
t-stat	**3.8**						**172.8**	
TSMOM (21-days)	**0.8%**	**-0.01**	0.00	**0.02**	**0.02**	**0.02**	**0.47**	
t-stat	**3.4**	**-3.5**	-0.5	**2.9**	**3.4**	**5.0**	**176.7**	

This table reports spanning regressions in which the dependent variable is a cross-section (CSMOM) or time-series (TSMOM) factor momentum strategy and the right-hand-side variables are the returns of the Fama-French five factor (Fama and French [2015] - MKT, SMB, HML, RMW, CMA) plus the other factor momentum strategy (TSMOM or CSMOM). We use daily returns from Jul/1/1963 to Dec/31/2018 and a holding period of 21 days, with the same methodology of Jegadeesh and Titman [1993]. The alpha is annualized and reported in excess of the risk free rate. Panel A report results for the one-day factor momentum and Panel B for the one-month (or 21 days) factor momentum, using our subsample of 16 factors. Subsections 4.1.2 and 4.2.2 preset more details.

Table A4: Time-series Momentum: other cases

Panel A	**103 Factors**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**15.0%**	**3.46**	**-10%**	**15.5%**	**7.7%**	**1.63**	**-12%**	**7.7%**
t-stat	**24.2**			**23.9**	**11.9**			**12.1**
MOM [t-21:t-1]	**5.9%**	**1.46**	**-12%**	**5.9%**	**3.5%**	**0.82**	**-14%**	**2.9%**
t-stat	**10.7**			**10.7**	**6.2**			**5.1**
MOM [t-21:t-1] + [t-1]	**10.4%**	**3.10**	**-5%**	**10.6%**	**5.6%**	**1.34**	**-12%**	**5.3%**
t-stat	**22.1**			**22.1**	**9.9**			**9.4**
MOM [t-252:t-1]	**2.8%**	**0.80**	**-15%**	**0.8%**	**2.3%**	**0.63**	**-15%**	0.1%
t-stat	**6.0**			**2.2**	**4.7**			0.2
MOM [t-252:t-1] + [t-1]	**8.8%**	**3.09**	**-7%**	**8.0%**	**5.0%**	**1.54**	**-10%**	**3.9%**
t-stat	**22.2**			**21.0**	**11.3**			**9.8**

Panel B	**15 Industry-neutral Factors**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**16.8%**	**3.31**	**-9%**	**17.4%**	**8.8%**	**1.66**	**-11%**	**8.9%**
t-stat	**23.0**			**22.9**	**12.0**			**12.3**
MOM [t-21:t-1]	**7.3%**	**1.52**	**-11%**	**7.5%**	**4.1%**	**0.85**	**-17%**	**3.6%**
t-stat	**11.1**			**11.3**	**6.4**			**5.5**
MOM [t-21:t-1] + [t-1]	**12.0%**	**3.07**	**-5%**	**12.3%**	**6.5%**	**1.37**	**-13%**	**6.2%**
t-stat	**21.7**			**22.0**	**10.0**			**9.8**
MOM [t-252:t-1]	**4.0%**	**0.93**	**-19%**	**1.9%**	**3.5%**	**0.81**	**-19%**	**1.3%**
t-stat	**6.9**			**4.2**	**6.0**			**2.9**
MOM [t-252:t-1] + [t-1]	**10.2%**	**3.04**	**-7%**	**9.5%**	**6.1%**	**1.63**	**-10%**	**5.1%**
t-stat	**21.7**			**20.9**	**11.9**			**10.9**

Table A4: - continued from previous page

Panel C	**16 Factors (Large-cap Factors)**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**25.6%**	**2.83**	**-27%**	**27.0%**	**8.5%**	**0.90**	**-20%**	**9.3%**
t-stat	**19.1**			**19.2**	**6.8**			**7.2**
MOM [t-21:t-1]	**7.3%**	**0.86**	**-19%**	**8.0%**	**3.9%**	**0.45**	**-25%**	**3.4%**
t-stat	**6.5**			**6.9**	**3.6**			**2.9**
MOM [t-21:t-1] + [t-1]	**16.2%**	**2.37**	**-14%**	**17.1%**	**6.2%**	**0.75**	**-20%**	**6.3%**
t-stat	**16.6**			**17.0**	**5.7**			**5.6**
MOM [t-252:t-1]	**4.0%**	**0.53**	**-23%**	0.4%	**3.3%**	**0.42**	**-22%**	-0.6%
t-stat	**4.1**			0.6	**3.3**			-0.8
MOM [t-252:t-1] + [t-1]	**14.4%**	**2.43**	**-19%**	**13.2%**	**6.0%**	**0.89**	**-16%**	**4.3%**
t-stat	**17.1**			**16.1**	**6.7**			**5.1**

