Pontifícia Universidade Católica
do Rio de Janeiro

Conrado de Godoy Garcia

Essays on Empirical Finance

Tese de Doutorado

Thesis presented to the Programa de Pós–graduação em Economia of PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Economia.

Advisor : Prof. Marcelo Cunha Medeiros
Co-advisor: Prof. Ruy Monteiro Ribeiro

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Abstract

Garcia, Conrado de Godoy; Medeiros, Marcelo Cunha (Advisor); Ribeiro, Ruy Monteiro Ribeiro (Co-Advisor). **Essays on Empirical Finance**. Rio de Janeiro, 2021. 112p. Tese de doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

This thesis is composed by two chapters. The first chapter 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 on a daily frequency. This phenomenon is not explained by the previously reported industry, large-cap to small-cap and other lead-lag effects. One-day factor momentum is directly related to the existence 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. The second chapter shows how factor momentum impacts the performance of standard short-term single-equity reversal strategies in the US equity market. Significant benefits in performance can be achieved if the effects of factor momentum is considered in the construction of reversal strategies. Standard short-term reversal strategies have a negative exposure to factor momentum since they sell winner stocks that on average are more exposed to the winner factors and buy loser stocks that on average are more exposed to loser factors. The best way to neutralize this effect that drags down short-term reversal performance is to hedge stocks exposures simultaneously to a very large set of factors. For instance, hedging only with the 3 Fama-French factors does not eliminate the exposure to factor momentum. Sorting stocks using residual returns is not as efficient as sorting on total returns as it does not completely neutralize the negative exposure to factor momentum. We propose a fully-hedged reversal strategy that, differently from conventional short-term reversal strategies, is profitable after trading costs, that do not present crashes, that has Sharpe ratio 2.5 times higher than the conventional reversal strategies and that is profitable even if we restrict our sample to only large-cap stocks.

Keywords

Stock lead-lag Effects Factor Momentum Stock Short-term reversal Return Prediction Equity Risk Factors

Resumo

Garcia, Conrado de Godoy; Medeiros, Marcelo Cunha; Ribeiro, Ruy Monteiro Ribeiro. **Ensaios em Finanças Empíricas**. Rio de Janeiro, 2021. 112p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Esta tese é composta por dois capítulos. O primeiro capítulo mostra que a presença de efeitos lead-lag no mercado de ações dos EUA é um fenômeno mais amplo do que previamente reportado pela literatura e está associado à existência de momentum de fatores de um dia. Os efeitos lead-lag estão presentes na frequência diária, sempre que as ações são expostas ao mesmo fator de risco, difundidas por quase 100 fatores. Este fenômeno não é explicado pelo efeito por indústria, reportado previamente pela literatura, efeitos de firmas de baixo valor de mercado reagindo a firmas com maior valor de mercado, assim como outros efeitos de lead-lag. O momentum de fatores de um dia está diretamente relacionado à existência de autocovariância cruzada entre ações expostas aos mesmos fatores de risco e está presente tanto na seção transversal quanto na série temporal. O momentum do fator de um dia é rentável mesmo após os custos de negociação e não apresenta quedas bruscas como outras estratégias de momentum. O momentum do fator de um mês é absorvido pelo momentum do fator de um dia, apresentando alfa negativo. A relevância do efeito do primeiro dia é confirmada com técnicas de machine learning. As reversões de curto prazo em ações também se tornam mais fortes depois de controlarmos para esse efeito de autocovariância cruzada que vem pelo componente de fatores. O segundo capítulo mostra como o momentum de fatores impacta o desempenho das estratégias de reversão de curto prazo em ações nos Estados Unidos. Benefícios significativos no desempenho podem ser alcançados se os efeitos do momento do fator forem considerados na construção de estratégias de reversão. As estratégias tradicionais de reversão de curto prazo em ações padrão têm uma exposição negativa ao momentum de fatores, uma vez que vendem as ações vencedoras de curto prazo que, em média, estão mais expostas aos fatores vencedores de curto prazo e compram ações perdedoras de curto prazo que, em média, estão mais expostas aos fatores perdedores de curto prazo. A melhor maneira de neutralizar esse efeito que prejudica a rentabilidade da reversão de curto prazo é proteger simultaneamente as exposições das ações a um conjunto elevado de fatores de risco. Por exemplo, o hedge feito apenas para os 3 fatores Fama-French não elimina completamente a exposição ao momentum de fatores. Classificar ações pelo usando o resíduo dos retornos não é tão eficiente quanto classificar nos retornos totais, pois tal estratégia não neutraliza completamente a exposição negativa ao momentum do fator. Propomos uma estratégia de reversão totalmente hedgeada que, diferentemente das estratégias convencionais de reversão de curto prazo, é lucrativa após os custos de transação, que não apresenta quedas bruscas como outras estratégias de momentum tradicional, que tem índice de Sharpe 2,5 vezes maior do que as estratégias de reversão convencionais e que é lucrativa mesmo se for restrita a apenas a ações com alto valor de mercado.

Palavras-chave

Efeitos de antecipação e defasagem Momentum de fatores Reversão de curto prazo de ações Previsibilidade de retornos Fatores de risco em ações

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List of Abreviations

AMEX	American Stock Exchange
AR	Autoregressive
B/M	Book-to-Market
BIC	Bayesian Information Criterion
CMA	Conservative minus Aggressive (investment factor)
CRSP	Center for Research in Security Prices
CSMOM	cross-sectional momentum
FACMOM	factor momentum
HML	High Minus Low (value factor)
I/B/E/S	Institutional Brokers' Estimate System
INV	Investment
Lasso	least absolute shrinkage and selection operator
LT REV	Long-Term Reversal Factor
MKT	market factor
MOM	momentum
NASDAQ	National Association of Securities Dealers Automated Quotations
NYSE	New York Stock Exchange
OLS	ordinary least squares
OOS	out-of-sample
OP	Operating Profitability
R^2_{OOS}	out-of-sample R-squared
ret	return
RMW	Robust Minus Weak (profitability factor)
SAS	Statistical Analysis System
SIC	Standard Industrial Classification
SMB	Small Minus Big (size factor)
ST	short-term
UMD	Up Minus Down (momentum factor)

1
Factor-Driven Lead-Lag Effects and Factor Momentum

1.1
Introduction

The presence of lead-lag effects among stocks has already been widely reported in the literature. While most papers in the literature focus only on one specific economic link across firms at time, we show that lead-lag effects among stocks occurs in multiple and complementary dimensions at the same time, whenever stocks are exposed to common risk exposures, being a broader phenomenon than previously found. In this chapter, we present evidence for almost 100 factors (or characteristics) using data from 1963 to 2018 and show that these lead-lag effects are strong on a daily frequency, despite most of paper focus on the monthly frequency. These lead-lag effects are present even for large-cap stocks and industry is just one particular case, mostly explained by the factor-related lead-lag effects that we report in this paper. So the previous size and industry lead-lag effects, reported by Lo & MacKinlay (1990), Hou (2007) and Cohen & Frazzini (2008), are not the causes of this broader pattern that we report. This pattern across stocks is possibly driven by slow information diffusion among stocks with similar risks.

To illustrate with an example: a shock that affects Apple stock today, such as new information related to its cash flow or discount rate, will also affect several other stocks with similar risk factor characteristics, not only today but also in the next day. In the same way, Apple stock is also affected by other shocks that occurred in the previous day in all risk factors that it has exposure. It is evident that information about Apple may tell you something about tech stocks in the future, and vice-versa, but it may hold for multiple more dimensions, with additional information that is not included in the industry lead-lag effects, in both directions. Indeed, we show that most of the information of the industry lead-lag effects is already included in other factors' effects. As of December of 2018, Apple has a large market cap (percentile 99.9%), low book to market (percentile 22.7%), high earnings (percentile 82.7%), high momentum (percentile 83.9%), low market beta (percentile 26.1%), aggressive investment (percentile 70.9%), low net share issues (percentile 8.2%), high dividends (percentile 72.7%), high short-term reversal (percentile 8.7%), low residual variance (percentile 23.7%), mid operating profitability (percentile 8.2%), mid cash flow to price (percentile 67.0%), mid accruals (percentile 50.4%), mid return variance (percentile 52.8%) and mid long-term reversal (percentile 69.0%) [1.1]. So a hypothetical shock related to Apple will also affect all stocks that have the same high (momentum, earnings, investments, among others) or low (market beta, book-to-market, residual variance, among others) risk factor exposure. In other words, there are multiple factor-related lead-lag effects between stocks and each of these effects carries complementary information, with almost no redundancy between them.

The lead-lag effects literature is extensive. For instance, Lo & MacKinlay (1990) show that returns of large stocks lead smaller stocks returns. Menzly & 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 & 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 & 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.

To compute stocks lead-lag effects across all characteristic/factor dimensions, we decompose the autocorrelation in factor returns into two different components following a similar approach to Lo & MacKinlay (1990): one due to autocorrelation in stock return and the other one due to the cross-autocorrelation between stock returns, 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, with the cross-autocorrelation between stocks (i.e. the lead-lag effect) being responsible for 90% of factor return autocorrelation on average (the autocorrelation in returns for these 103 factors is 0.098, while the cross-autocorrelation component is 0.091). There is no evidence of relevant redundancy of this lead-lag effects between factors, that could occur due to correlation between the individual sorts.

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

[1.1]We select characteristics to 16 variables that are used to define risk factors in the Kenneth French´s public library - https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html in this chapter. Cross-autocorrelation in stock returns 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 in factor returns 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 chapter. Industries portfolios have on average positive cross-autocorrelation component of 0.07, with this term being responsible for practically all of autocorrelation in its returns. However, when we control the exposure of industry portfolios to other risk factors, creating factor-neutral industries, the autocorrelation in industry portfolio returns decreases due to a decrease in the cross-autocorrelation component, which reduces by more than half on average, to 0.03. This drop becomes more pronounced as it is increased the number of factors that it are used to neutralize industries' factor exposures. This finding shows that relevant part of the previously reported industry-driven lead-lag effects comes from the factor-driven lead-lag effects that we report in this chapter.

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 stock returns and neither autocorrelation in factor 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 factor momentum is directed related to the existence of the factor-based lead-lag effects that we present here. 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. 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 chapter. This same one-day momentum is present in industries or style-based portfolios.

Factor momentum based on longer lookback windows, such as the one-month momentum of Gupta & Kelly (2019) and Ehsani & 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 annualized performance of the one-month factor strategy goes from 8.0% to -4.6% (t-statistic of -3.8). Moreover, autocorrelation in returns of 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.

Conventional short-term reversal strategies (Lehmann, 1990; Jegadeesh, 1990) have a negative exposure to the one-day factor momentum that we introduce in this chapter, since they sell winner stocks that on average are more exposed to the winner factors and buy loser stocks that on average are more exposed to loser factors. The best way to neutralize this negative relation is to hedge stocks exposures simultaneously to a very large set of factors, as reported in Garcia *et al.* (2020b).

Most empirical asset pricing papers work with monthly frequency data, probably due to turnover and transaction costs issues. This work 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 chapter is organized as follows. Section 1.2 covers data and the methodology. Section 1.3 presents the empirical results for lead-lag effects. Section 1.4 presents the empirical results for one-day factor momentum. Section 1.5 presents the setup and results for the Machine Learning models. Section 1.6 discusses additional robustness analysis. Section 1.7 concludes.

1.2 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[1.2] and follow all the premises used in Green *et al.* (2017), as for example including delisting returns as in Shumway & Warther (1999). We follow Fama & 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 compute 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 Appendix. 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 & Grinblatt (1999) using 20 industry portfolio. We use the two-digit SIC codes from CRSP

[1.2] https://sites.google.com/site/jeremiahrgreenacctg/home 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 [1.3]. 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 are done using daily returns from 1930. Results are similar regardless of the data set.

1.3 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 chapter.

1.3.1 Autocorrelation in factor returns

Persistence in factor returns is a fact already reported by the literature. Among other papers, Gupta & 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 work, we find that autocorrelation in factor return 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 ?? in the Appendix A. 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.

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

1.3.2 Autocorrelation in factor returns: Individual and cross components of stock returns

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

$$\operatorname{Cov}\left(R_t^{fact}, R_{t-1}^{fact}\right) = \sum_{i=1}^{N} \operatorname{Cov}\left(w_t^i R_t^i, w_{t-1}^i R_{t-1}^i\right) + \sum_{i=1}^{N} \sum_{j \neq i} \operatorname{Cov}\left(w_t^i R_t^i, w_{t-1}^j R_{t-1}^j\right) \tag{1.1}$$

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

The first term of equation (1.1) is composed by the autocorrelation in stock returns and can be computed by the diagonal of the covariance matrix. This contribution to the autocorrelation in factor return has the same signal of the autocorrelation in stock return, since the weight w^i becomes positive with squared value. Since stocks have on average negative autocorrelation in returns (see Appendix C for details), positive autocorrelation in factors returns must come from the second term of the equation, as is shown in the subsection below.

The second term of equation (1.1) is composed by the cross-autocorrelation among stocks returns and can have a positive or negative impact on autocorrelation in factor returns. If two stocks are on the same long or short side of a factor portfolio, their contribution will have the same sign of their return cross-autocorrelation. If they are on different portfolio (one stock in the short portfolio and other stock in the long portfolio), the impact on factor return autocorrelation will be in the opposite direction of the stock cross-autocorrelation.

We can also decompose the autocorrelation in factor return into its long and short portfolios contributions (or high and low characteristics portfolios). 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:

$R^{fact} = R_t^L + R_t^S$.

$$\mathrm{Cov}\left(R_t^{fact}, R_{t-1}^{fact}\right) = \mathrm{Cov}\left(R_t^L, R_{t-1}^L\right) + \mathrm{Cov}\left(R_t^S, R_{t-1}^S\right) + \mathrm{Cov}\left(R_t^L, R_{t-1}^S\right) + \mathrm{Cov}\left(R_t^S, R_{t-1}^L\right) \quad (1.2)$$

The first term is the autocorrelation in the long portfolio returns, the second term is the autocorrelation in the short portfolio, and the last two terms are the cross-autocorrelations between the returns of these long and short portfolios returns.

1.3.3 Factor-driven lead-lag effects

Most of the autocorrelation in factors returns comes from the cross-autocorrelation component, that is, from the lead-lag effects. Figure A.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 B.1 in the Appendix B 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[1.4]). 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 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 returns with similar characteristics, that are on the same long or short portfolios, and not due to negative cross-autocorrelation of stocks returns in opposite portfolios. Both long and short sides of portfolio (i.e. high and low characteristics) present the same pattern of the factor that they compose, with high positive autocorrelation in returns, caused by the cross-component. We report the results for the subsample of 16 factors that we describe above in the Appendix C.

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

1.3.3.1
Factor-driven lead-lag effect for industry-neutral factors

Industry-driven lead-lag effects have already been reported by Moskowitz & 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 & Polk, 1996; 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 returns. These industry-neutral factors are, by construction, unrelated to both past and future industry returns.

Industry-neutral factors present high first-order return autocorrelation due to the cross-autocorrelation among stocks returns, i.e. the lead-lag effect component, and not due to industry-specific risks. Table B.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.

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.

1.3.3.2
Factor-driven lead-lag effects for large-cap stocks

Lo & 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 & 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 B.1 report results for factor portfolios constructed only with large stocks. The mean autocorrelation of those factors returns 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 B.1), the effect is stronger, with values of 0.15 and 95%.

1.3.3.3
Redundancy of lead-lag effects between factors

We consider the possibility that lead-lag effects are present only for a smaller subset of factor portfolios once we take into account the correlation between the individual sorts. In order to address this concern, we use a conditional double sort approach, in which we neutralize the effects of one factor to others, similar to the Fama-French factor construction of the HML (High minus low) factor and other factors which are neutral to size based on double sorts.

We select a subset of 22 factors of our broad sample, and for each factor we neutralize the effects of the other 21 factors, one by one. In the Appendix C we show that all of the selected factors continue to have a statistically significant positive cross-autocorrelation component (i.e. the lead-lag effect), and this cross-autocorrelation component continues to be very relevant, with almost 80% of the value from the regular factor. That is, eventual redundancies between the factors represent little more than 20% of the lead-lag effects on average.

1.3.4
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 & 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 & Grinblatt (1999) and construct factor-neutral industries for two subsets: three Fama-French factors and a broad sample of 16 factors described in Subsection 3.3. To compute betas, we use a one-year (252 days) rolling window and re-estimate betas every month.

Industry-driven lead-lag effects are also relevant at the daily frequency. Table B.3 reports the results for the 20 industry portfolios that we analyze. The mean autocorrelation across industry portfolio returns is 0.07, with the cross-stock component corresponding to almost all of this 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 in returns and its cross-autocorrelation 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 B.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 returns 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 chapter, 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 returns. That fact helps to reconcile the existence of several lead-lags effects already reported in the literature, such as the within industries (Hou, 2007; Moskowitz & Grinblatt, 1999), across industries (Menzly & Ozbas, 2006) or other specific economic links (Cohen & Frazzini, 2008; Parsons *et al.*, 2018; Feng *et al.*, 2019), that can be seen as different ways of express common risk exposures.

1.3.5 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 same 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 do not present autocorrelation in their returns 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 A.3 plots the daily autocorrelation in return 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 in returns across all random factor is -0.0022, while in regular factors this value is 0.09. Figure A.4 plots the breakdown composition of autocorrelation returns into individual and cross-autocorrelation components. This analysis provide further evidence that our finding comes from common risks shared by stocks.

1.4
One-day factor momentum

A short-term one-day factor momentum is related to this persistence in risk factor returns, associated with the daily lead-lag effects which we report in this chapter. 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 of these longer lookback windows strategies.

We also show that one-month factor momentum is directly related and partially explained by this daily phenomenon, with almost 70% of its performance coming from the influence of one-day momentum.

1.4.1
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 lookback 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 & Kelly (2019) and Ehsani & Linnainmaa (2019), and with industries (Moskowitz & 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 & 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 A.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.

1.4.1.1
Performance and trading costs

Table B.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 A.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].

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 B.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 & 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.

1.4.1.3 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-1]), and other for high ret[t-1] (MOM[t-21:t-2]|High[t-1]). 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.

1.4.2 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 lookback 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:

$$w^i_{t+1:t+hp} = \min\left(\max\left(\frac{r^i_{t-k:t}}{\sigma^i_{t,1y}}, -2\right), 2\right), \tag{1.3}$$

where $r^i_{t-k:t}$ is the cumulative return of factor i over the lookback 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,

$$\text{TSMOM}_{t+1} = \frac{\sum_{i=1}^{N} w^i_{t+1} r^i_{t+1}}{\sum_{i=1}^{N} |w^i_{t+1}|} \tag{1.4}$$

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 lookback 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 & Kelly (2019) reports cross-sectional and time-series momentum in equity factors, stronger with one-month lookback window.

1.4.2.1
Performance and trading costs

Table B.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 A.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.

1.4.2.2
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 B.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 & 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.

1.4.2.3
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 lookback window, reaching 0.96. In the 1-day lookback 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 Appendix C, we confirm that one-day factor momentum in time-series dominates the cross-section case.

1.4.3
Other cases of one-day factor momentum

Table B.7 presents results for a variety of cross-sectional and time-series momentum strategies using other subsets: i) all 103 factors, ii) large-cap factors, iii) small-cap factors, iv) long side of factor portfolios, v) short side of factor portfolios, vi) random factors, vii) industry-neutral factors, viii) 20 industry portfolios and ix) 20 factor-neutral industry portfolios.