Panel D	**16 Factors (Small-cap Factors)**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**29.1%**	**3.29**	**-16%**	**30.9%**	**17.9%**	**2.05**	**-16%**	**18.9%**
t-stat	**21.8**			**22.2**	**14.4**			**15.0**
MOM [t-21:t-1]	**14.5%**	**1.86**	**-15%**	**15.5%**	**7.3%**	**0.91**	**-21%**	**7.0%**
t-stat	**13.2**			**14.1**	**6.9**			**6.3**
MOM [t-21:t-1] + [t-1]	**21.7%**	**3.29**	**-13%**	**23.0%**	**12.5%**	**1.64**	**-13%**	**12.8%**
t-stat	**22.4**			**23.5**	**11.8**			**11.9**
MOM [t-252:t-1]	**5.8%**	**0.85**	**-22%**	**2.3%**	**4.9%**	**0.70**	**-22%**	0.9%
t-stat	**6.4**			**3.1**	**5.3**			1.2
MOM [t-252:t-1] + [t-1]	**17.0%**	**3.02**	**-11%**	**16.0%**	**11.3%**	**1.92**	**-12%**	**9.7%**
t-stat	**21.0**			**20.1**	**13.8**			**12.5**

Table A4: - continued from previous page

Panel E	**15 Long side of Factors**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**30.5%**	**2.21**	**-45%**	**33.6%**	**13.6%**	**0.97**	**-34%**	**16.6%**
t-stat	**14.9**			**15.1**	**7.3**			**8.0**
MOM [t-21:t-1]	**12.6%**	**0.90**	**-36%**	**16.1%**	**3.9%**	**0.28**	**-31%**	**5.2%**
t-stat	**6.8**			**7.9**	**2.6**			**2.6**
MOM [t-21:t-1] + [t-1]	**21.6%**	**2.00**	**-35%**	**24.6%**	**8.9%**	**0.71**	**-31%**	**10.7%**
t-stat	**13.9**			**15.0**	**5.5**			**5.9**
MOM [t-252:t-1]	**5.5%**	**0.40**	**-38%**	1.1%	**4.6%**	**0.33**	**-38%**	-0.8%
t-stat	**3.4**			0.6	**2.9**			-0.5
MOM [t-252:t-1] + [t-1]	**17.9%**	**1.84**	**-29%**	**16.5%**	**9.5%**	**0.91**	**-27%**	**7.7%**
t-stat	**12.9**			**11.7**	**6.8**			**5.2**

Panel F	**15 Short side of Factors**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**38.0%**	**2.23**	**-46%**	**42.7%**	**14.3%**	**0.83**	**-38%**	**18.0%**
t-stat	**14.7**			**15.0**	**6.4**			**7.1**
MOM [t-21:t-1]	**13.6%**	**0.80**	**-41%**	**17.4%**	**4.0%**	**0.24**	**-31%**	**5.1%**
t-stat	**6.2**			**7.0**	**2.4**			**2.1**
MOM [t-21:t-1] + [t-1]	**25.9%**	**1.94**	**-37%**	**29.5%**	**9.3%**	**0.60**	**-33%**	**11.3%**
t-stat	**13.4**			**14.2**	**4.9**			**5.1**
MOM [t-252:t-1]	**4.3%**	**0.25**	**-43%**	-2.2%	3.0%	**0.17**	**-43%**	**-4.3%**
t-stat	**2.5**			-1.1	1.9			**-2.2**
MOM [t-252:t-1] + [t-1]	**20.8%**	**1.74**	**-30%**	**18.5%**	**9.1%**	**0.71**	**-32%**	**6.4%**
t-stat	**12.2**			**10.7**	**5.6**			**3.6**