One-day momentum (MOM[t-1]) is present in industry-neutral factors and in factors constructed only with large-cap stocks. Styled based portfolios also present one-day momentum, expressed as both long and short sides of factor portfolios. Random factors do not present factor momentum, since there is neither cross-autocorrelation in its stocks returns that leads to a autocorrelation in factor returns. Industry portfolios present one-day factor momentum, but performance from factor-neutral industries portfolios decay by more than half in relation to simple industry case, indicating that part of industry momentum comes from factor momentum.

These results are in line with those of Section 3, which explores the presence of lead-lag effect in all these different portfolios, and are also in line with a stronger one-day momentum (MOM[t-1]) compared to one-month factor momentum (MOM[t-21:t-1]). In the Appendix C, we present more results for factor momentum strategies with other lookback windows.

1.4.4
Short-term reversals in individual stocks and factor momentum

There is a potentially close connection between lead-lag effects and short-term reversal strategies. For instance, Lo & MacKinlay (1990) suggested that profitability of short-term reversal strategies may be associated with the existence of lead-lag effects, and not simply by over-reaction. However, Jegadeesh & Titman (1995a) find that only a small fraction of the profitability of the short-term reversal strategies is due to lead-lag effects.

Interestingly, Garcia *et al.* (2020b) find that the performance of short-term reversal strategies can be significantly improved when factor momentum is accounted for. In the Appendix C, we present some results showing the high profitability of hedged short-term reversal strategies.

1.5
Machine learning models and the importance of last day return

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. Net of costs Sharpe ratio 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 variation in factor return autocorrelation 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 trading costs.

1.5.1 Models setup

We choose the following models: *Lasso*, proposed by Tibshirani (1996), *Ridge*, proposed by Hoerl & Kennard (1970), *Elastic Net*, proposed by Zou & 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.* (2020) 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:

$$\hat{\mathbf{\Phi}}_\Omega = \underset{\Phi}{\operatorname{argmin}} \left(\sum_{t=0}^{T} (r_{t+1} - \mu - \sum_{m=0}^{M} \phi_m r_{t-m})^2 + \text{Penalty}(\Omega, \Phi) \right), \tag{1.5}$$

where $\boldsymbol{r_t}$ is the return of period t, $\boldsymbol{\mu}$ is the intercept, $\mathbf{\Phi}$ 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, $\mathbf{\Omega}$ is the hyperparameters for which $\mathbf{\Phi}$ is minimized.

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

$$\text{Penalty}(\alpha) = \alpha \sum_{m=0}^{M} |\phi_m| \tag{1.6}$$

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

$$\text{Penalty}(\gamma) = \gamma \sum_{m=0}^{M} \phi_m^2 \tag{1.7}$$

Elastic Net uses a combination of L1 and L2 norms:

$$\text{Penalty}(\gamma, \alpha) = \gamma \left(\frac{(1-\alpha)}{2} \sum_{m=0}^{M} \phi_m^2 + \alpha \sum_{m=0}^{M} |\phi_m| \right) \tag{1.8}$$

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

$$\text{Penalty}(\alpha, \varepsilon) = \left(\alpha \sum_{m=0}^{M} |\phi_m| + \varepsilon \sum_{m=1}^{M} |\phi_m - \phi_{m-1}| \right) \tag{1.9}$$

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.[1.5]

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:

$$\mathbf{R}^2_{OOS,i} = 1 - \frac{\sum_t (r_{i,t+1} - \hat{r}_{i,t+1})^2}{\sum_t (r_{i,t+1} - r^{benchmark}_{i,t+1})^2} \tag{1.10}$$

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

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

1.5.1.1 Factor return predictability

Table B.8 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, so we chose Lasso that is more easily replicable. 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

[1.5] 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.

capture momentum. We also report in Table 7 results based on OLS and other historical means of returns.

Panel A of Table B.8 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.

1.5.1.2 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 daily lags 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 A.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.

1.5.1.3
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 in factors returns 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 Appendix C.

1.6 Robustness

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

1.6.1 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 factor momentum: i) not scaling the strategy weight by factor current volatility, ii) scaling by volatility but not by the magnitude of cumulative performance on the lookback window, iii) re-scale both long and short sides to form a unit-leverage TSMOM portfolio ($1 long and $1 short together), as done in Gupta & Kelly (2019). Conclusions do no change in these alternative approaches.

1.6.2 Kenneth French's database and longer sample windows

Factor momentum also holds for the factors in the Kenneth French's database[1.6]: 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 autocorrelation in factor returns. Results for factor and style-based portfolios (both CSMOM and TSMOM) are presented in the Appendix C.

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

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 the Appendix C.

1.7 Conclusion

This chapter 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 that exploit this high-frequency 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 autocorrelation in factor return 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 in returns due to cross-autocorrelation components, with respective mean values of 0.059 and 0.051.

One-day factor momentum is related to the autocorrelation in factor returns 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 lookback windows, such as the one-month reported by Gupta & Kelly (2019) and Ehsani & 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.

2
Short-term Reversals and the Negative Impact of Factor Momentum

2.1
Introduction

Short-term reversal strategies were first introduced in the literature by Lehmann (1990) and Jegadeesh (1990), who showed that a strategy that buys (sells) stocks with low (high) total returns over the past month (or week) tend to be profitable in the following period. It was later explored by other works, such as Ball *et al.* (1995), Conrad *et al.* (1997) and Avramov *et al.* (2006) who defend that performance disappear once trading costs are considered; Blitz *et al.* (2013) who focus on the dynamic exposures of the conventional strategies to the 3 Fama-French factors (Fama & French, 1993), and then construct a short-term reversal strategy based on stocks residual returns (we will refer this strategy as the short-term residual reversal); among other works. Factor momentum was introduced more recently in the literature. Gupta & Kelly (2019) showed that factor momentum is a global phenomenon, present in both cross-section and time-series and strong using one-month look-back window; Ehsani & Linnainmaa (2019) showed that the relation between momentum in individual stock returns emanates from momentum in factor returns; and Garcia *et al.* (2020a) showed that factor momentum is mostly a daily phenomenon directed related to factor-based lead-lag effects for almost a 100 factors.

In this chapter, we connect these two short-term effects that occur in opposite directions: short-term reversals in single stocks and one-day factor momentum. When stocks are aggregated into portfolios based on common characteristics, individual stocks' negative autocorrelation in the short-term is overridden and converted into a positive returns autocorrelation in the portfolio level. When we consider at the same time both factor momentum and individual stock reversals, it is possible to construct strategies with a performance that is much better than these two ones can deliver in isolation.

We first show that short-term reversal strategies, constructed with either stocks' total returns or residual returns to the 3 Fama-French factors, exhibit negative and significant exposure to the one-day factor momentum, with respective values of -1.76 (t-stat of -33.8) and -0.54 (t-stat of -12.1). The negative exposure of conventional short-term reversals in single equities, constructed with stocks' total return (ST regular), reported by Lehmann (1990) and Jegadeesh (1990), is more intuitive since this strategy sells recent winner stocks, that are on average more exposed to the winner factors, and buys loser stocks, that are on average more exposed to loser factors. The negative exposure of short-term residual reversals (ST residual), reported by Blitz *et al.* (2013), comes from the fact that stocks residuals computed to only 3 factors do not neutralize all other factor exposures and these additional ones also present factor momentum. As reported in Garcia *et al.* (2020a), factor momentum is present in a wide range of factors, on a daily basis, scattered in more than 100 cases.

The best way to neutralize this negative effect of factor momentum into short-term reversals is to hedge stock exposure to its several risk factors. As we increase the number of factors that are used, hedged short-term reversal performance monotonically increases and its exposure to factor momentum decreases. As we use a broad sample of 16 factors to hedge stocks, the performance of the hedged strategy goes from 5.7% to 14.2% per year, the maximum drawdown goes from -33% to -11%, and the loading to factor momentum goes from -1.76 to 0.02, all in comparison to the conventional short-term reversal strategy. The hedged strategy is also profitable after 2000's, different from the regular strategy that posses performance statistically indistinguishable from zero in this period.

Using stocks residuals to construct short-term reversals, as done by Blitz *et al.* (2013) (ST residual) also improves performance in comparison to conventional short-term reversal strategies, but it is less effective than the hedged reversal strategy that we propose in this chapter. Even when it is used a broad sample of factors to compute stock residuals, the short-term residual performance is entirely subsumed by our proposed hedged strategy, with its alpha being only 0.4% per year and statistically indistinguishable from zero. Scaling or not the residual by its volatility does not change the results significantly of the residual reversal strategies. As in the hedged strategy case, increasing the number of factors to compute stocks residual also helps to increase the performance of short-term residuals: using only the 3 Fama & French (1993) factor leads to a performance of 7.5% per year while using a broad sample of 16 factors results in a performance of 9.4% per year, with a lower exposure to one-day factor momentum.

The benefits of our proposed hedged short-term strategy are even larger when trading costs are taken into consideration. As argued by several authors, such as Conrad *et al.* (1997) and Avramov *et al.* (2006), the profitability of conventional short-term strategies almost disappears after the trading costs are considered. In line with what other authors have found, the net of costs performance of regular short-term reversal is statistically indistinguishable from zero in our sample, from July 1963 to December 2018. The hedge strategy that we propose exhibits a net of costs annualized return of 7.9%, and Sharpe ratio larger than 1.50. Even if our estimates of trading costs are doubled, our proposed hedged strategy's performance continues to be positive and statistically different from zero.

Results are still strong if we restrict our sample to only large-cap stocks. The performance of the large-cap hedged short-term reversal is 11.4% per year, not much less of a strategy that uses both small and large-cap stocks, that has a performance of 14.2% per year. This fact suggests that non-synchronous trading or liquidity effects, reported by Jegadeesh & Titman (1995b) and Boudoukh *et al.* (1994), are not responsible for the good performance of the strategy that we introduce in this work. Results are strong for large-cap stocks even after trading costs, with net of costs Sharpe ratio of 0.76 (using a conservative estimate of trading costs of 10 bps per unit of turnover).

An interesting point that we focus on in this work is the negative effect that occurs if we hedge stocks exposure to factors in the short-term residual reversals. We create a "Pure short-term residual reversal strategy" that consider both approaches that we separately described above: i) define winner and loser according to residual stock returns and then ii) hedging stock exposure to factors. This strategy has a worse performance in comparison to the other hedged and residual strategies. If the short-term reversal effect in stocks is caused only by the idiosyncratic component of returns (represented by the estimated residuals), the systematic component of return should not influence the strategy performance. However, in practice, that is not what happens, since almost 50% of short-term residual reversals performance comes from the systematic component of stock return. If we take an additional step and hedge stocks factor components, the return of short-term residual strategy falls from 9.4% to 4.9% per year. It is related to a negative contemporaneous correlation between the idiosyncratic and the systematic components of stock returns, which is partially related to the factor-driven lead-lag effects present within stocks exposed to similar risk factors, as better described in Garcia *et al.* (2020a).

Stocks with better residual performance in the short run (both one-week or one-month) have, on average, negative performance on their systematic component, measured by their factor betas multiplied by their respective factor returns. The opposite happens for recent loser residual stocks. Both facts are reflected in the breakdown of the total returns in the formation period of short-term residual reversals. The average total return of loser residual stocks (stocks with worse residual return performance) is -7.5%, with the systematic components responding for 1.3% and the residual component responding for -8.6%; and for the winner residual stocks, the respective numbers are 8.7%, -0.3% and 9.0%. Already, when its used stocks total return to construct regular short-term reversal, both components of returns have the same signal: the winner portfolio has a total return of 10.7%, with 2.9% from systematic components and 7.4% from residual component; and the loser portfolio with respective numbers of -9.0%, -2.0% and -7.0%.

Other interesting points of the our proposed hedged short-term reversal strategies: i) using one-week or one-month look-back window leads to very similar performance after stocks factor exposure are hedged, showing that the difference of one-week or one-month regular strategies comes mostly from factor momentum exposure; ii) a higher frequency daily rebalance strategy leads to higher returns, but also to higher turnovers, almost in the same proportion, showing the existence of some kind of cost barrier; iii) the seasonal pattern of regular reversal strategy is less pronounced in the hedged strategy, with all calendar months presenting positive and significant performance; iv) after hedging, performance is well distributed among both long and short sides (recent loser and winners portfolios).

The rest of the chapter is organized as follows. Section 2.2 covers data and the methodology to construct short-term reversal and other factors portfolios. Section 2.3 presents the negative relationship between Factor momentum and Short-term reversal in single equities strategies. Section 2.4 presents the Hedged Short-term reversal strategies and shows that it is the best way to neutralize this negative effect of factor momentum into short-term reversals. This section also shows that “Pure short-term residual reversal” does not work so well, due to a negative contemporaneous correlation between the idiosyncratic and the systematic components of stock returns. Section 2.5 shows other interesting aspects of the Hedged Short-term reversal strategies, as the effects of one-week or one-month look-back windows, a higher frequency daily rebalance strategy, and the less pronounced seasonal pattern of the hedged strategy. Section 2.6 concludes.

2.2 Data

We use equity data from CRSP, Compustat, and I/B/E/S to construct short-term reversals and all other factors portfolios that are used in this work, for the period beginning in first of July 1963 and ending in 31 of December 2018. To compute firm characteristics and construct factor portfolios, we use the code provided by Jeremiah Green [2.1] and follow all the premises used by him in Green *et al.* (2017), as for example including delisting returns per Shumway & Warther (1999). To construct factors we follow Fama & 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 in a daily frequency, but we compute firms' characteristics to rebalance portfolios every month. All factors portfolios are value-weighted, and the high and low side portfolios are set to guarantee a positive expected daily return.

To ensure diversification in factor portfolios, we discard periods in which a factor has less than 30 stocks. 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 our sample, regular short-term reversal has an annualized cumulative return of 6.0% per year, with a Sharpe ratio of 0.62. Short-term residual reversal (to the 3 Fama-French factors, Fama & French (1993)) has an annualized cumulative return of 7.4% per year, with a Sharpe ratio of 1.15.

2.3 Exposure of Short-term reversal to Factor Momentum

This section explores the negative relationship between Factor momentum and Short-term reversal in single equities strategies. Those both strategies occur in the short-term, but in the opposite direction: factor returns present persistence and single equities returns present a reversal effect (negative autocorrelation). Somehow, when stocks are aggregated into risk portfolios, the negative autocorrelation of individual stocks is overridden and converted into a positive return persistence in risk factor portfolios.

We first present this effect in conventional single equities short-term reversal (ST regular), constructed from one-month stocks total returns (Jegadeesh, 1990); and then present to short-term residual reversal (ST residual),

[2.1] https://sites.google.com/site/jeremiahrgreenacctg/home constructed from residual stocks returns to the 3 Fama-French factors (Blitz *et al.*, 2013). For factor momentum (FACMOM), we use the same methodology of Garcia *et al.* (2020a) and construct cross-section momentum for a broad sample of 103 factors, using a look-back window of 1 day and a holding period of 21 days. Results are robust to the way we compute factor momentum strategies, such as a smaller sample of factors (16 factors), or other look-back windows (one-month),or other holding periods (one-day), or a time-series approach instead of a cross-section momentum.

2.3.1
Conventional Short-term reversal

Regular short-term reversal strategies exhibit negative and statistically significant exposure to factor momentum. Table E.1 in the Appendix E shows that ST regular (one-month) has a strong negative loading to factor momentum, with the value of -1.76 (t-stat of -33.8). It does not come from indirect exposures to other traditional factors, such as Market (MKT), Size (SMB), Value (HML), Investment (CMA), Profitability (RMW), and traditional single equities momentum (UMD); since loading value to factor momentum almost does not change with the inclusion of these control factors (-1.65 with t-stat of -31.9). This negative exposure comes from both long and short sides of ST regular, with loading values of -0.91 and -0.74, respectively (when regressed together with the 6 factors described above). The huge difference in alphas when Factor momentum is included in the regressions illustrates the magnitude of the performance that is dragged from conventional short-term reversals by the negative effect of factor momentum (alpha increase by almost three times).

This negative exposure of conventional short-term reversals in single equities (ST regular) is intuitive to be understood, since this strategy sells recent winner stocks, that are on average more exposed to the winner factors, and buys loser stocks, that are on average more exposed to loser factors, creating almost a direct mechanism. To confirm this, we regress against FACMOM both systematic and idiosyncratic components of winner and loser portfolios' returns in the formation window of short-term reversal strategies. Panel A from table 6 describes the results. The long side portfolio, composed by recent loser stocks, has a very negative average return in the formation window by construction and a negative loading to FACMOM of -0.64 (t-stat of -12.7). This negative exposure comes mostly from the systematic part of its return, measured by their factor betas multiplied by its respective factor returns, with a loading value of -0.50 (t-stat of -10.7). The short side of ST regular, composed by recent winner stocks, has a positive loading value to

FACMOM of 0.54 (t-stat of 10.6), which comes from only the systematic part of return.

2.3.2 Short-term residual reversal

Short-term residual reversal (ST residual), constructed using stocks residual returns to the 3 Fama-French factors, as done in Blitz *et al.* (2013), also presents negative exposure to factor momentum. Table E.1 shows that ST residual (one-month) still has a negative loading to FACMOM of -0.50 (t-stat of -12.1), even after controlling for the Fama-French 5 factor plus UMD. As happens in the regular short-term reversals, the negative exposure comes from both long and short sides of ST regular: -0.30 and -0.19, respectively. There is also a difference in alphas when Factor momentum is included in the regressions, but in smaller magnitude when compared to ST regular case. Adjusting the residual stocks returns by its volatility, does not change the results, as can be seen in the last row (Vol adj residual).

This negative exposure of short-term residuals (ST residual) shows that controlling residuals to 3 factors is not enough to neutralize the effect of factor momentum on reversal strategies. As better described in subsection 2.4.3, this negative exposure does not come from the systematic component of return from the winner and loser residual portfolios, which indicates some kind of negative contemporaneous structure between the residual and the systematic component of stock returns.

2.4 Short-term reversal neutralized for Factor Momentum

This section shows that the best way to neutralize this negative effect of factor momentum into short-term reversals is to hedge each stock exposure to its several risk factors, constructing “Hedged Short-term reversal” strategies (ST hedged). We first show that as we hedge stock exposure to more factors, the ST hedged performance increases monotonically, and its exposure to factor momentum also decreases monotonically. Then we show that short-term residual strategies are less profitable than the hedged strategies, being completed subsumed in controlled time-series regressions.

We also show that the profitability of our proposed hedged short-term strategy is even larger when trading costs are taken into consideration; and that the performance is still large even if we restrict our sample to only large-cap stocks, showing the results does not come from the bid-ask spread and any other kind of liquidity or micro-structure effects.

An interesting point we focus on in section is that "pure short-term residual reversal" strategies do not present a good performance. We first present two different approaches to neutralize the relations of factor momentum and conventional short-term reversals. One approach is to consider stocks residuals to construct recent winner and loser portfolios, instead of total return, as already done by Blitz *et al.* (2013) to only the 3 Fama-French factors. The other approach is to continue defining recent winner and loser portfolios by their total returns, but then hedging stocks exposures of several risk factors. When considering both approaches at the same time, that is, sorting stocks according to their residual returns and also hedging each stock exposure to its risk factors, we got a worse performance than the other neutral short-term reversals that we describe above. We present evidence that this fact is related to a negative contemporaneous correlation between the idiosyncratic and the systematic components of stock returns, which is partially related to the lead-lag effects present within risk factors, as better described in Garcia *et al.* (2020a).