Table A4: - continued from previous page

Panel G	**15 Random factors**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**0.7%**	**0.57**	**-3%**	**0.8%**	**-0.5%**	**-0.42**	**-3%**	**-0.4%**
t-stat	**4.3**			**4.5**	**-3.1**			**-2.6**
MOM [t-21:t-1]	**-0.4%**	**-0.41**	**-3%**	**-0.4%**	-0.1%	**-0.08**	**-3%**	0.0%
t-stat	**-3.1**			**-2.6**	-0.5			-0.3
MOM [t-21:t-1] + [t-1]	0.2%	**0.17**	**-3%**	0.2%	**-0.3%**	**-0.30**	**-3%**	-0.2%
t-stat	1.3			1.7	**-2.2**			-1.8
MOM [t-252:t-1]	-0.1%	**-0.13**	**-2%**	-0.1%	0.0%	**0.04**	**-2%**	0.0%
t-stat	-1.0			-0.8	0.3			0.4
MOM [t-252:t-1] + [t-1]	**0.3%**	**0.39**	**-2%**	**0.3%**	**-0.2%**	**-0.30**	**-2%**	-0.2%
t-stat	**3.0**			**3.2**	**-2.2**			-1.8

Panel H	**20 Industries portfolio**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**35.5%**	**2.69**	**-29%**	**38.5%**	**9.8%**	**0.70**	**-33%**	**12.3%**
t-stat	**17.6**			**17.6**	**5.5**			**6.2**
MOM [t-21:t-1]	**9.0%**	**0.69**	**-34%**	**12.1%**	2.4%	**0.18**	**-30%**	3.1%
t-stat	**5.4**			**6.5**	1.8			1.7
MOM [t-21:t-1] + [t-1]	**21.9%**	**2.10**	**-28%**	**24.6%**	**6.2%**	**0.50**	**-31%**	**7.6%**
t-stat	**14.5**			**15.4**	**4.1**			**4.3**
MOM [t-252:t-1]	**3.1%**	**0.25**	**-38%**	-1.5%	2.2%	**0.17**	**-36%**	**-3.3%**
t-stat	**2.3**			-1.0	1.8			**-2.2**
MOM [t-252:t-1] + [t-1]	**18.6%**	**2.03**	**-22%**	**17.1%**	**6.4%**	**0.64**	**-27%**	**4.3%**
t-stat	**14.2**			**12.8**	**5.0**			**3.2**

Table A4: - continued from previous page

Panel I	**20 Factor-neutral Industries**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
	Excess return	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**8.6%**	**2.12**	**-18%**	**8.7%**	**2.9%**	**0.71**	**-17%**	**2.9%**
t-stat	**15.1**			**15.0**	**5.3**			**5.1**
MOM [t-21:t-1]	**2.3%**	**0.76**	**-8%**	**2.4%**	**1.6%**	**0.51**	**-7%**	**1.7%**
t-stat	**5.6**			**5.6**	**3.8**			**3.9**
MOM [t-21:t-1] + [t-1]	**5.4%**	**1.89**	**-12%**	**5.5%**	**2.3%**	**0.69**	**-11%**	**2.3%**
t-stat	**13.6**			**13.4**	**5.2**			**5.1**
MOM [t-252:t-1]	**1.4%**	**0.51**	**-12%**	**1.5%**	**1.4%**	**0.49**	**-7%**	**1.4%**
t-stat	**3.8**			**3.8**	**3.6**			**3.6**
MOM [t-252:t-1] + [t-1]	**5.0%**	**1.93**	**-13%**	**5.1%**	**2.1%**	**0.80**	**-11%**	**2.2%**
t-stat	**14.0**			**13.8**	**5.9**			**5.8**

Notes: This table reports the performance of time-series momentum for several cases: 103 factor portfolios (Panel A), 15 industry-neutral factors (Panel B), 16 large-cap factors (Panel C), 16 small-cap factors (Panel D), 15 Long side of factors (Panel E), 15 Short side of factors (Panel F), 15 Random Factors (Panel G), 20 Industries portfolios (Panel H), 20 Factor-neutral Industries portfolios (Panel I). In time-series momentum, we take a long position if the factor absolute performance is positive in the look-back window (1 day, 21 days, 21 days excluding last day, 252 days, 252 days excluding last day and last 21 days), or a short position if it is negative. Subsection 4.2 gives more details on how these strategies are constructed. We use daily returns from Jul/1/1963 to Dec/31/2018 and two different holding periods: 1 day and 21 days, using the same methodology as Jegadeesh and Titman [1993]. It´s reported the annualized excess return, Sharpe ratio, maximum drawdown in 3 months, average daily turnover of both long and short legs, and the break even trading cost, that is, the cost per unit of turnover that would erode all the performance.