2.4.1 Hedged Short-term reversals

The best way to neutralize the negative effect of factor momentum into short-term reversals is to hedge stock exposures to its several risk factors, constructing "Hedged Short-term reversal" (ST hedged). We still use total returns to define recent winner and loser stocks, as in the conventional reversal strategy, but we do an extra step and hedge each stock to its exposures to several risk factors. When doing it for a sufficient number of factors, we successfully neutralize this negative effect that factor momentum produces in the reversal strategies that we better described in the section above.

To construct the hedged strategy, we compute stocks betas every month using daily data and rolling windows of 252 days. We use these betas for 1 month to hedge stocks exposures to risk factors, always in an out-of-sample method to make the strategies applicable in practice. Results do not change if we increase our estimation window.

Table E.2 presents results for several hedged short-term reversal strategies, each one using a different subset of risk factors. As a benchmark, we present in the first row the results for the ST regular, which has an annualized excess return of 5.7%, a Sharpe ratio of 0.59, a maximum drawdown of -33% and an monthly average turnover of 3.6 (measured as units of trading), which leads to net of costs performance of 1.2% per year, statistically indistinguishable from zero (t-stat of 1.0)[2.1]. We assume average trading costs of 10 bps per unit of turnover, based on the estimates of Frazzini *et al.* (2015). In the following rows, we show ST hedged strategies results to several sets of risk factors. We first present results for hedges strategies to only one risk factor at a time, and in those cases, there are just a small increment in performance and there are still high negative loading values to factor momentum. The following rows show results for increasing subsets of factors, from the 3 Fama-French factors (Fama & French, 1993) to a large subset of 16 factors (we chose the same factors that are reported in Kenneth French database [2.2]: Accruals, Market Beta, Value, Cashflow/price, Net Share Issues, dividend yield, earnings-price, daily residual variance, Investment, stock momentum, short-term reversal, long-term reversal, size, operating profitability, daily variance, and Market).

Hedged short-term reversal to the 3 Fama-French factors presents larger results than the corresponding strategy constructed from the correspondent residual strategy to the 3 Fama-French factors (ST residual), presented by Blitz *et al.* (2013): an annualized excess return of 10.1% (against 7.5% of ST residual to the same group of factors) and a Sharpe ratio of 1.58 (against 1.15 of ST residual). Even if its considered the larger turnover (4.0 against 3.5 per month), results continue to be better: net of costs annual excess return of 4.9% (t-stat of 5.7) against 3.0% (t-stat of 3.5) of ST residual.

As we increase the number of factors that are used to hedge stocks, ST hedged performance increases monotonically. The fully 16-factor hedge strategy has an annualized excess return of 14.2%, more than 2.5 times the conventional strategy (not hedged to any factor), and a Sharpe ratio of 3.12. Despite an increase in the average turnover in the hedged case, from 3.6 per month in the regular case to 4.7, the net of costs excess return is still 7.9% per year (t-stat of 12.4) and the Sharpe ratio is 1.74 after trading costs. The alpha to the Fama-French five factors plus single stocks and factor momentum (UMD and FACMOM) is 14.8% (t-stat of 22.6), almost the same value of the hedged strategy excess return (14.2%), and also almost the same value of the alpha from ST regular (14.6%). This fact put together with the loading value to factor momentum of only 0.02 (t-stat of 0.8) shows that our approach successfully neutralizes the effects of factor momentum on short-term reversal.

Another advantage of the hedged short-term reversal strategies is that they do not suffer from crashes, as happens to the regular short-term reversal

[2.1] In line with the results of Conrad *et al.* (1997) and Avramov *et al.* (2006), that demonstrate that the profitability of conventional short-term strategies almost disappears after the trading costs is considered.

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

or stock momentum (Jegadeesh & Titman, 1993). The maximum drawdown is only -11%, compared to -33% of the regular short-term reversal, or to -22% of the short-term residual reversal to 3 Fama-French factors. This same crash-free pattern occurs in the one-day factor momentum, as reported in Garcia *et al.* (2020a). Figure D.1 in the Appendix D plot the performance over time from the conventional and the hedged short-term reversal strategies, and shows that the hedged strategies continues to be profitable after 2000‘s, a period in which the conventional short-term reversal is not profitable.

2.4.2
Short-term residual reversal

We now investigate the effects of increasing the number of factors to compute stocks' residual returns and then construct short-term residual reversal strategies. Blitz *et al.* (2013) used only the 3 Fama-French factors (Fama & French, 1993), and as shown in the section above, as we increase the number of factors used to hedge stocks, the performance improves substantially. We follow a similar approach that we use in the hedged short-term reversal strategies and compute stocks residuals every month with daily data and rolling windows of 252 days. Winner and loser portfolios are constructed with stocks' residual return of the previous month (or previous week). Results remain similar if a larger estimation window is used.

As shown in Table E.3, the performance of short-term residual reversal strategies (ST residual) also improves as we increase the number of factors used to compute stocks' residual returns. Still, exposure to Factor momentum continues to be statistically significant for all factor subsets that we used. Loading values to factor momentum in univariate regressions go from -1.76 (t-stat of -33.8) in the conventional Short-term reversal, to -0.54 (t-stat of -12.1) in the Fama-French 3 factors case, and to -0.10 (t-stat of -3.1) in the fully 16 factors case. If we control for the Fama-French 5 factors (Fama & French, 2015) plus stocks individual momentum (UMD), results remain almost the same. We use the same set of factors used for hedge stocks in the Hedged Short-term reversals strategies of the section above. As happens in the hedged strategy case, as we increase the number of factors, residual strategies' performance increases monotonically. The 16-factor case strategy has an annualized excess return of 9.4%, a Sharpe ratio of 1.98. an average turnover of 3.5 per month, which leads to a net of costs excess return of 4.9% per year (t-stat of 7.5). All performance metrics are larger than the 3 Fama-French factors case but are smaller than the hedged short-term reversal strategy that we introduced in this chapter.

2.4.3
Spanning tests

Our proposed Hedged Short-term reversal strategy subsumes the residual strategy. Table E.4 reports several spanning regressions for Hedged ST hedged (16 factors) and ST residual (16 factors), controlling for each other and also for the Fama-French 5 factors (Fama & French, 2015) plus traditional stock momentum (UMD), Factor momentum, and conventional Short-term reversal (ST regular).

The annualized alpha of ST hedged (16 factors) remains high and statistically significant when controlled for ST residual(16 factors), with a respective value of 8.3% (t-statistic of 16.4). However, the performance of ST residual (16 factors) is completely explained by ST hedged (16 factors), with a non statistically significant annualized alpha of 0.4% (t-statistic of 0.7). The respective loading values of one strategy to each other are 0.59 and 0.65, respectively.

Hedged short-term reversals are also not explained by Fama-French 5 factors, traditional stock momentum (UMD), factor momentum, or convectional short-term reversal (ST regular), presenting an alpha of 7.8% (t-statistic of 14.6) when controlled for all those factors. The loading of ST hedged to convectional Short-term reversal is 0.09 (t-stat of 8.9), smaller than the ST residual case, which is 0.16 (t-stat of 16), showing that the hedged strategy is less exposed to the convectional case.

Figure D.2 plots the performance over time from both residual and hedged short-term reversal strategies to the broad sample of 16 factors and visually shows that the hedged strategy is more profitable over time than the residual strategy.

2.4.4
Pure short-term residual reversal

Up to now, we compared two different approaches to neutralize the relations of factor momentum and conventional short-term reversals: i) Hedged short-term reversal and ii) Short-term residual reversal. We show that neutralizing for the return persistence that exists in factors and, consequently, in the systematic component of stock returns, leads to a significant increase in the reversal strategy performance. If the short-term reversal effect is only caused by the idiosyncratic component of returns (represented by the estimated residuals), the systematic component of return should not influence the strategy performance. However, in practice, that is not what happens, since almost 50% of short-term residual reversals performance comes from the systematic component of stock return, as we show below. To show these effects, we construct "pure short-term residual reversal" strategies, considering both approaches that we separately used above, that is: i) define winner and loser according to residual stock returns and then ii) hedging stock exposure to factors.

As can be seen in Table E.5, these Pure short-term residual reversal strategies have worse performance than the other presented strategies, and this difference in performance increases as we raise the number of factors that are used in the process. The ST residual performance is dragged down 2.5% per year, going from 7.5% per year to 5.0% as we hedge stocks' exposure to the 3 Fama-French factors (Fama & French, 1993). For the 16 factor case, performance goes from 9.4% per year to 4.9%, with a larger difference of 4.5% per year. The difference in the Sharpe ratio also increases between those two approaches.

The fact that hedging stocks from both winner and loser residual portfolios remove its performance, indicates that sorting stocks according to their residual returns induces some kind of systematic risk structure in these groups of stocks. The increase that occurs in the loading values to Factor momentum also reinforces this fact: the loading value increase from -0.54 (t-stat of -12.1) to -0.62 (t-stat of -17.2) in the 3 Fama-French factor case, and from -0.10 (t-stat of -3.1) to -0.40 (t-stat of -12.8) in the 16 factors case. It is important to remember that those two strategies - hedged and residual - lead to different groups of selected stocks.

2.4.4.1
Components of return from Losers and Winners stocks

To investigate the different effect that hedging causes over these two distinct groups (stocks sorted on the total return or stocks sorted on residual return), we decompose the return of these groups into the systematic and the idiosyncratic components in their formation period and then analyze their relation to factor momentum, market, and other relevant factors. To compute the systematic and idiosyncratic components of returns, we use the same 16 factors mentioned in the sections above and the same methodology that is used to compute stock betas, re-estimating every month with daily data and 252-days rolling windows, always using out-of-sample approach.

Panel A of Table E.6 presents the results for the case of stocks sorted on total returns, which is both used in the conventional and the hedged short-term reversal strategies. By definition, the long side is formed by recent loser stocks, and the short side is formed by the recent winner stocks. To keep the same pattern with other tables, we annualize the returns. The first fact to point out is that both systematic and idiosyncratic components have on average the same signal, being both positive or negative. This fact is intuitive since the total return takes into consideration both components of return. The second fact to be mentioned is the negative exposure to factor momentum that is created in the formation window. The long portfolio, composed by the recent loser stocks, has a negative loading to factor momentum of -0.64 (t-stat of -12.7), with most of this exposure coming from the systematic part of its return (measured by their factor betas multiplied by its respective factor returns), with loading value of -0.50 (t-stat of -10.7). As expected, the short side of ST regular, composed by recent winner stocks, has a positive loading value to factor momentum of 0.54 (t-stat of 10.6), which comes only from the systematic part of return.

Already for stocks sorted on previous residual return, a different pattern arises. By construction, the stocks with the larger (smaller) previous residual return are selected, and if the idiosyncratic component of return (measured by residual returns) is totally uncorrelated to the systematic component of return, sorting by residuals should not lead to any kind of structure, and both long and short sides should have similar values of this systematic component, being something close to the unconditional expected return. By panel B of Table E.6, we can see that this is not what happens. The winner and loser residual return stocks have their systematic component of return in the opposite direction of the idiosyncratic return, with a corresponding value of -3.4% and 16.5% per year. Despite the loading value to factor momentum being only 0.09 (t-stat of 2.1) in the formation window to both long and short sides together, the systematic part has a large value of 0.24 (t-stat of 9.1), which is consistent with the fact that hedging removes part of the performance from short-term residual reversal strategies.

This fact illustrates evidence of a negative contemporaneous correlation between the idiosyncratic and the systematic components of stock returns, which is partially related to the stock lead-lag effects present within risk factors, as better described in Garcia *et al.* (2020a). In non-tabled results, we compute the correlation between those two components of stock return. Using out-of-samples betas that we computed every month with 252 days rolling windows and the 16 factors (the same ones used above), we find an average correlation of -0.23 between those two return components for all stocks of our sample (systematic and idiosyncratic components). Results remain negative if we change the number of factors that are used (-0.07 correlation for the 3 Fama-French factors) or use other estimation windows (-0.12 if we use 756 days and -0.07 if we use 2520 days), which lead us to believe that results are not due to estimation error bias. We have to use out-of-sample betas to compute the components of returns because in sample estimations, by construction, residuals regressions are orthogonal to the predicted value (β'factors)

2.4.5
Size effects: Hedged short-term reversal for large-cap stocks

Results are still strong if we restrict our sample to only large-cap stocks, suggesting that non-synchronous trading or liquidity effects, reported by Jegadeesh & Titman (1995b) and Boudoukh *et al.* (1994), are not responsible for the good performance of the strategy that we introduce in this work.

Panel A of Table E.10 shows results for hedged short-term reversal strategies constructed only with large-cap stocks, whose market value is above the NYSE median breakpoint, represented by the largest 800 stocks on average over time, from July of 1963 to December of 2018. The regular short-term reversal strategy with only large-cap stocks has an annualized return of 2.8% (t-stat of 2.2), with a Sharpe ratio of only 0.25 compared to 5.7% (t-stat of 4.6) and 0.59 using all size stocks. If we conservatively consider the same trading cost estimates that we use in the calculation above with all size stocks, of 10 bps per unit of turnover (Frazzini *et al.*, 2015), the regular short-term reversal with large-cap stocks is non-profitable, with a negative excess return of -1.3% per year (t-stat of -1.0), confirming results previously found by literature.

Already, hedged short-term reversal strategies with only large-cap stocks are profitable, even after trading costs. Using our broad sample of 16 factors, the annualized excess return is 11.4% (t-stat of 14.1), Sharpe ratio is 1.99 compared to 14.2% (t-stat of 21.7) and 3.12 using all size stocks. Using conservative trading costs estimates, performance after trading costs for large-cap stocks remain at 4.3% per year (t-stat of 5.5) and with a Sharpe ratio of 0.76. Exposure to Factor momentum is almost zero and statistically indistinguishable from zero. Figure D.5 plots the performance over time from both long and short sides of the hedged short-term reversal strategy, constructed only with large-cap stocks. It can be noted that the strategy continues to be profitable even after 2000‘s, and both long and short sides are profitable.

2.5
Other effects and Robustness

In this section, we address other interesting points of our proposed hedged short-term reversal strategies.

We first show that the larger performance of the one-week look-back window in regular short-term reversal strategies comes mostly due to a small exposure to one-day factor momentum, since the performance of those two different look-back windows are very similar for the hedge strategies. We then show that a higher frequency daily rebalance strategy leads to higher returns, but also to higher turnover, almost in the same proportion, indicating the existence of some kind of cost barrier. We next show that the seasonal pattern of regular reversal strategy is less pronounced in the hedged strategy, with all calendar months presenting positive and significant performance, and finally show that after hedging, performance is well distributed among both long and short sides (recent loser and winners).

2.5.1
One-week and one-month look-back windows

Up to now, we only use a one-month look-back window to define winner and loser stocks. In regular short-term reversal strategies, without the use of hedge, using one-week look-back windows leads to a stronger performance: annualized return of 11.3%, Sharpe ratio of 1.40 against an annualized return of 5.7% and a Sharpe ratio of 0.59 in the one-month look-back window case, as shown in Table E.7. Since we continue to rebalance the strategy once a month, turnover is very similar, with a mean value of 3.6 per month, also resulting in superior performance after trading costs. The loading to factor momentum is smaller in the shorter look-back window case, with a value of -0.78 (t-stat of -12.6) against -1.65 (t-stat of -31.9) of the one-month look-back window. This smaller exposure to factor momentum is probably due to a smaller size sample window.

In the hedged short-term reversal to 16 factors, exposure to factor momentum reduces to almost zero in both cases, with the one-week case presenting a loading value of 0.02, statistically indistinguishable from zero (t-stat of 0.08), demonstrating that the hedging procedure continues to work in neutralizing this exposure. Directly related to this, the performance of the one-week look-back window is very similar to the one-month case, with respective annualized returns of 14.8% and 14.2%. As in the regular case, turnover of both look-back windows cases are very similar, since rebalance continues to be once a month. Performance after trading costs of the one-week strategy is impressively 8.4% per year, with a Sharpe ratio of 1.91. In not table results, we run spanning tests regressions and confirm that both strategies continue to be profitable after controlled for each other, presenting positive statistically significant alphas. Figure D.3 plots the performance over time from both one-week and one-month look-back window strategies, and shows that the performance of the hedged case are very similar over time.

In line with previous results, if we only hedge for a smaller sample of factors (such as Fama & French (1993)), exposure to factor momentum continues to exist, and consequently, the performance is lower.

2.5.2
High-frequency rebalance

Up to now, we rebalance the portfolios once a month, defining winner and loser stocks at the end of each month. Panel A of Table E.8 presents the results for a high frequency daily rebalance case, in which everyday stocks are ranked according to their recent performance and then is defined which stocks to buy or to sell. This daily rebalance case naturally has a higher turnover. The regular short-term reversal (one-month look-back window), not hedged, has an average monthly turnover of 15.6 in the daily rebalance case, more than 4 times larger than the average turnover of the once in a month rebalance case. Performance is more than 5 times larger, which leads to a superior performance after trading costs, still being profitable after trading costs. Another point to be noted is the larger exposure to factor momentum, with a loading value of -2.61 (t-stat of -44.3).

As we hedged factor, performance continues to rise as we increase the number of factors in the daily rebalance case. In the 16-factors case (one-month look-back window), the annualized performance after trading costs is 11.3%, with a Sharpe ratio of 2.11 and a maximum drawdown of only -8%. Unlike the monthly rebalance case, the hedge is not capable of completely neutralize the exposure to factor momentum, with the 16-factors case presenting a loading value of -0.32 (t-stat of -10.6). One interesting point is that for almost all subsets of factors, the break-even trading costs (the cost per unit of turnover that would erode the strategy performance) are very similar, ranging from 0.14% to 0.15%, showing that the higher performance is achieved via an almost as high turnover.

An even higher frequency case that uses daily rebalance and a one-week look-back window to define winner and loser stocks, leads to an even higher turnover, which is not followed by the same proportional increase in performance. As a result that, these strategies are not profitable after trading costs, as presented in panel B of Table E.8.

2.5.3
Seasonal Patterns

Several authors document a strong seasonal pattern in reversal strategies, such as Grundy & Martin (2001). Table E.9 presents the performance per calendar month from conventional, residual, and hedged short-term reversal strategies. As previously reported, reversal returns in January are highly positive, with an average return of 2.0% (t-stat of 5.8)[2.1]. The only other month with a statistically positive return is July, with an average return of 1.1% (t-stat of 3.0), with all other 10 months presenting performance statistically indistinguishable from zero.

As we hedge stocks exposures to 16 factors, performance of the reversal strategy spreads across all calendar months, with all months presenting statistically positive returns. When we only hedge for the 3 Fama-French factors, two months cease to be statistically significant.

As previously reported by Blitz *et al.* (2013), returns of short-term residual reversal are also spread across calendar months. In the 3 Fama-French factors case, only 6 months are statistically indistinguishable from zero, while for the 16 factors case, all months are statistically positive.

2.5.4
Results of Long and Short sides

The performance from conventional short-term reversal strategies comes solely from a larger return rebound of previous loser stocks compared to previous winner stocks. As shown in Panel B of Table E.10, long and short sides have an annualized return of 8.9% (t-stat of 4.0) and -5.6% (t-stat of -2.0), respectively.

Already, for hedged short-term reversal strategies, performance comes both from the long and short side portfolios. For the 16-factor hedged case, performance of long and short sides are respectively 6.7% (t-stat of 17.3) and 7.1% (t-stat of 20.3), both profitable after trading costs, with Sharpe ratio net of costs of 1.09 and 1.39 and performance after trading costs being statistically positive. When both sides are aggregated, the average turnover reduces, and net of costs performance increases more than the sum of both sides. It is important to mention two facts: i) the huge increase in performance from the short side, which goes from -5.6% (t-stat of -2.0) to 7.1% (t-stat of 20.3), much more than any metric of the unconditional Market risk premium that is lost

[2.1] As reported by other authors, this is due to the tax-loss selling effect, in which fund managers sell loser stocks at the end of years, resulting in a downward price pressure in December, followed by an upward price pressure in January.

when stocks are sold; ii) there is a decrease in the long side, from 8.9% to 6.7%, but less than other metrics of risk premium. Figure D.4 plots the performance over time from both long and short sides of the hedged short-term reversal strategy, showing that the performance are very similar over time.

Taken the case of only large-cap stocks, whose market value is above the NYSE median breakpoint, represented by the largest 800 stocks on average over time, both long and short sides continue to be profitable, with annualized returns of 5.3% (t-stat of 11.1) and 5.9% (t-stat of 12.5), also profitable after trading costs, with a net of costs Sharpe ratios of 0.39 and 0.56.

It is also important to mention that both long and short sides do not present crashes, with maximum drawdown being less than 10%.

2.6
Conclusion

This chapter shows the effects of factor momentum on conventional short-term single-equity reversal strategies in the US equity market, and then the benefits in the strategy performance that can be achieved if this influence is considered.

We propose a hedged short-term reversal strategy that neutralizes this influence, that is profitable after trading costs, even if we restrict our sample to only large-cap stocks, that do not present crashes, and has Sharpe ratio 2.5 times higher than the conventional reversal strategies, with values larger than 1.50.

This hedged strategy that we propose is superior to other alternative ways, such as the Short-term residual reversal proposed in Blitz *et al.* (2013) that consider stocks residual returns to define recent winner and loser, or to a "Pure short-term residual reversals" that consider both residual return and latter hedge stocks exposure to factors. This fact arises from a negative contemporaneous correlation between the idiosyncratic and the systematic components of stock returns, which is partially related to the lead-lag effects present within risk factors, as better described in Garcia *et al.* (2020a).

We also explore other aspects of the hedged short-term reversal and show that after the hedge, using one-week or one-month look-back windows lead to similar performance; and that a higher frequency daily rebalance strategy leads to higher returns, but also to a higher turnover, almost in the same proportion, indicating the existence of some kind of cost barrier; and that the seasonal pattern of regular reversal strategy is less pronounced in the hedged strategy, with all calendar months presenting positive and significant performance and finally show that after hedging.

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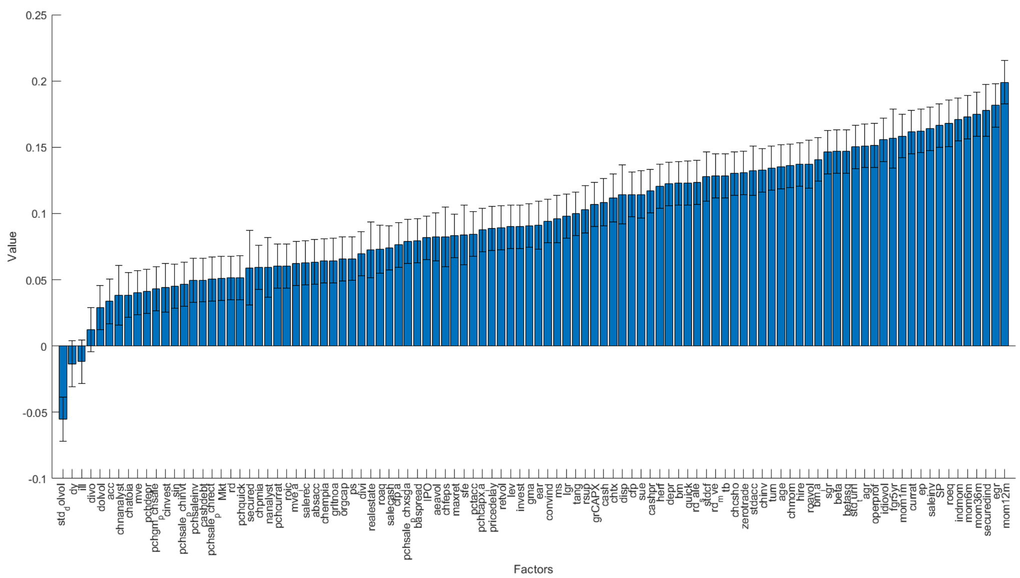
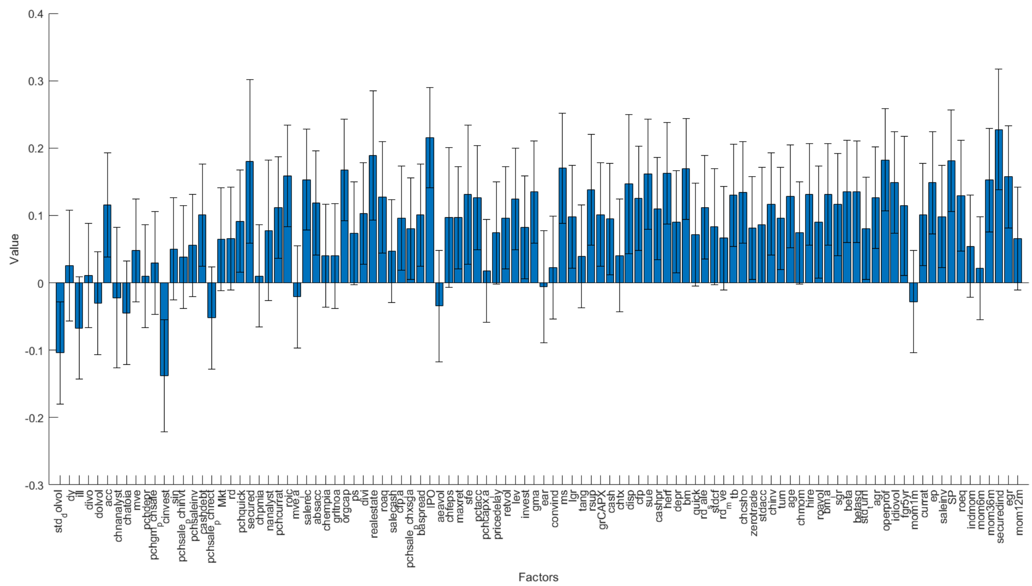
A
Figures of Chapter 1

Figure A.1: Factors autocorrelation



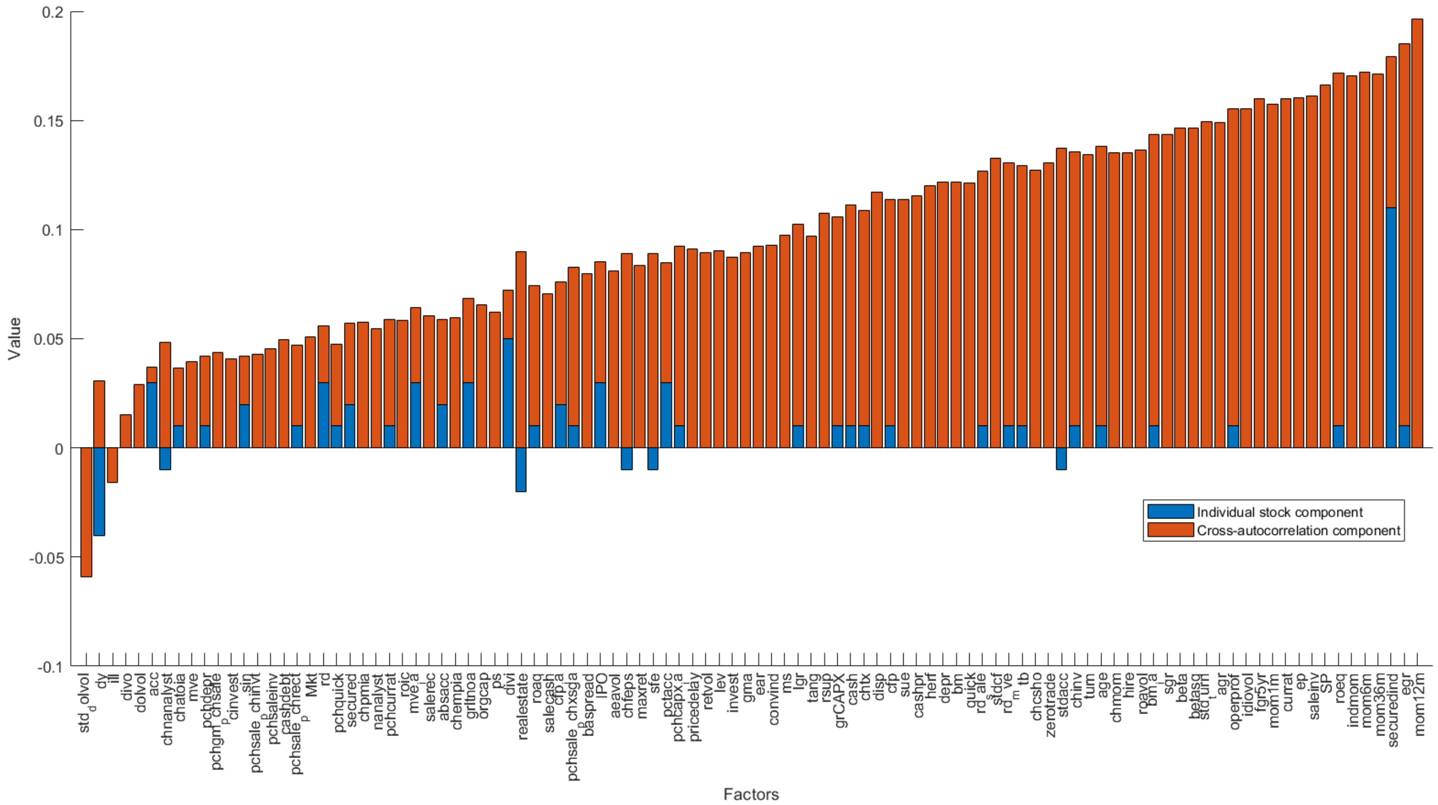
(a) daily frequency



(b) monthly frequency

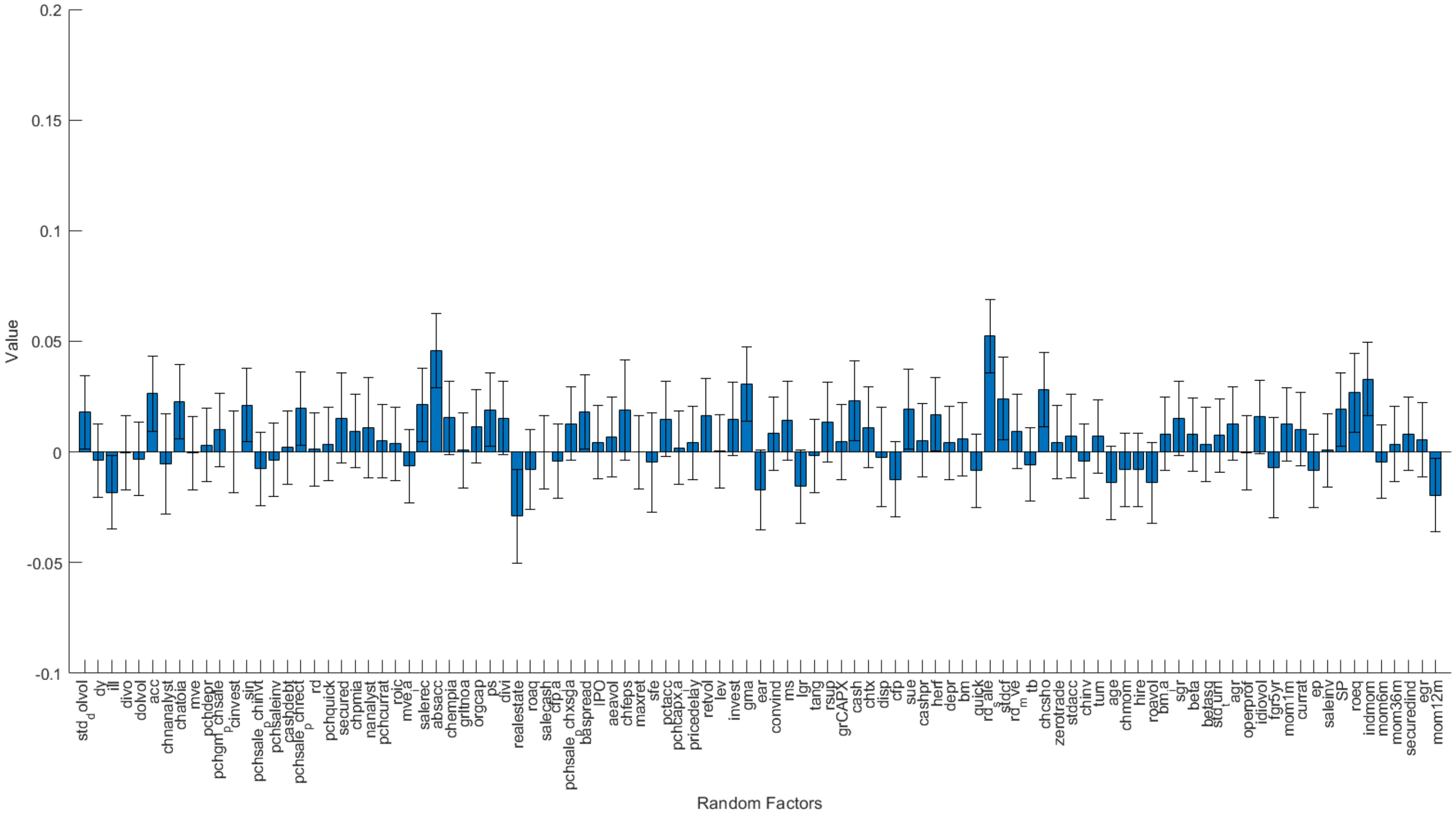
Notes: This figure reports the return autocorrelation for our sample of 103 factors along with 95% confidence intervals. This first order autocorrelation is computed using all factors returns available from Jul/1/1963 to Dec/31/2018. Panel A reports results for daily frequency and Panel B for monthly 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 A.2: Factor autocorrelation: individual and cross components (daily frequency)



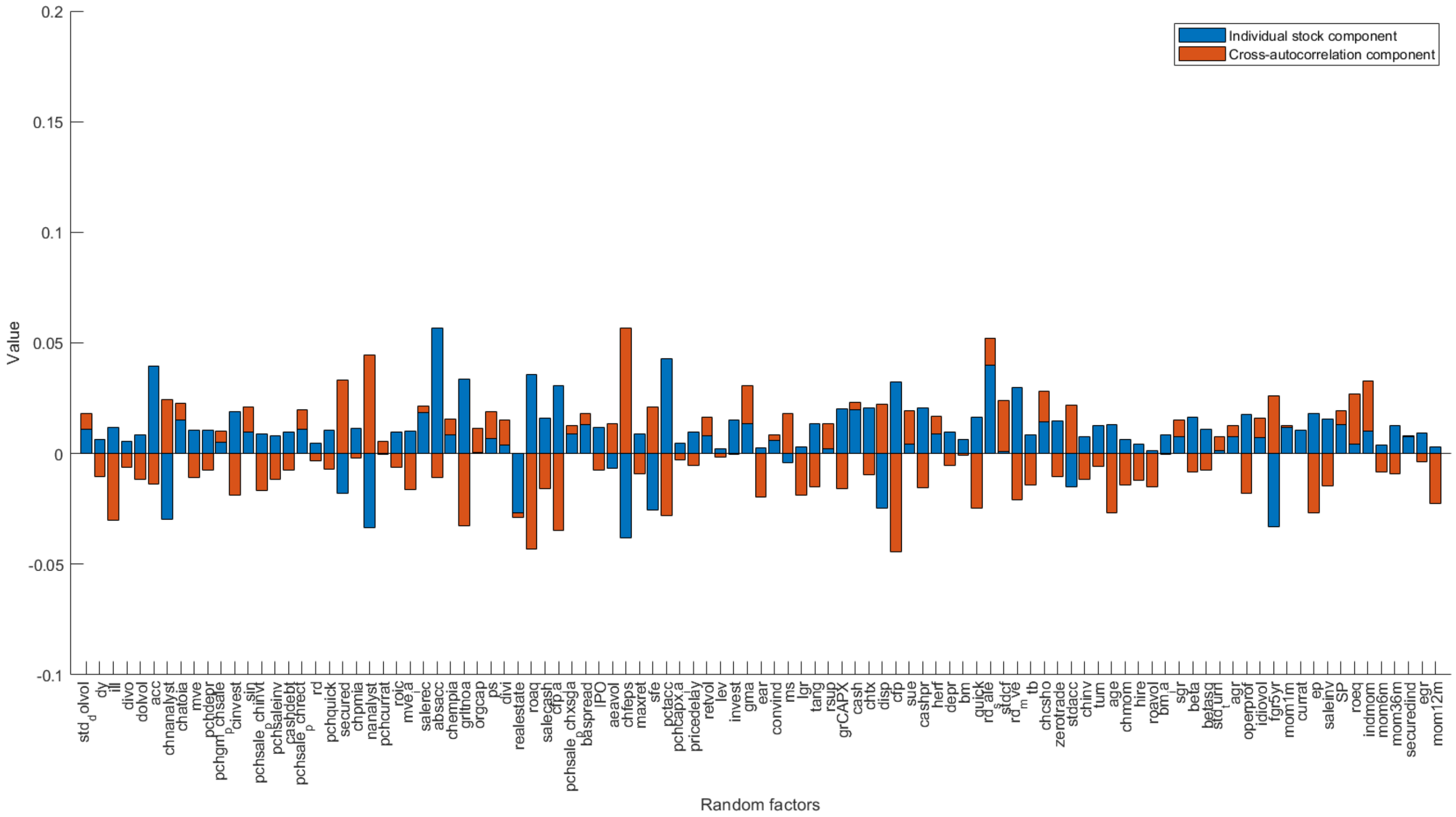
Notes: This figure reports the breakdown of factor returns autocorrelation into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, 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 A.3: Random factor autocorrelation (daily frequency)