Table A5: Cross-section and time-series momentum for Kenneth French database

Panel A	**7 Factors (Kenneth French)**							
Cross-section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
Jul/63 - Aug/18	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**47.8%**	**3.42**	**-22%**	**50.6%**	**5.7%**	**1.41**	**-10%**	**5.5%**
t-stat	**21.3**			**20.9**	**10.3**			**9.8**
MOM [t-21:t-1]	**18.1%**	**1.05**	**-37%**	**20.0%**	**4.8%**	**0.36**	**-30%**	**4.0%**
t-stat	**7.8**			**7.9**	**3.1**			**2.2**
MOM [t-21:t-1] + [t-1]	**32.7%**	**2.70**	**-26%**	**34.4%**	**5.4%**	**0.66**	**-18%**	**4.8%**
t-stat	**17.8**			**17.7**	**5.1**			**4.3**
MOM [t-252:t-1]	-2.0%	**-0.15**	**-57%**	1.3%	-1.2%	**-0.10**	**-55%**	1.9%
t-stat	-0.6			0.7	-0.3			1.1
MOM [t-252:t-1] + [t-1]	**20.9%**	**2.09**	**-33%**	**23.7%**	**2.4%**	**0.35**	**-30%**	**3.8%**
t-stat	**14.5**			**15.6**	**2.8**			**4.1**

Panel B	**7 Factors (Kenneth French)**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
Jul/63 - Aug/18	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 6 factors**
MOM [t-1]	**21.8%**	**3.65**	**-8%**	**22.4%**	**10.5%**	**1.65**	**-13%**	**9.9%**
t-stat	**24.7**			**24.1**	**11.9**			**11.2**
MOM [t-21:t-1]	**9.2%**	**1.57**	**-11%**	**9.0%**	**4.5%**	**0.71**	**-15%**	**3.2%**
t-stat	**11.3**			**10.8**	**5.4**			**3.7**
MOM [t-21:t-1] + [t-1]	**15.4%**	**3.30**	**-8%**	**15.5%**	**7.5%**	**1.28**	**-11%**	**6.5%**
t-stat	**23.0**			**22.3**	**9.4**			**8.1**
MOM [t-252:t-1]	**2.2%**	**0.26**	**-41%**	0.8%	**2.1%**	**0.24**	**-33%**	0.3%
t-stat	**2.2**			0.7	**2.1**			0.2
MOM [t-252:t-1] + [t-1]	**11.7%**	**2.23**	**-18%**	**11.3%**	**6.3%**	**1.10**	**-17%**	**5.1%**
t-stat	**15.9**			**14.8**	**8.1**			**6.5**

Table A5: - continued from previous page

Panel C	**5 Factors (Kenneth French)**							
Cross-section Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
Mar/30 - Aug/18	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 4 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 4 factors**
MOM [t-1]	**46.6%**	**2.21**	**-46%**	**51.8%**	**5.0%**	**0.95**	**-14%**	**5.4%**
t-stat	**18.4**			**18.8**	**9.1**			**9.8**
MOM [t-21:t-1]	**16.7%**	**0.80**	**-48%**	**21.7%**	0.7%	**0.05**	**-43%**	1.6%
t-stat	**8.1**			**9.1**	1.2			1.0
MOM [t-21:t-1] + [t-1]	**31.9%**	**1.97**	**-42%**	**35.9%**	**3.0%**	**0.32**	**-27%**	**3.4%**
t-stat	**17.2**			**18.2**	**3.4**			**3.5**
MOM [t-252:t-1]	0.8%	**0.06**	**-57%**	**3.1%**	0.6%	**0.04**	**-55%**	**2.6%**
t-stat	1.2			**2.2**	1.0			**2.0**
MOM [t-252:t-1] + [t-1]	**22.5%**	**1.75**	**-28%**	**25.1%**	**3.0%**	**0.39**	**-30%**	**4.0%**
t-stat	**15.7**			**17.1**	**4.0**			**5.3**

Panel D	**5 Factors (Kenneth French)**							
Time-series Momentum	**Holding period = 1 day**				**Holding period = 21 days**			
Mar/30 - Aug/18	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 4 factors**	**Excess return**	**Sharpe ratio**	**Max DD**	**Alpha 4 factors**
MOM [t-1]	**20.7%**	**2.60**	**-17%**	**21.7%**	**9.5%**	**1.11**	**-26%**	**10.6%**
t-stat	**23.0**			**23.2**	**10.6**			**11.4**
MOM [t-21:t-1]	**8.4%**	**1.06**	**-23%**	**9.7%**	**3.2%**	**0.38**	**-28%**	**3.1%**
t-stat	**10.1**			**11.1**	**4.0**			**3.5**
MOM [t-21:t-1] + [t-1]	**14.6%**	**2.37**	**-14%**	**15.6%**	**6.4%**	**0.83**	**-20%**	**6.8%**
t-stat	**21.6**			**22.5**	**8.1**			**8.3**
MOM [t-252:t-1]	**2.1%**	**0.20**	**-41%**	0.6%	1.4%	**0.13**	**-33%**	-0.5%
t-stat	**2.4**			0.5	1.7			-0.5
MOM [t-252:t-1] + [t-1]	**11.2%**	**1.70**	**-18%**	**10.8%**	**5.6%**	**0.76**	**-20%**	**5.0%**
t-stat	**15.8**			**15.1**	**7.4**			**6.7**

Table A5: - continued from previous page

Panel E	40 style-based portfolios (Kenneth French)							
Cross-section Momentum	Holding period = 1 day				Holding period = 21 days			
Mar/30 - Aug/18	Excess return	Sharpe ratio	Max DD	Alpha 4 factors	Excess return	Sharpe ratio	Max DD	Alpha 4 factors
MOM [t-1]	**10.9%**	**1.35**	**-29%**	**11.9%**	**2.5%**	**1.19**	**-7%**	**2.5%**
t-stat	**12.7**			**13.1**	**11.4**			**11.6**
MOM [t-21:t-1]	**7.6%**	**0.89**	**-33%**	**8.8%**	**4.2%**	**0.61**	**-26%**	**3.8%**
t-stat	**8.7**			**9.5**	**6.1**			**5.3**
MOM [t-21:t-1] + [t-1]	**9.4%**	**1.44**	**-26%**	**10.3%**	**3.4%**	**0.80**	**-14%**	**3.1%**
t-stat	**13.5**			**14.5**	**7.7**			**7.2**
MOM [t-252:t-1]	**2.8%**	**0.34**	**-30%**	0.8%	**2.4%**	**0.30**	**-30%**	0.1%
t-stat	**3.6**			1.1	**3.2**			0.1
MOM [t-252:t-1] + [t-1]	**6.9%**	**1.17**	**-25%**	**6.5%**	**2.5%**	**0.57**	**-17%**	**1.3%**
t-stat	**11.1**			**10.8**	**5.6**			**3.5**

Panel F	40 style-based portfolios (Kenneth French)							
Time-series Momentum	Holding period = 1 day				Holding period = 21 days			
Mar/30 - Aug/18	Excess return	Sharpe ratio	Max DD	Alpha 4 factors	Excess return	Sharpe ratio	Max DD	Alpha 4 factors
MOM [t-1]	**30.6%**	**1.96**	**-39%**	**33.8%**	**13.1%**	**0.80**	**-37%**	**16.5%**
t-stat	**17.1**			**17.5**	**8.0**			**8.9**
MOM [t-21:t-1]	**11.5%**	**0.72**	**-38%**	**15.3%**	**3.7%**	**0.23**	**-39%**	**4.6%**
t-stat	**7.3**			**8.6**	**2.9**			**2.6**
MOM [t-21:t-1] + [t-1]	**21.3%**	**1.76**	**-33%**	**24.3%**	**8.6%**	**0.58**	**-35%**	**10.3%**
t-stat	**15.9**			**17.2**	**6.1**			**6.4**
MOM [t-252:t-1]	**4.8%**	**0.30**	**-50%**	-0.1%	**4.0%**	**0.25**	**-58%**	-1.8%
t-stat	**3.6**			-0.1	**3.1**			-1.4
MOM [t-252:t-1] + [t-1]	**17.7%**	**1.57**	**-27%**	**15.8%**	**9.0%**	**0.73**	**-28%**	**7.1%**
t-stat	**14.4**			**13.3**	**7.3**			**5.7**