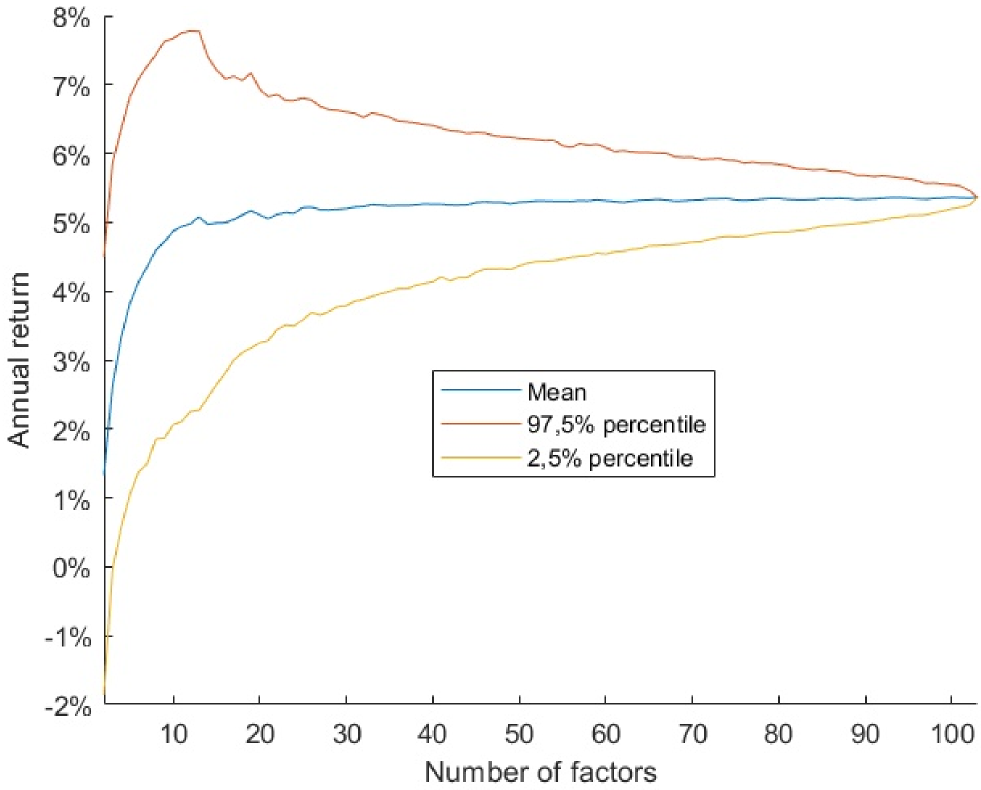
Notes: This figure reports the daily return autocorrelation for the 102 random factors that we construct using the same time-series of stocks returns, market value, and availability of characteristics from Jul/1/1963 to Dec/31/2018, but randomly sort stocks into high, neutral, or low portfolios to construct 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 A.4: Random factor autocorrelation: individual and cross components (daily frequency)



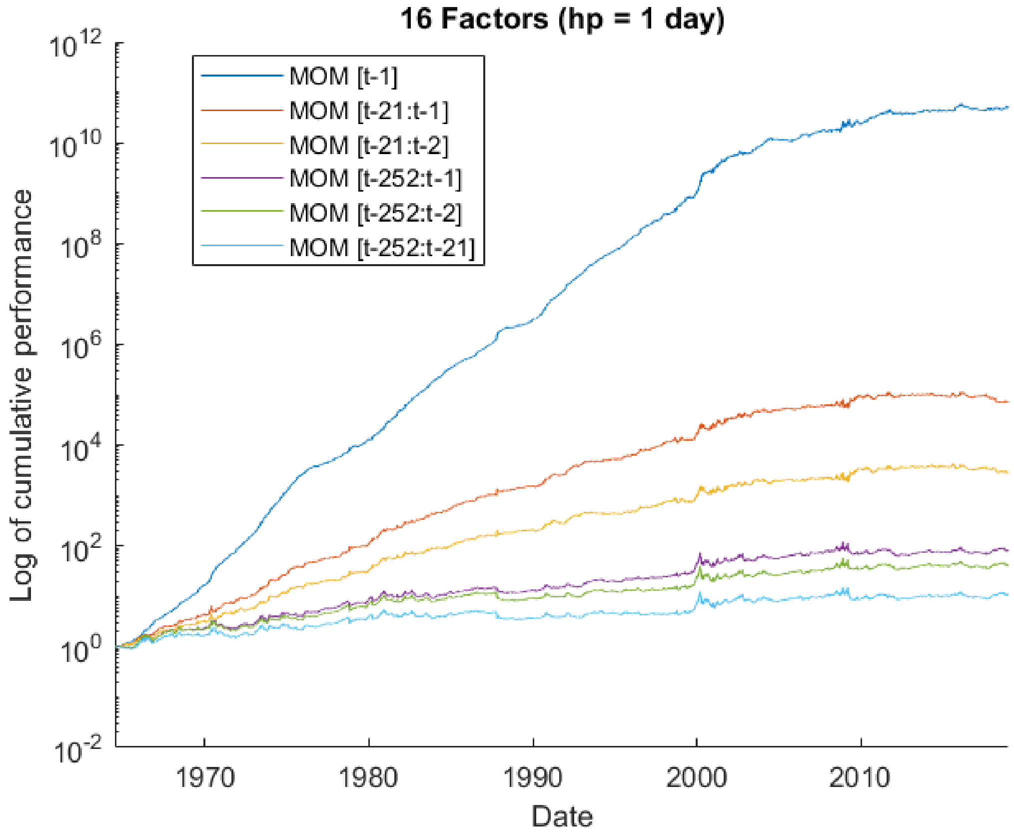
Notes: This figure reports the breakdown of the random factor returns autocorrelation into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 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 A.5: One-day Factor Momentum: Performance for random subsets



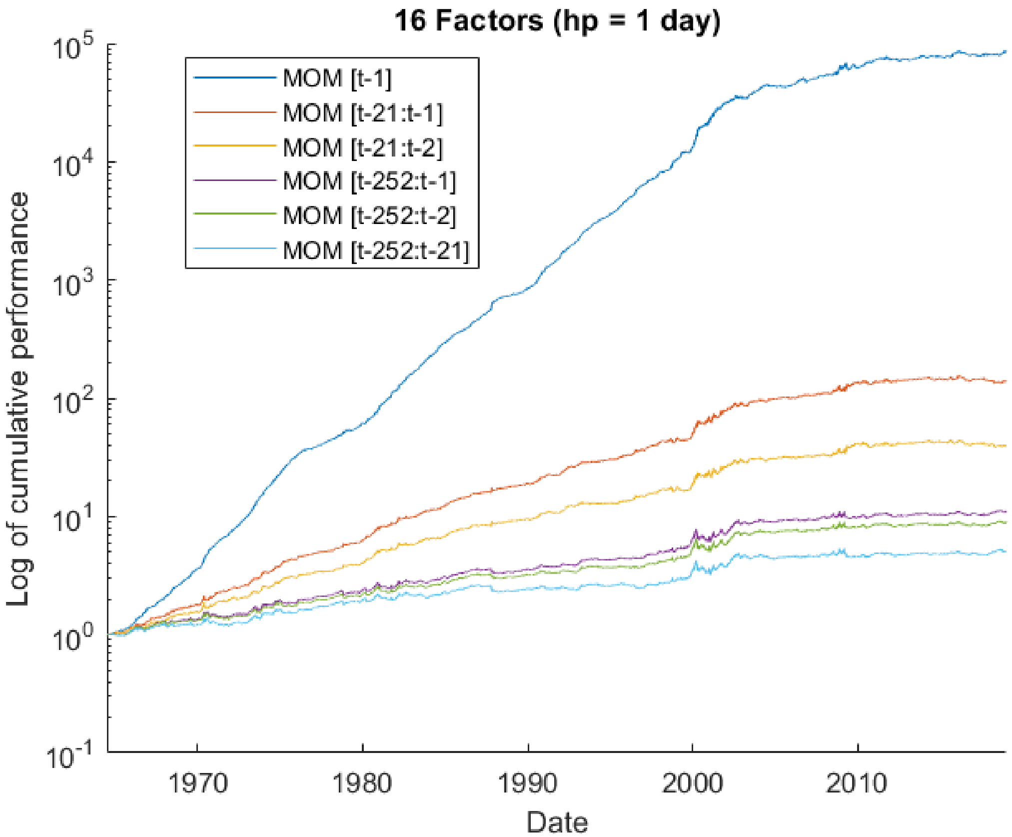
Notes: This figure plots the results for one-day momentum strategies constructed with random sets of factors, from sets of 2 to all 103 available factors. We use the bootstrap method with 50.000 simulations for each set size, from 2 to 103, and construct a factor momentum strategy. Blue line represents 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 & 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 A.6: Cross-section Factor Momentum: Performance



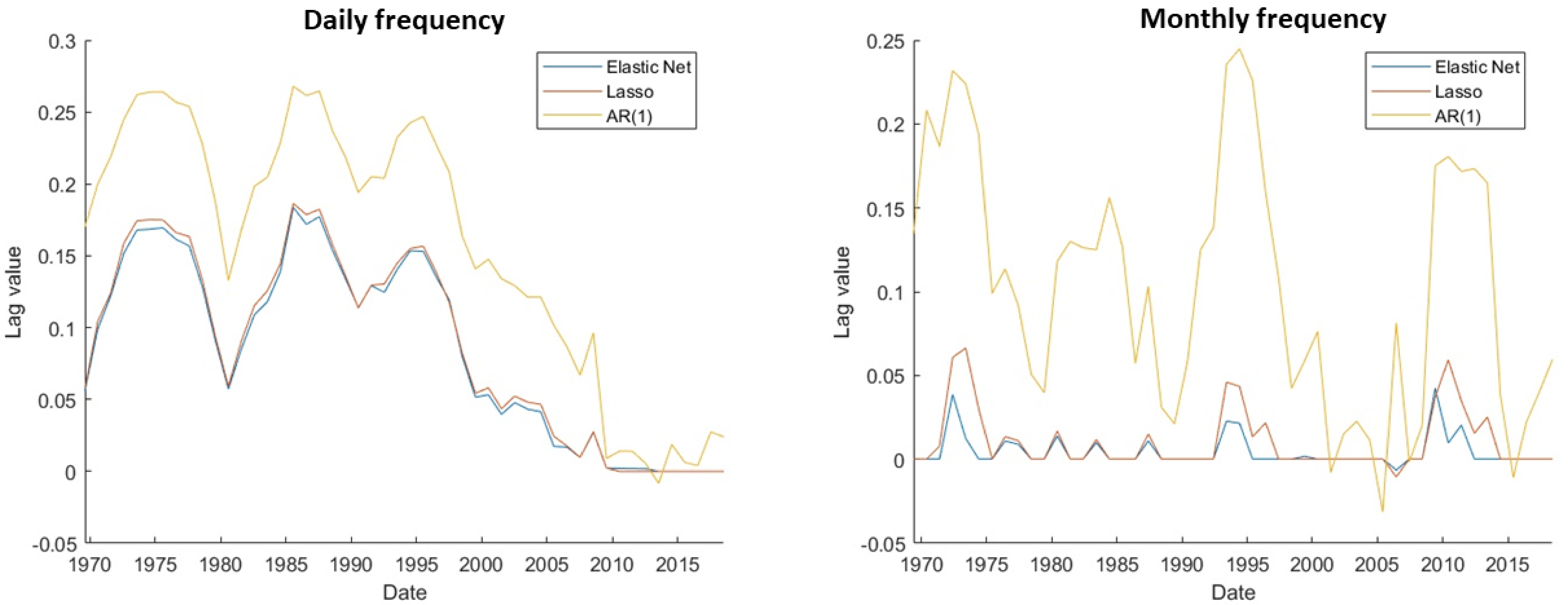
Notes: This figure plots the cumulative performance of cross-section factor momentum strategies, from 1963 to 2018, for several lookback windows: 1 day, 21 days (skipping and not 1 day) and 252 days (skipping and not 1 and 21 days) and a holding period of 1 day. To construct factor momentum strategies 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 A.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 lookback 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 lookback 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 A.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.

B
Tables of Chapter 1

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

Factors	Regular: Auto correlation	Regular: Components Individual	Regular: Components Cross	Regular: Components % of Cross	Industry-neutral: Auto correlation	Industry-neutral: Components Individual	Industry-neutral: Components Cross	Industry-neutral: Components % of Cross	Industry-neutral hedged: Auto correlation	Industry-neutral hedged: Components Individual	Industry-neutral hedged: Components Cross	Industry-neutral hedged: Components % 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 B.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 & 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 B.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 & 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 B.5: Factor Momentum: Spanning Tests

Cross-Section case	Regressor variables								
Hp = 21 days	**Alpha**	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**UMD**	**MOM[t-1]**	**MOM[t-21:t-1]**
MOM[t-1]	**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[t-21:t-1]	**-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[t-252:t-1]	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[t-1]	**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[t-21:t-1]	**-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[t-252:t-1]	**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 & French (2015) - MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD), and other factor momentum strategy with a different lookback 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 & 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 B.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**	**MOM[t-21:t-1] Loading**	**Excess return**	**Sharpe ratio**	**MOM[t-21:t-1] alpha**	**MOM[t-21:t-1] 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 & 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 B.7: Factor Momentum – other cases

Panel A	One day - MOM [t-1]				One month - MOM [t-21:t-1]			
Cross-Section Momentum	Holding period = 1 day		Holding period = 21 days		Holding period = 1 day		Holding period = 21 days	
	Excess return	Sharpe ratio	Excess return	Sharpe ratio	Excess return	Sharpe ratio	Excess return	Sharpe ratio
All Factors (103)	35.0%	3.41	4.1%	1.32	15.2%	1.40	6.4%	0.71
t-stat	22.2		9.7		10.1		5.5	
Large-cap Factors	57.3%	2.76	4.0%	0.73	16.0%	0.75	5.3%	0.32
t-stat	17.0		5.5		6.0		2.9	
Small-cap Factors	85.6%	3.74	11.2%	1.63	36.4%	1.58	11.6%	0.63
t-stat	21.0		11.7		10.9		5.1	
Long side of Factors	23.5%	3.41	3.3%	1.57	11.2%	1.57	4.2%	0.72
t-stat	23.1		11.6		11.3		5.5	
Short side of Factors	21.2%	2.45	2.8%	1.19	9.9%	1.13	4.3%	0.64
t-stat	16.9		8.8		8.4		4.9	
Random Factors	1.7%	0.58	-0.2%	-0.36	-1.2%	-0.43	-0.2%	-0.14
t-stat	4.4		-2.6		-3.1		-1.0	
Industry-neutral Factors	35.5%	3.32	4.5%	1.40	16.3%	1.44	4.5%	1.40
t-stat	21.5		10.3		10.4		10.3	
20 Industries portfolio	33.2%	2.96	3.1%	1.11	12.2%	1.04	5.4%	0.59
t-stat	19.5		8.2		7.8		4.6	
Factor-neutral Industries portfolio	17.8%	2.08	1.5%	0.69	5.6%	0.68	1.5%	0.69
t-stat	14.4		5.1		5.2		5.1	

Panel B	One day - MOM [t-1]				One month - MOM [t-21:t-1]			
Time-series Momentum	Holding period = 1 day		Holding period = 21 days		Holding period = 1 day		Holding period = 21 days	
	Excess return	Sharpe ratio	Excess return	Sharpe ratio	Excess return	Sharpe ratio	Excess return	Sharpe ratio
All Factors (103)	15.0%	3.46	7.7%	1.63	5.9%	1.46	3.5%	0.82
t-stat	24.2		11.9		10.7		6.2	
Large-cap Factors	25.6%	2.83	8.5%	0.90	7.3%	0.86	3.9%	0.45
t-stat	19.1		6.8		6.5		3.6	
Small-cap Factors	29.1%	3.29	17.9%	2.05	14.5%	1.86	7.3%	0.91
t-stat	21.8		14.4		13.2		6.9	
Long side of Factors	30.5%	2.21	13.6%	0.97	12.6%	0.90	3.9%	0.28
t-stat	14.9		7.3		6.8		2.6	
Short side of Factors	38.0%	2.23	14.3%	0.83	13.6%	0.80	4.0%	0.24
t-stat	14.7		6.4		6.2		2.4	
Random Factors	0.7%	0.57	-0.5%	-0.42	-0.4%	-0.41	-0.1%	-0.08
t-stat	4.3		-3.1		-3.1		-0.5	
Industry-neutral Factors	16.8%	3.31	8.8%	1.66	7.3%	1.52	8.8%	1.66
t-stat	23.0		12.0		11.1		12.0	
20 Industries portfolio	35.5%	2.69	9.8%	0.70	9.0%	0.69	2.4%	0.18
t-stat	17.6		5.5		5.4		1.8	
Factor-neutral Industries portfolio	8.6%	2.12	2.9%	0.71	2.3%	0.76	2.9%	0.71
t-stat	15.1		5.3		5.6		5.3	

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, with equal weight across factor/industry 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 & 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 and the Sharpe ratio.

Table B.8: 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%**

Panel B

16 Factors	**Elastic Net**			**Lasso**			**OLS & historical mean**		
Monthly frequency	**regular**	**without**	**1 year**	**regular**	**without**	**1 year**	**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”).

C
Supplement to Chapter 1

C.1
Individual and cross components of autocorrelation

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

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

The figure C.2 plots the breakdown of returns autocorrelation for our broad sample of 102 industry-neutral factors, into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects.

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

Figures C.3 and C.4 plot the breakdown of returns autocorrelation for our broad sample of large-cap and small-cap factors, into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects.

C.4
Factor-driven lead-lag effects for long and short sides of factor portfolios

Table C.1 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. Both long and short sides portfolio have high positive autocorrelation, with mean autocorrelation of 0.08 in both long and short portfolios, with the cross-component accounting for practically all of this result. This fact shows that lead-lag effects of factors come mostly 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 portfolio.

C.5
Redundancy of lead-lag effects between factors

Figure C.5 shows that all of the selected factors continue to have a statistically significant positive cross-autocorrelation component (i.e. the lead-lag effect), and figure C.5 shows that this cross-autocorrelation component continues to be very relevant, with almost 80% of the value from the regular factor. Eventual redundancies between the factors represent little more than 20% of the lead-lag effects on average.

Despite being very similar in their construction, E/P (earnings to price) continues to have additional lead-lag effects in relation to D/P (dividend yield) and CFP (cash flow to price), for example.

C.6
One-day factor momentum: cross-sectional or time-series?

In spanning tests, we confirm that one-day factor momentum in time-series dominates the cross-section case. Table C.2 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 & Kelly (2019).

C.7
Other cases of one-day factor momentum

Tables **??** and C.4 present results for a variety of cross-sectional and time-series momentum strategies using other subsets: i) all 103 factors, ii) large-cap factors, iii) small-cap factors, iv) long side of factor portfolios, v) short side of factor portfolios, vi) random factors, vii) industry-neutral factors, viii) 20 industry portfolios and ix) 20 factor-neutral industry portfolios.

We present results for the one-day ([t-1]), one-month ([t-21:t-1]), one-year ([t-252:t-1]) factor momemtum strategies, and the combined one-day to the one-month and one-year strategies. Besides the annualized excess return and Sharpe ratio, we also report the maximum drawdown in 3 months, and the annualized alpha for the Fama-French 5 factors plus traditional stock momentum (UMD). We found similar results for theses cases, with the one-day momentum (MOM[t-1]) presenting better performance in relation to one-month and one-year factor momentum strategies.

Table C.5 presents results for factor momentum for the sample of Kenneth French's database[C.1]: 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. We can expand our sample window and compute factor momentum from 1930 to 2018, but with only a few available factors.

Results for this database is also similar to results found in the rest of this paper with the one-day momentum (MOM[t-1]) presenting better performance in relation to one-month and one-year factor momentum strategies.

C.8
Performance of machine learning strategies

As shown in Table C.6, 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.

C.9
Hedged Short-term reversal strategies

Garcia *et al.* (2020b) shows the connection between conventional short-term reveral strategies (Jegadeesh (1990) and Jegadeesh (1990)) and the one-day factor momentum that is presented in this paper. Besides other points, Garcia *et al.* (2020b) find that the performance of short-term reversal strategies can be significantly improved when each stock of the winner and loser portfolio is hedged to different factors (Hedged Short-term reversal strategies).

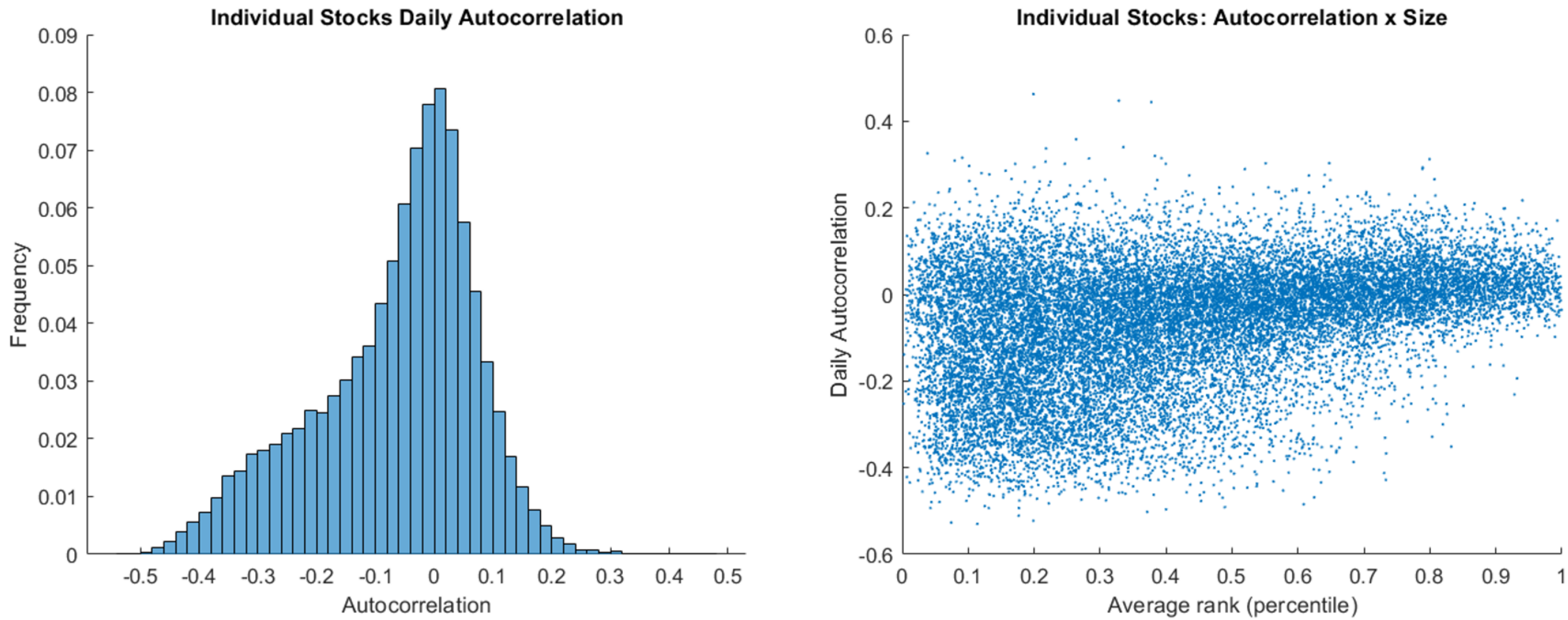
Table C.7 presents results for short-term reversals hedged for a variety of factors (Hedged STREV). The first point to emphasize is the huge performance difference when we depart the original case (STREV) and consider the short-

[C.1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html 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].

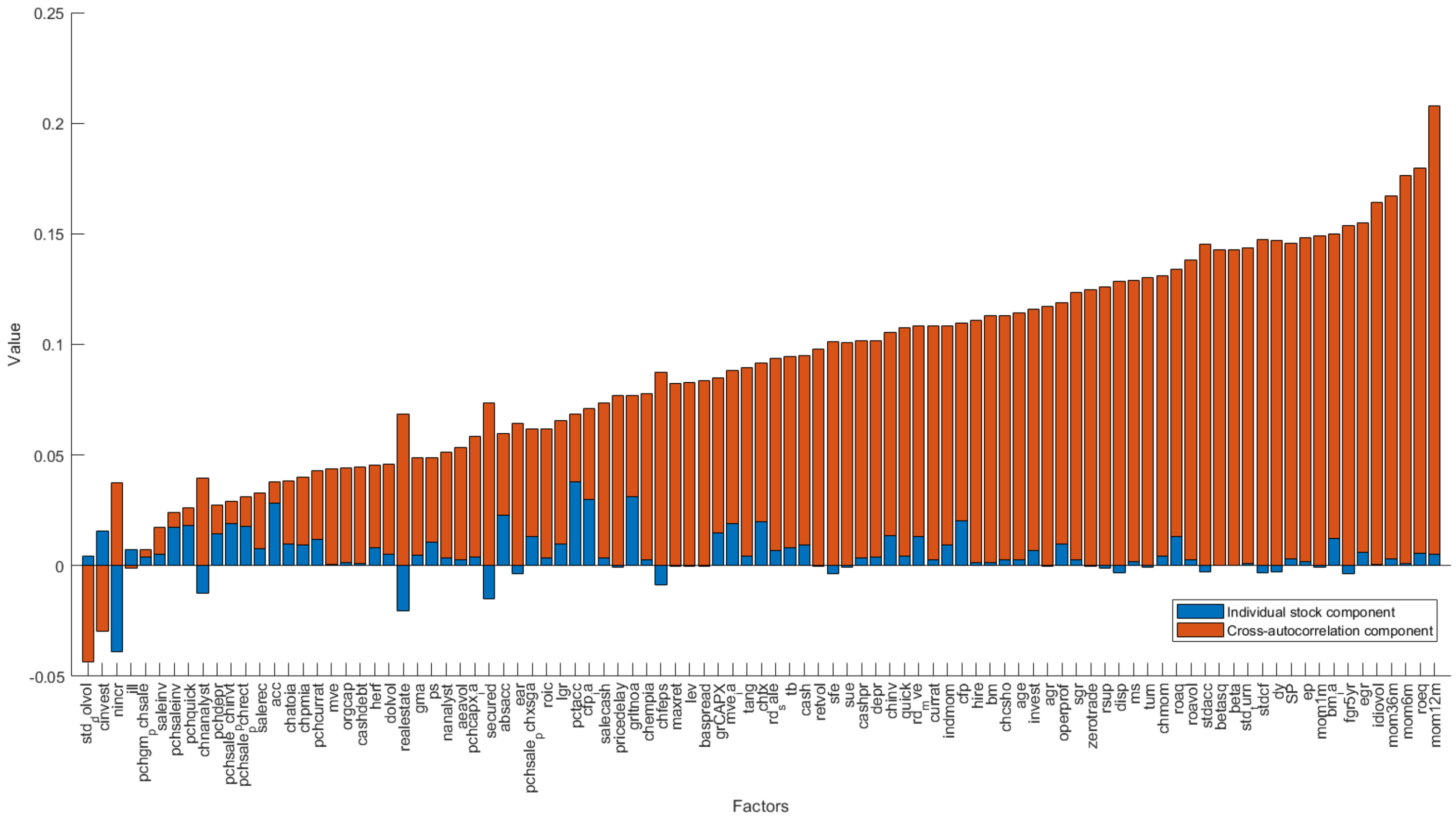
The loadings of CSMOM[t-1] also reinforce our points. STREV has a negative loading of -1.14 to CSMOM[t-1], evidencing that buying recent losers and selling recent winner stocks indirectly creates a negative exposure to factor momentum. This loading decreases significantly to -0.30 when we use the 3 Fama-French 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.

Figure C.1: Stocks daily autocorrelation



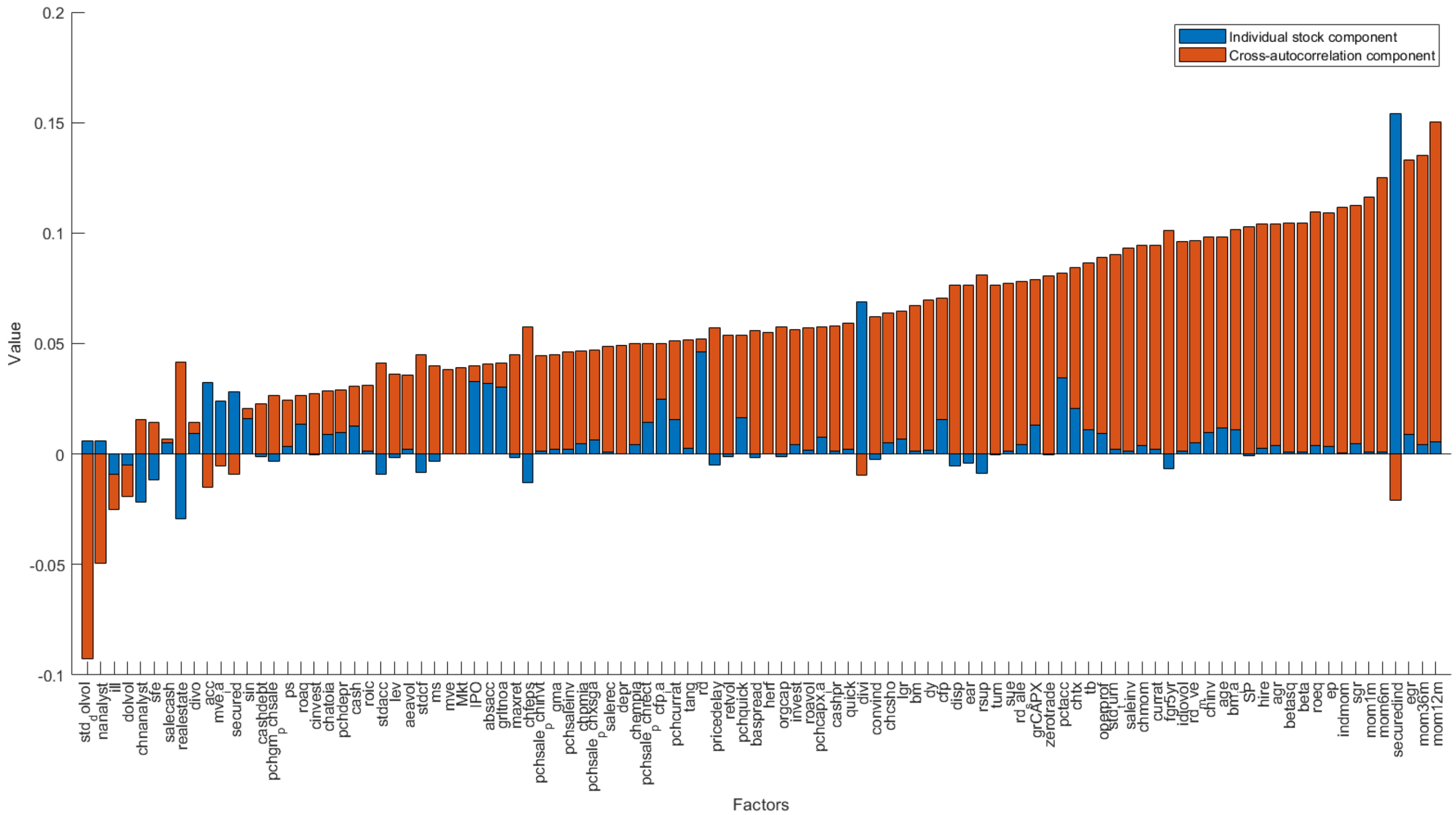
Notes: This figures plot the daily autocorrelation of individual stocks returns. Sample is composed by daily returns from Jul/1/1963 to Dec/31/2018 and 19.996 stocks. In the left is plotted the histogram of stocks autocorrelation and on the right a scatter plot of stocks autocorrelation and its size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

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



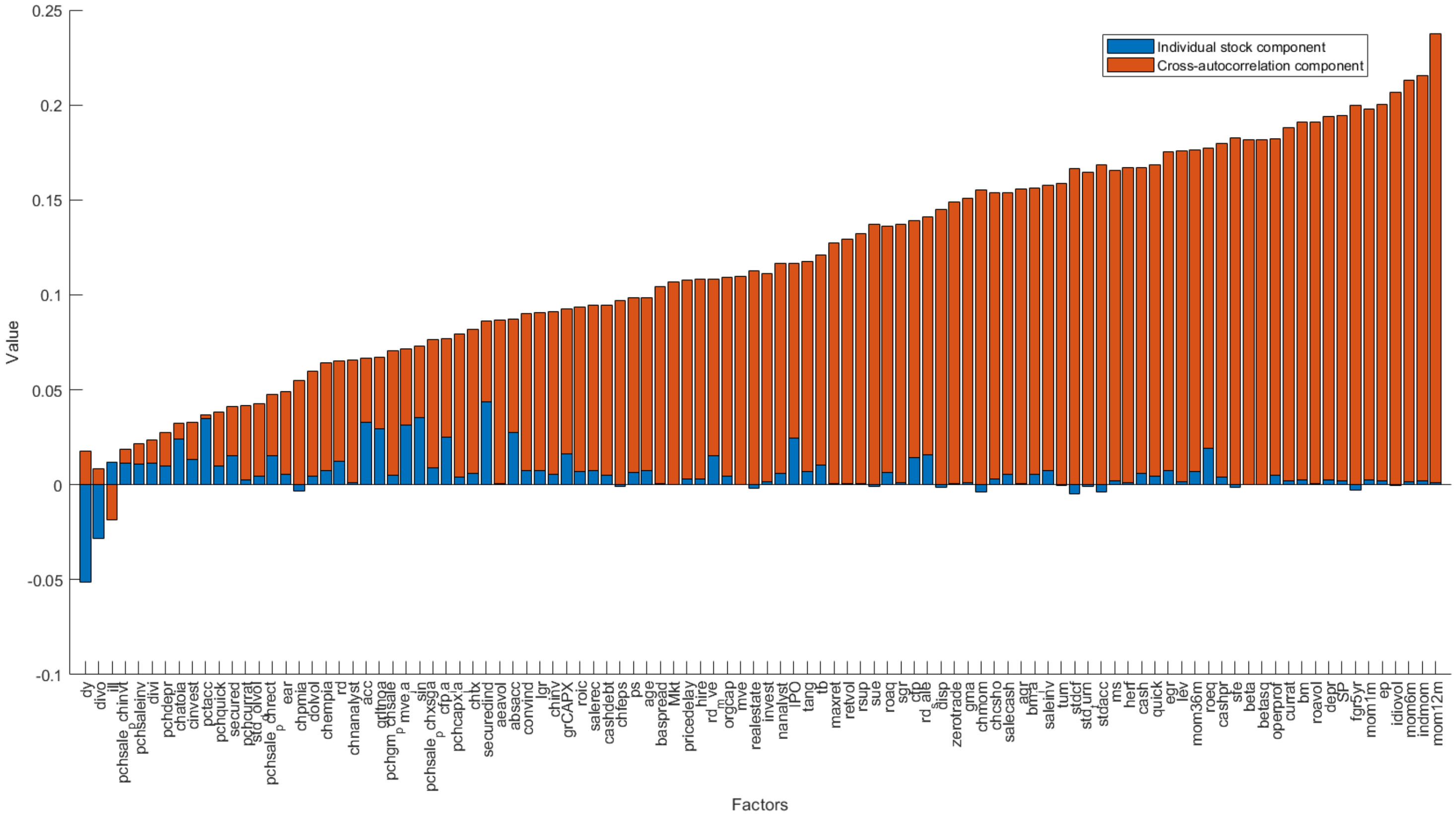
Notes: This figure reports the breakdown of industry-neutral factor autocorrelation into two different components: individual stocks autocorrelation and cross-autocorrelation between stocks, that is, the lead-lag effects. This two components are computed using daily stock returns data from Jul/1/1963 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 C.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 C.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 C.5: Lead-lag effect of double sort factor portfolios: t-stat of cross-autocorrelation component

	Cross-autocorrelation t-stat of Factor...																					
Neutral for factor...	mom12m	mom36m	sp	roeq	saleinv	ep	currat	mom1m	idiovol	std_turn	agr	betasq	beta	operprof	sgr	stdacc	chcsho	bm	cfp	retvol	invest	dy
mom12m	-	13,5	14,8	10,5	10,5	13,6	13,5	17,0	15,1	13,9	10,9	13,8	13,8	10,3	11,6	11,9	11,2	10,7	8,8	7,5	8,6	7,3
mom36m	20,3	-	14,9	10,3	9,7	14,6	12,8	17,3	15,0	15,8	7,5	14,7	14,7	10,1	7,1	13,6	9,2	10,1	7,6	9,8	5,7	3,8
sp	23,2	17,1	-	13,6	11,4	15,1	11,4	16,2	17,3	16,3	13,0	16,2	16,2	12,5	12,2	9,8	12,7	9,6	6,1	10,2	5,3	7,2
roeq	23,3	14,8	16,3	-	9,6	13,8	13,1	17,0	16,4	16,6	11,3	15,6	15,6	10,1	11,8	11,3	12,1	11,5	10,9	10,6	9,7	5,6
saleinv	22,0	15,4	14,1	11,2	-	15,0	10,5	14,9	16,6	14,0	11,9	15,3	15,3	9,8	12,0	9,8	12,2	10,5	8,0	8,9	4,6	8,2
ep	21,9	15,1	13,8	12,5	11,0	-	15,0	16,8	16,6	15,0	12,2	15,9	15,9	12,6	13,2	11,2	10,7	8,8	8,4	9,4	6,8	3,7
currat	22,1	17,0	13,8	13,6	4,4	15,2	-	16,0	17,2	16,5	15,7	16,6	16,6	13,8	15,2	12,7	13,1	12,3	11,1	10,1	7,3	6,7
mom1m	22,1	13,6	16,0	13,7	12,4	13,5	13,5	-	16,1	14,9	12,2	14,6	14,6	12,7	14,0	13,0	12,7	12,2	9,4	7,8	7,8	5,2
idiovol	19,4	11,5	12,4	10,3	8,8	10,2	11,9	15,8	-	4,1	12,0	7,7	7,7	12,1	8,5	7,5	5,8	10,7	7,2	4,6	3,7	2,9
std_turn	21,8	15,1	12,9	14,6	11,7	14,3	13,8	15,4	16,0	-	13,7	14,7	14,7	12,4	12,4	11,0	9,1	12,0	9,9	8,3	6,3	5,6
agr	22,5	15,8	17,1	15,0	12,3	16,0	14,4	17,1	17,5	16,6	-	16,1	16,1	11,6	6,7	15,5	12,9	10,2	10,9	10,5	4,0	5,5
betasq	22,5	8,9	13,5	12,0	8,6	11,3	12,4	17,1	7,5	9,5	8,1	-	-	11,6	9,0	9,0	4,8	10,8	8,1	5,3	4,9	2,9
beta	22,5	8,9	13,5	11,9	8,6	11,3	12,4	17,1	7,5	9,5	8,1	-	-	11,6	9,0	9,0	4,8	10,7	8,1	5,3	4,9	2,9
operprof	22,3	16,9	15,1	14,3	10,0	15,5	14,2	19,0	17,2	16,1	11,3	16,4	16,4	-	11,3	13,2	11,3	13,3	11,1	11,7	5,9	4,6
sgr	20,8	15,0	16,8	12,9	13,0	17,7	15,4	17,3	17,1	16,3	8,1	16,6	16,6	10,8	-	14,5	11,5	11,5	12,1	10,6	7,8	5,7
stdacc	21,7	14,4	13,0	14,5	13,2	11,9	11,6	16,5	14,7	15,1	12,3	15,1	15,1	12,4	12,7	-	12,5	13,6	10,5	10,3	7,3	4,5
chcsho	23,0	15,5	14,6	13,6	14,0	15,5	18,1	17,6	17,9	16,8	9,6	17,1	17,1	13,6	11,1	11,6	-	11,5	8,0	9,9	6,0	6,6
bm	22,4	14,0	9,6	9,7	10,1	9,8	12,9	17,2	15,4	15,8	7,9	15,0	15,0	9,9	9,5	13,3	10,4	-	9,3	10,6	3,1	6,1
cfp	19,7	12,8	10,3	11,1	9,6	7,9	12,0	13,8	16,1	12,5	7,1	14,4	14,4	10,3	6,6	8,6	9,0	7,8	-	8,1	3,6	5,5
retvol	23,9	13,4	22,0	12,7	10,7	13,2	12,6	16,1	16,0	7,6	11,1	15,6	15,6	11,7	10,7	8,8	8,7	11,8	7,6	-	5,9	6,0
invest	22,7	15,1	14,2	14,5	15,0	14,1	13,7	16,4	15,9	14,4	0,9	15,8	15,8	13,5	9,5	12,7	13,0	12,9	10,7	9,4	-	5,9
dy	30,2	18,3	17,8	14,2	15,8	4,3	16,1	23,3	14,9	14,5	7,6	20,0	20,1	15,1	12,1	7,3	7,8	7,9	8,0	12,9	4,9	-
t-stat of cross-correl of regular factor	23,7	20,1	19,9	17,8	19,3	19,2	19,2	18,8	18,6	17,9	17,8	17,5	17,5	17,2	17,1	14,5	15,2	14,5	12,1	10,6	10,4	3,5

Notes: This figure reports the t-stat of the cross-autocorrelation component between stocks of double-sorted factors. This cross component is computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the factors. This cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation, and represents the lead-lag effects. Subsection 3.2 describes with more details how each of the component is computed. Subsection 3.3.2 gives more details on how these factors are constructed. We use a conditional double sort approach to neutralize the effects of one factor to others, similar to the approach of Fama-French factor construction of the HML (High minus low) factor and other factors which are neutral to size based on double sorts.