Notes: This table reports the performance of daily momentum strategies using Kenneth French public library (*http : //mba : tuck : dartmouth : edu/pages/faculty/ken : french/datalibrary : html*), for both cross-section and time series cases. Panels A and B report results for the 7 factors (MKT, SMB, HML, CMA. RMW, UMD and LTREV) with data available from Jul/60 to Aug/18; Panels C and reports results for the 5 factors (MKT, SMB, HML, UMD and LTREV) with data available from Mar/30 to Aug/18; Panels E and F report results for 57 style-based portfolios with data available from Jul/60 to Aug/18; and Panels G and H for 40 style-based portfolios with data available from Mar/30 to Aug/18. We report results for two holding periods: 1 day and 21 days, using the same methodology as Jegadeesh and Titman [1993]. Section 4 gives more details on how these strategies are constructed. It´s reported the annualized excess return, Sharpe ratio, maximum drawdown in 3 months and the annualized alpha to the 5 Fama-French factors plus stock momentum (UMD).

Table A6: Performance from Machine Learning Models

ML Models	16 Factors									
	Holding period = 21 days									
	Cross-section Momentum					Time-series Momentum				
	Excess return	Sharpe ratio	Max DD	Daily turnover	Breakeven trade cost	Excess return	Sharpe ratio	Max DD	Daily turnover	Breakeven trade cost
MOM [t-1]	**6.3%**	**1.32**	**-10%**	**13%**	**0.18%**	**11.4%**	**1.59**	**-15%**	**22%**	**0.19%**
t-stat	**9.7**					**11.3**				
Elastic Net	**5.7%**	**1.66**	**-9%**	**8%**	**0.27%**	**12.8%**	**1.58**	**-18%**	**24%**	**0.20%**
t-stat	**11.6**					**10.7**				
Lasso	**5.9%**	**1.68**	**-8%**	**8%**	**0.27%**	**12.8%**	**1.54**	**-17%**	**24%**	**0.20%**
t-stat	**11.8**					**10.5**				
MOM [t-21:t-1]	**8.0%**	**0.60**	**-31%**	**15%**	**0.20%**	**4.9%**	**0.75**	**-20%**	**8%**	**0.23%**
t-stat	**4.8**					**5.7**				
MOM [t-21:t-1] + [t-1]	**7.3%**	**0.84**	**-20%**	**11%**	**0.24%**	**8.0%**	**1.27**	**-16%**	**13%**	**0.24%**
t-stat	**6.4**					**9.3**				

Notes: This table reports the performance of the cross section and time-series factor momentum, including the performance of strategies using the return forecast done by Elastic Net and Lasso models. For the one-day and one-month factor momentum, we use the same methodology explained in table 4 and Section 4. For the machine learning cross-sectional strategies, we use the factor return forecasts to rank all factors, and then buy the top winners and sell the bottom losers factors to form cross-section momentum. The long position is formed with the highest ranked factors, and the short position with the lowest factors (4 of 16 factors for each leg), with equal weight across factor portfolios. For the time-series machine learning strategies, if the factor return forecast is positive, we take a long position, and if it is negative, we take a short position in the factor. We use daily returns from Jul/1/1963 to Dec/31/2018 and a holding periods of 21 days, using the same methodology as Jegadeesh and Titman [1993]. Section 5 explains with more details how we compute forecasts of factor returns with Elastic Net and Lasso. It´s reported the annualized excess return, Sharpe ratio, maximum drawdown in 3 months, average daily turnover of both long and short legs, and the break even trading cost, that is, the cost per unit of turnover that would erode all the performance.