Figure C.6: Lead-lag effect of double sort factor portfolios: percentage of the regular factor (t-stat of cross-autocorrelation component)

	% Cross-autocorrelation t-stat of neutral Factor in proportion of the regular Factor																					
Neutral for factor...	mom12m	mom36m	sp	roeq	saleinv	ep	currat	mom1m	idiovol	std_turn	agr	betasq	beta	operprof	sgr	stdacc	chcsho	bm	cfp	retvol	invest	dy
mom12m	-	67%	74%	59%	54%	71%	70%	90%	81%	78%	61%	79%	79%	60%	68%	82%	74%	74%	73%	70%	83%	209%
mom36m	86%	-	75%	58%	50%	76%	67%	92%	81%	89%	42%	84%	84%	58%	41%	94%	60%	70%	63%	92%	55%	109%
sp	98%	85%	-	76%	59%	78%	59%	86%	93%	91%	73%	93%	93%	72%	71%	67%	84%	66%	51%	95%	51%	208%
roeq	98%	74%	82%	-	50%	72%	68%	90%	88%	93%	64%	89%	89%	58%	69%	78%	80%	79%	90%	100%	94%	160%
saleinv	93%	77%	71%	63%	-	78%	55%	79%	89%	78%	67%	87%	87%	57%	70%	68%	81%	73%	66%	84%	44%	234%
ep	93%	75%	69%	70%	57%	-	78%	89%	89%	84%	68%	91%	91%	73%	77%	77%	71%	61%	70%	89%	65%	107%
currat	93%	85%	69%	76%	23%	79%	-	85%	93%	92%	88%	95%	95%	80%	89%	87%	86%	85%	92%	95%	71%	192%
mom1m	94%	68%	80%	77%	64%	70%	70%	-	87%	83%	69%	83%	84%	74%	82%	90%	84%	84%	78%	73%	75%	150%
idiovol	82%	57%	62%	58%	45%	53%	62%	84%	-	23%	67%	44%	44%	70%	49%	51%	38%	74%	59%	43%	36%	83%
std_turn	92%	75%	65%	82%	61%	74%	72%	82%	86%	-	77%	84%	84%	72%	73%	76%	60%	83%	82%	78%	61%	160%
agr	95%	79%	86%	84%	64%	83%	75%	91%	94%	93%	-	92%	92%	67%	39%	107%	85%	70%	90%	99%	38%	157%
betasq	95%	44%	68%	67%	44%	59%	64%	91%	41%	53%	46%	-	-	67%	53%	62%	32%	74%	67%	50%	47%	83%
beta	95%	44%	68%	67%	44%	59%	64%	91%	41%	53%	46%	-	-	67%	53%	62%	32%	74%	67%	50%	47%	83%
operprof	94%	84%	76%	80%	52%	80%	74%	101%	93%	90%	63%	94%	94%	-	66%	91%	75%	92%	92%	110%	56%	132%
sgr	88%	74%	85%	72%	67%	92%	80%	92%	92%	91%	46%	95%	95%	63%	-	100%	76%	79%	100%	100%	75%	165%
stdacc	92%	72%	65%	82%	68%	62%	61%	87%	79%	85%	69%	86%	86%	72%	75%	-	82%	93%	87%	97%	71%	129%
chcsho	97%	77%	73%	76%	73%	81%	94%	94%	96%	94%	54%	98%	98%	79%	65%	80%	-	80%	66%	93%	58%	191%
bm	95%	70%	48%	54%	52%	51%	67%	91%	83%	89%	45%	86%	86%	57%	55%	92%	69%	-	76%	99%	30%	174%
cfp	83%	64%	52%	62%	50%	41%	63%	73%	87%	70%	40%	82%	82%	60%	38%	60%	59%	54%	-	76%	35%	158%
retvol	101%	66%	110%	71%	55%	69%	66%	85%	86%	43%	62%	89%	89%	68%	63%	60%	57%	82%	63%	-	57%	171%
invest	96%	75%	71%	81%	77%	73%	72%	87%	85%	81%	5%	90%	90%	78%	56%	87%	86%	89%	88%	88%	-	169%
dy	128%	91%	90%	79%	82%	22%	84%	124%	80%	81%	43%	114%	115%	88%	71%	50%	51%	55%	66%	121%	47%	-
Mean	95%	72%	73%	71%	57%	68%	70%	90%	83%	78%	57%	88%	88%	69%	63%	77%	68%	76%	75%	86%	57%	154%

Notes: This figure reports the proportion of t-stat of the cross-autocorrelation component of double-sorted factors in proportion to the regular factor. This cross component is computed using daily stock returns data from Jul/1/1963 to Dec/31/2018, for each of the factors. This cross component is the contribution of stocks cross-autocorrelation for factor autocorrelation, and represents the lead-lag effects. Subsection 3.2 describes with more details how each of the component is computed. Subsection 3.3.2 gives more details on how these factors are constructed. We use a conditional double sort approach to neutralize the effects of one factor to others, similar to the approach of Fama-French factor construction of the HML (High minus low) factor and other factors which are neutral to size based on double sorts.

Table C.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 C.2: 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 & 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 & 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 C.3: 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
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
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

Table C.3: Cross-sectional Momentum: other cases (cont.)

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

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

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

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 & 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 C.4: 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

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

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

Table C.4: Time-series Momentum: other cases (cont.)

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**

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**

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 lookback 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 & 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 C.5: 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
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 C.5: Cross-section and time-series momentum for Kenneth French database (cont.)

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 (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.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 & 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 C.6: 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 & 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.

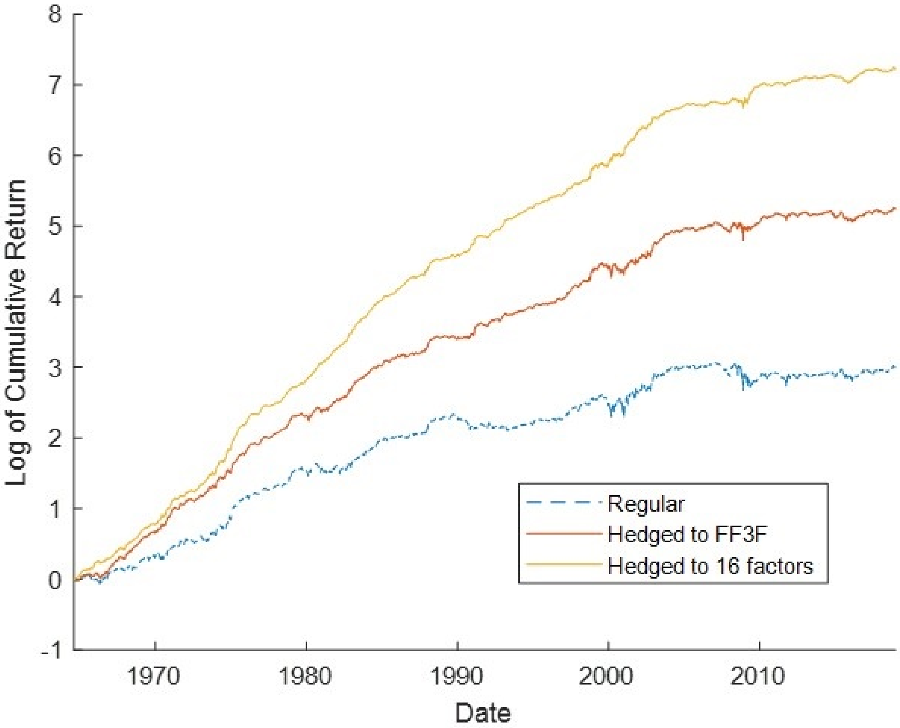
Table C.7: Hedged Short-term reversal

Short-term reversals 1-month	Excess return	Sharpe ratio	Max DD	Daily Turnover	Break-even trading cost	Alpha		Loading to Fact mom	
						3 factors	6f + CSMOM	Univariate	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 lookback 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 & French, 1993) and 5 Fama-French factors (FF5F) (Fama & 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.

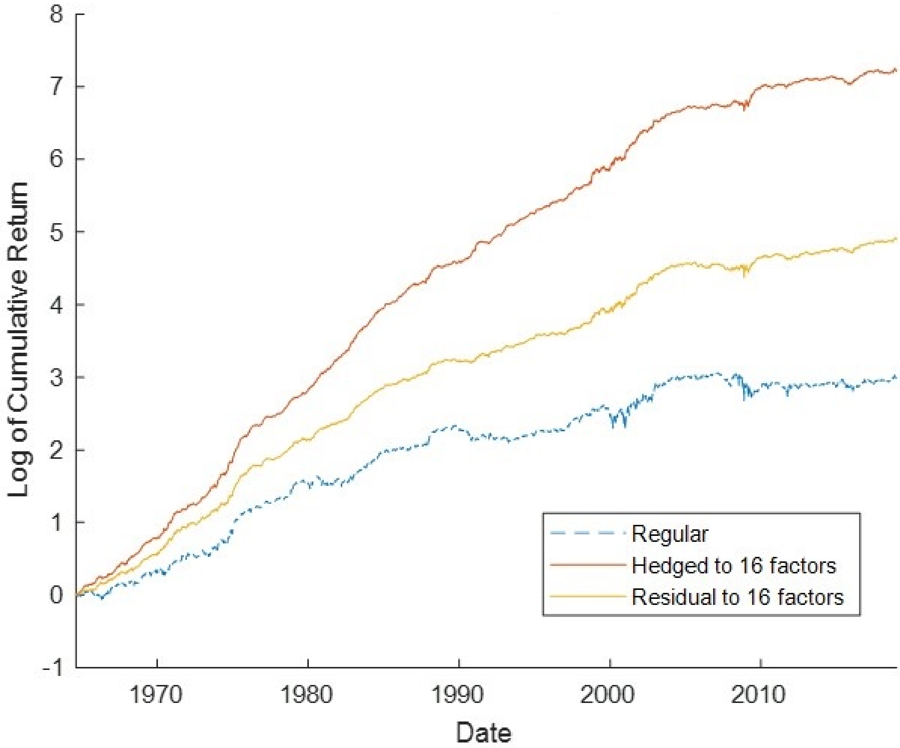
D
Figures of Chapter 2

Figure D.1: Hedged Short-term reversal strategies



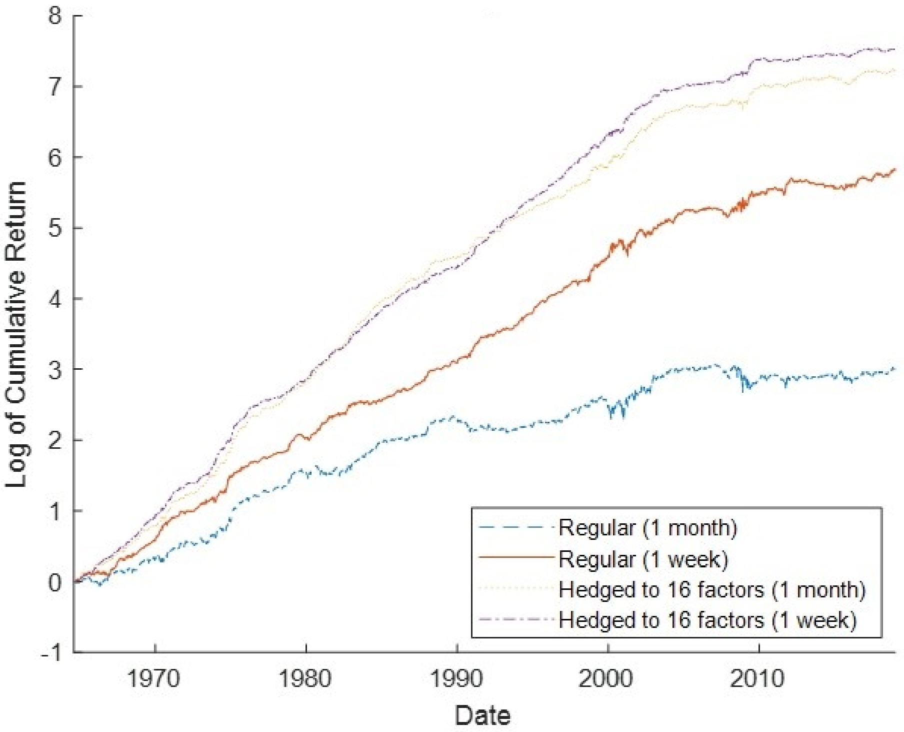
Notes: This figure plots the cumulative performance of conventional (or regular) short-term reversal and Hedged short-term reversal strategies to the 3 Fama-French factors (Fama & French, 1993) and to a broad sample of 16 factors, from Jul/1/1963 to Dec/31/2018. Conventional short-term reversal are constructed using one-month stocks total returns (Lehmann, 1990; Jegadeesh, 1990), and in hedged Short-term reversal strategies, each stock is hedged to its risk factor exposures, as better described in Section 2.4.

Figure D.2: Hedged and residual Short-term reversal strategies



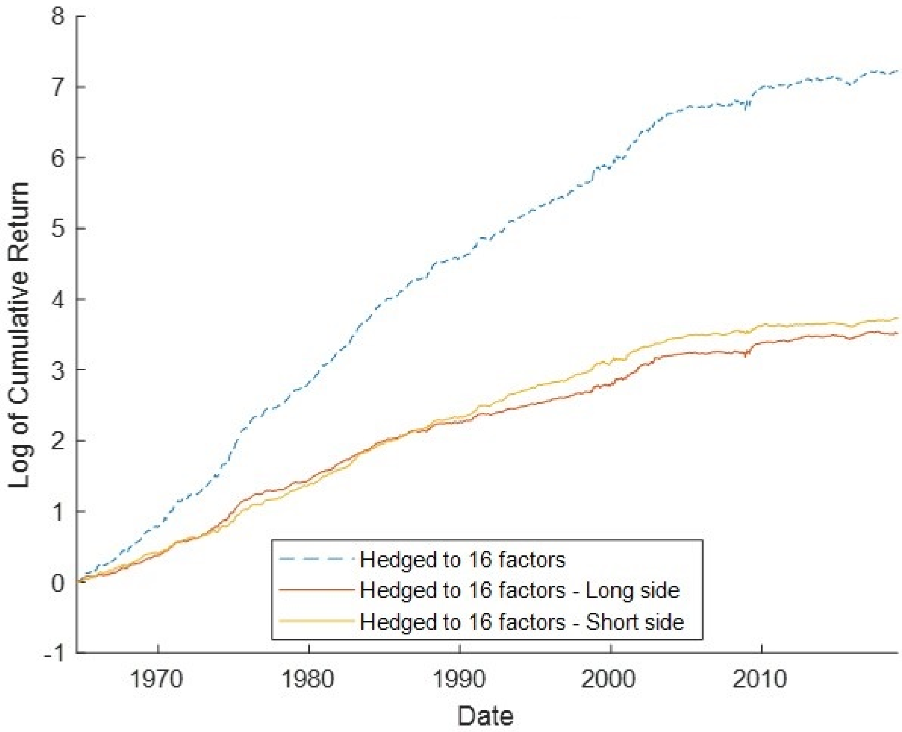
Notes: This figure plots the cumulative performance of conventional (or regular) short-term reversal, Short-term residual reversal and Hedged short-term reversal strategies to a broad sample of 16 factors, from Jul/1/1963 to Dec/31/2018. Conventional short-term reversal are constructed using one-month stocks total returns (Lehmann, 1990; Jegadeesh, 1990); Short-term residual reversal are constructed using residual returns to define winner and loser stocks; and in hedged Short-term reversal strategies, each stock is hedged to its risk factor exposures, as better described in Section 2.3.

Figure D.3: Effects of one-week and one-month look-back windows in Short-term reversal strategies



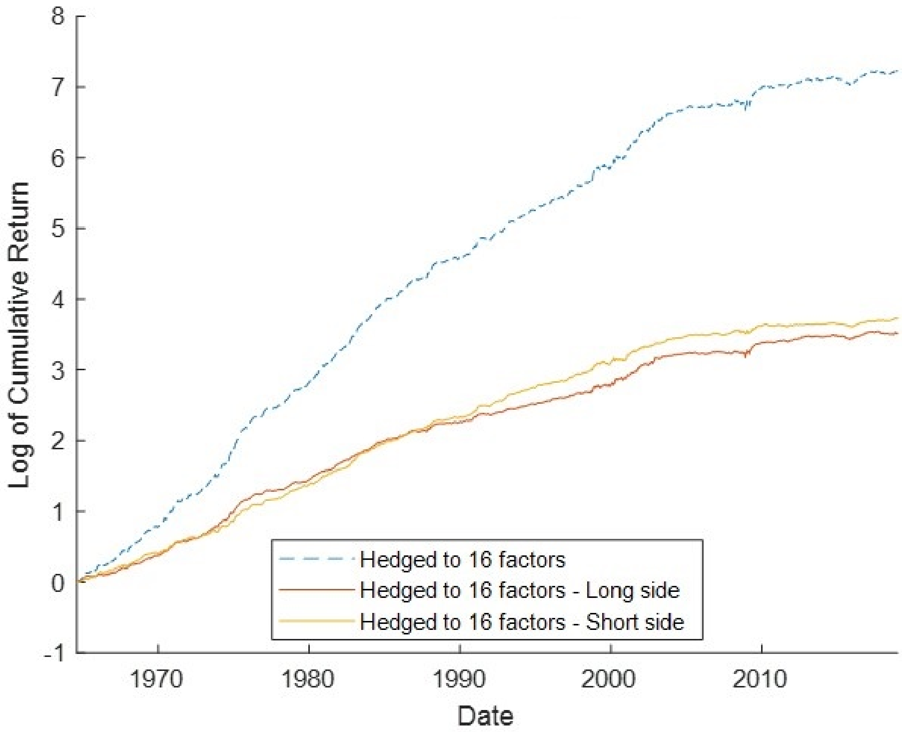
Notes: This figure plots the cumulative performance of conventional (or regular) short-term reversal and Hedged short-term reversal strategies to a broad sample of 16 factors, using two different look-back windows do define winner and loser stocks: one-week and one-month. In both cases, portfolios are rebalanced in the end of each month. Conventional short-term reversal are constructed using stocks total returns (Lehmann, 1990; Jegadeesh, 1990), and in hedged Short-term reversal strategies, each stock is hedged to its risk factor exposures, as better described in Section 2.4. Returns are computed from from Jul/1/1963 to Dec/31/2018.

Figure D.4: Long and short sides of Hedged Short-term reversal strategies



Notes: This figure plots the cumulative performance of both long and short sides from the Hedged short-term reversal strategies. We use one-month look-back window do define winner and loser portfolios (that will form the short and long side respectively), and a broad sample of 16 factors to hedge stock risk exposures, as better described in Section 2.5. Portfolios are rebalanced ate end of each month. Returns are computed from from Jul/1/1963 to Dec/31/2018.

Figure D.5: Hedged Short-term reversal strategies for Large-cap stocks



Notes: This figure plots the cumulative performance of both long and short sides from the Hedged short-term reversal strategies, using only large-cap stocks, whose market value is above the NYSE median breakpoint, represented by the largest 800 stocks on average over time, from Jul/1/1963 to Dec/31/2018. We use one-month look-back window do define winner and loser portfolios (that will form the short and long side respectively), and a broad sample of 16 factors to hedge stock risk exposures, as better described in Section 2.5. Portfolios are rebalanced ate end of each month.

E
Tables of Chapter 2

Table E.1: Connection of Short-term reversals and one-day Factor momentum

Short-term reversals (1-month)	Excess return	Sharpe ratio	Alpha 3 factors	6 factors	6f + facmom	Loading to Factor mom Univariate	Plus 6 factors
Regular	**5.7%**	0.59	**5.0%**	**7.4%**	**14.6%**	**-1.76**	**-1.65**
t-stat	**4.6**		**3.9**	**5.8**	**12.7**	**-33.8**	**-31.9**
Long side	**8.9%**	0.47	**1.7%**	**3.5%**	**7.2%**	**-2.34**	**-0.91**
t-stat	**4.0**		**2.2**	**4.8**	**11.0**	**-22.5**	**-29.3**
Short side	**-5.6%**	-	**3.3%**	**3.8%**	**6.9%**	**0.57**	**-0.74**
t-stat	**-2.0**		**5.3**	**6.2**	**12.2**	**5.8**	**-29.3**
Residual to FF3f	**7.5%**	1.15	**6.9%**	**8.7%**	**10.9%**	**-0.54**	**-0.50**
t-stat	**8.4**		**7.7**	**9.8**	**12.0**	**-12.1**	**-12.1**
Long side	**10.0%**	0.56	**2.8%**	**4.3%**	**5.5%**	**-1.70**	**-0.30**
t-stat	**4.6**		**5.1**	**8.1**	**10.4**	**-17.4**	**-13.4**
Short side	-5.0%	-	**4.0%**	**4.3%**	**5.1%**	**1.16**	**-0.19**
t-stat	-1.6		**8.9**	**9.5**	**10.9**	**11.4**	**-8.7**
Vol adj residual	**7.6%**	1.20	**7.2%**	**9.1%**	**11.3%**	**-0.52**	**-0.51**
t-stat	**8.8**		**8.2**	**10.3**	**12.5**	**-11.0**	**-11.7**

Notes: This table reports the performance of short-term reversal strategies. In the first three rows it is presented the conventional short-term reversal, constructed from one-month stocks total returns (Lehmann, 1990; Jegadeesh, 1990), opened by its long and short sides. In the following three rows it is presented the short-term residual reversal (Blitz *et al.*, 2013), constructed from residual stocks returns to the 3 Fama-French factors (Fama & French, 1993), also opened by its long and short sides. In the last row it is presented the short-term residual reversal, in which residual stocks returns are scaled by its volatility. We use daily returns from Jul/1/1963 to Dec/31/2018, and rebalance the factors at the end of each month, following the approach of Fama & French (1993) to construct the factor and weight the stock according to its market equity value, as better described in section 2.2. In the first two columns, it is reported the annualized excess return and Sharpe ratio. In the next three columns, it is reported the annualized alpha of time-series regressions, in which the right-hand-side variables are subsets of the returns from the Fama-French five factor (MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD) and one-day factor momentum, introduced by Garcia *et al.* (2020a). In the last two columns it is reported the loading values to one-day factor momentum from time-series regressions.

Table E.2: Hedged Short-term reversals

Short-term reversals (1-month)	**Excess return**	**Sharpe ratio**	**Max DD**	**Average Turnover**	**Net of costs Exc ret**	**Net of costs SR**	**Break-even trading cost**	**Alpha 3 factors**	**Alpha 6 factors**	**Alpha 6f + facmom**	**Loading to Fact mom Univariate**	**Loading to Fact mom Plus 6 factors**
Regular	**5.7%**	0.59	-33%	3.6	1.2%	0.12	0.13%	**5.0%**	**7.4%**	**14.6%**	**-1.76**	**-1.65**
t-stat	**4.6**				1.0			**3.9**	**5.8**	**12.7**	**-33.8**	**-31.9**
Hedged to Mkt	**6.5%**	0.86	-25%	3.7	1.8%	0.24	0.14%	**6.0%**	**8.1%**	**12.2%**	**-0.98**	**-0.94**
t-stat	**6.4**				1.8			**5.8**	**8.0**	**12.3**	**-21.1**	**-21.7**
Hedged to SMB	**6.3%**	0.69	-34%	4.0	**4.9%**	0.77	0.13%	**5.6%**	**8.0%**	**14.3%**	**-1.54**	**-1.44**
t-stat	**5.3**				**4.2**			**4.6**	**6.6**	**12.7**	**-29.7**	**-28.7**
Hedged to HML	**7.8%**	1.00	-30%	3.8	**3.1%**	1.00	0.17%	**6.8%**	**9.0%**	**12.5%**	**-0.88**	**-0.82**
t-stat	**7.4**				**3.0**			**6.4**	**8.5**	**11.9**	**-15.4**	**-16.1**
Hedged to ST_REV	**5.9%**	0.65	-28%	4.0	**4.9%**	0.77	0.12%	**6.0%**	**6.7%**	**12.8%**	**-1.44**	**-1.42**
t-stat	**5.0**				**4.2**			**4.8**	**5.4**	**11.1**	**-27.7**	**-27.2**
Hedged to UMD	**7.4%**	0.91	-32%	3.7	**2.8%**	0.34	0.16%	**6.6%**	**9.1%**	**13.6%**	**-1.16**	**-1.01**
t-stat	**6.8**				**2.6**			**5.98**	**8.50**	**13.22**	**-21.93**	**-22.44**
Hedged to FF3f	**10.1%**	1.58	-22%	4.0	**4.9%**	0.77	0.20%	**9.5%**	**11.5%**	**13.7%**	**-0.51**	**-0.50**
t-stat	**11.3**				**5.7**			**10.5**	**13.1**	**15.5**	**-11.9**	**-13.7**
Hedged to 6 factors	**12.6%**	2.25	-21%	4.3	**6.9%**	1.24	0.23%	**12.0%**	**13.6%**	**14.9%**	**-0.33**	**-0.28**
t-stat	**15.8**				**8.9**			**15.1**	**17.6**	**19.1**	**-8.7**	**-9.3**
Hedged to 9 factors	**12.9%**	2.69	-13%	4.4	**7.0%**	1.47	0.23%	**12.4%**	**13.9%**	**14.1%**	**-0.10**	-0.04
t-stat	**18.8**				**10.6**			**18.1**	**21.0**	**21.1**	**-3.3**	-1.7
Hedged to 12 factors	**13.2%**	2.87	-11%	4.5	**7.2%**	1.57	0.23%	**12.8%**	**14.1%**	**14.1%**	-0.05	0.00
t-stat	**20.0**				**11.3**			**19.5**	**21.9**	**21.6**	-1.9	-0.1
Hedged to 16 factors	**14.2%**	3.12	-11%	4.7	**7.9%**	1.74	0.23%	**13.9%**	**15.1%**	**14.8%**	0.02	**0.07**
t-stat	**21.7**				**12.4**			**21.2**	**23.4**	**22.6**	0.8	**2.8**

Notes: This table reports the performance of Hedged Short-term reversal strategies, in which each stock is hedged to its risk factor exposures, as better described in section 2.3. The first row presents results for conventional short-term reversal, constructed from one-month stocks total returns (Lehmann (1990) and Jegadeesh (1990)). The following five rows present results for hedged strategies to only one risk factor (MKT, SMB HML, ST rev, UMD). The following 5 rows present results for Hedged Short-term reversal strategies, to several subsets of risk factors, from the 3 factors of Fama & French (1993) to a large subset of 16 factors, described in section 2.3. It´s reported the annualized excess return; Sharpe ratio; maximum drawdown in 3 months horizons; average monthly turnover; net of costs annualized excess returns and Sharpe ratio, using trading costs estimates of Frazzini *et al.* (2015); the break even trading cost, that is, the cost per unit of turnover that would erode all the performance; the annualized alphas of time-series regressions to several risk factors (Fama & French (2015) - MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD) and one-day factor momentum, introduced by Garcia *et al.* (2020a), and the loading value to one-day factor momentum. We use daily returns from Jul/1/1963 to Dec/31/2018.

Table E.3: Short-term residual reversal

Short-term reversals (1-month)	Excess return	Sharpe ratio	Max DD	Average Turnover	Net of costs Exc ret	Net of costs SR	Break-even trading cost	Alpha 3 factors	Alpha 6 factors	Alpha 6f + facmom	Loading to Fact mom Univariate	Loading to Fact mom Plus 6 factors
Regular	**5.7%**	0.59	-33%	3.6	1.2%	0.12	0.13%	**5.0%**	**7.4%**	**14.6%**	**-1.76**	**-1.65**
t-stat	**4.6**				1.0			**3.9**	**5.8**	**12.7**	**-33.8**	**-31.9**
Residual to Mkt	**6.3%**	0.81	-24%	3.6	1.9%	0.24	0.14%	**5.9%**	**8.0%**	**12.4%**	**-1.09**	**-1.01**
t-stat	**6.1**				1.8			**5.5**	**7.6**	**12.1**	**-23.0**	**-21.5**
Residual to SMB	**5.5%**	0.62	-32%	3.6	1.2%	0.12	0.12%	**4.7%**	**7.3%**	**13.5%**	**-1.54**	**-1.43**
t-stat	**4.7**				1.0			**4.0**	**6.2**	**12.6**	**-31.3**	**-30.2**
Residual to HML	**7.5%**	0.94	-30%	3.6	**3.0%**	0.37	0.17%	**6.8%**	**8.5%**	**11.8%**	**-0.79**	**-0.76**
t-stat	**7.0**				**2.8**			**6.1**	**7.5**	**9.8**	**-10.6**	**-11.1**
Residual to ST_REV	**5.6%**	0.63	-27%	3.6	1.1%	0.13	0.13%	**5.1%**	**7.7%**	**13.5%**	**-1.48**	**-1.35**
t-stat	**4.9**				1.0			**4.3**	**6.6**	**12.3**	**-27.8**	**-25.4**
Residual to UMD	**6.4%**	0.78	-25%	3.6	1.9%	0.23	0.14%	**5.4%**	**7.7%**	**12.1%**	**-1.17**	**-1.01**
t-stat	**5.9**				1.8			**4.9**	**7.0**	**11.3**	**-20.7**	**-19.8**
Residual to FF3F	**7.5%**	1.15	-22%	3.5	**3.0%**	0.47	0.17%	**6.9%**	**8.7%**	**10.9%**	**-0.54**	**-0.50**
t-stat	**8.4**				**3.5**			**7.7**	**9.8**	**12.0**	**-12.1**	**-12.1**
Residual to 6 factors	**8.0%**	1.47	-17%	3.5	**3.5%**	0.65	0.18%	**7.5%**	**8.8%**	**10.0%**	**-0.32**	**-0.28**
t-stat	**10.6**				**4.8**			**9.9**	**11.6**	**12.9**	**-9.1**	**-8.4**
Residual to 9 factors	**9.0%**	1.82	-15%	3.5	**4.5%**	0.91	0.20%	**8.6%**	**9.8%**	**10.2%**	**-0.11**	**-0.09**
t-stat	**13.0**				**6.7**			**12.3**	**14.2**	**14.5**	**-3.3**	**-2.9**
Residual to 12 factors	**9.0%**	1.85	-15%	3.5	**4.5%**	0.93	0.20%	**8.5%**	**9.7%**	**10.1%**	**-0.10**	**-0.08**
t-stat	**13.3**				**6.8**			**12.6**	**14.6**	**14.9**	**-3.2**	**-2.9**
Residual to 16 factors	**9.4%**	1.98	-15%	3.5	**4.9%**	1.03	0.21%	**9.0%**	**10.1%**	**10.4%**	**-0.10**	**-0.07**
t-stat	**14.1**				**7.5**			**13.4**	**15.3**	**15.5**	**-3.1**	**-2.5**

Notes: This table reports the performance of Short-term residual reversal strategies, in which winner and loser stocks are defined according to their residual returns, as better described in section 2.3. The first row presents results for conventional short-term reversal, constructed from one-month stocks total returns (Lehmann, 1990; Jegadeesh, 1990). The following five rows present results for strategies using only one risk factor to define stocks residual returns (MKT, SMB HML, ST rev, UMD). The following 5 rows present results for strategies using different subsets of risk factors, from the 3 factors of Fama & French (1993) to a large subset of 16 factors. It´s reported the annualized excess return; Sharpe ratio; maximum drawdown in 3 months horizons; average monthly turnover; net of costs annualized excess returns and Sharpe ratio, using trading costs estimates of Frazzini *et al.* (2015); the break even trading cost, that is, the cost per unit of turnover that would erode all the performance; the annualized alphas of time-series regressions to several risk factors (Fama & French (2015) - MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD) and one-day factor momentum, introduced by Garcia *et al.* (2020a), and the loading value to one-day factor momentum. We use daily returns from Jul/1/1963 to Dec/31/2018.

Table E.4: Spanning tests of Hedged Short-term reversals and Short-term residuals

Case of 16 factors	**Regressor variables**										
(1-month)	**Alpha**	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**UMD**	**Fact mom**	**ST regular**	**ST hedged**	**ST residual**
ST hedged	**8.3%**										**0.59**
t-stat	**16.4**										**54.3**
	13.2%								**0.16**		
	21.6								**16.7**		
	15.1%	**0.01**	**0.04**	0.01	**-0.05**	**-0.03**	**-0.09**				
	23.4	**2.3**	**5.0**	1.0	**-3.8**	**-2.2**	**-12.4**				
	7.8%	0.00	**0.01**	**-0.02**	**-0.04**	-0.02	**-0.03**	**0.26**	**0.09**		**0.51**
	14.6	1.1	**2.0**	**-2.4**	**-3.2**	-1.3	**-4.1**	**9.8**	**8.9**		**36.9**
ST residual	0.4%									**0.65**	
t-stat	0.7									**47.96**	
	8.1%								**0.22**		
	13.6								**20.4**		
	10.1%	**0.01**	**0.05**	**0.04**	-0.01	-0.02	**-0.10**				
	15.3	**2.1**	**6.3**	**3.7**	-0.4	-1.7	**-15.0**				
	0.6%	**-0.01**	**0.02**	**0.05**	**0.04**	0.00	**-0.03**	**0.15**	**0.16**	**0.52**	
	1.2	**-2.5**	**2.6**	**4.9**	**3.4**	0.0	**-5.4**	**5.1**	**16.0**	**38.7**	

Notes: This table reports spanning regressions in which the dependent variable is the hedged short-term reversal (or the short-term residual reversal), both considering 16 factors, as better described in section 2.3, and the right-hand-side variables are the returns of the Fama-French five factor (Fama & French (2015) - MKT, SMB, HML, RMW, CMA), stock momentum (UMD), the one-day factor momentum (Garcia *et al.*, 2020a) and the short-term residual reversal (or the hedged short-term reversal). We use the subsample of 16 factors, described in subsection 4.1, to hedge or compute stock residual returns. The alpha is annualized and reported in excess of the risk free rate. The first three rows reports results for the hedged short-term reversal as the dependent variable, the next three ones use the short-term residual reversal as the dependent variable. We use daily returns from Jul/1/1963 to Dec/31/2018. Section 2.3 presents more details of the spanning tests and how both hedged and residual short-term reversal strategies are constructed.

Table E.5: Pure Short-term residual reversal

Short-term reversals (1-month)	Excess return	Sharpe ratio	Max DD	Alpha 3 factors	Alpha 6 factors	Alpha Plus FACMOM	Loading to Fact mom Univariate	Loading to Fact mom Plus 6 factors
Regular	**5.7%**	0.59	-33%	**5.0%**	**7.4%**	**14.6%**	**-1.76**	**-1.65**
t-stat	**4.6**			**3.9**	**5.8**	**12.7**	**-33.8**	**-31.9**
To Mkt	**5.8%**	0.78	-26%	**5.2%**	**7.4%**	**11.1%**	**-0.93**	**-0.86**
t-stat	**5.9**			**5.2**	**7.4**	**11.4**	**-20.6**	**-20.7**
To SMB	**4.8%**	0.54	-34%	**4.0%**	**6.4%**	**12.2%**	**-1.46**	**-1.36**
t-stat	**4.2**			**3.4**	**5.5**	**11.3**	**-28.8**	**-28.4**
To HML	**5.7%**	0.72	-29%	**4.8%**	**7.0%**	**10.8%**	**-0.97**	**-0.90**
t-stat	**5.4**			**4.5**	**6.6**	**10.2**	**-18.0**	**-17.9**
To ST_REV	**5.6%**	0.66	-26%	**5.5%**	**6.9%**	**12.0%**	**-1.28**	**-1.20**
t-stat	**5.1**			**4.8**	**6.0**	**10.9**	**-23.9**	**-21.6**
To UMD	**5.8%**	0.65	-30%	**5.2%**	**8.0%**	**12.9%**	**-1.28**	**-1.13**
t-stat	**5.0**			**4.3**	**6.6**	**10.9**	**-17.3**	**-19.3**
To FF3F	**5.0%**	0.80	-22%	**4.5%**	**6.4%**	**8.9%**	**-0.62**	**-0.59**
t-stat	**6.0**			**5.2**	**7.8**	**10.9**	**-17.2**	**-18.2**
To 6 factors	**4.9%**	0.87	-19%	**4.4%**	**6.2%**	**8.4%**	**-0.57**	**-0.52**
t-stat	**6.5**			**5.7**	**8.4**	**11.6**	**-16.7**	**-18.4**
To 9 factors	**5.3%**	0.98	-16%	**4.9%**	**6.7%**	**8.7%**	**-0.52**	**-0.47**
t-stat	**7.3**			**6.5**	**9.5**	**12.6**	**-16.0**	**-17.6**
To 12 factors	**4.9%**	0.96	-17%	**4.5%**	**6.3%**	**7.9%**	**-0.44**	**-0.39**
t-stat	**7.1**			**6.4**	**9.5**	**12.1**	**-13.3**	**-15.1**
To 16 factors	**4.9%**	0.98	-15%	**4.5%**	**6.2%**	**7.6%**	**-0.40**	**-0.36**
t-stat	**7.2**			**6.4**	**9.4**	**11.7**	**-12.8**	**-14.3**

Notes: This table reports the performance of "pure short-term residual reversal strategies", in which we define winner and loser stocks according to its residual returns and then hedge their exposure to risk factors, as better described in subsection 4.4. The first row presents results for conventional short-term reversal, constructed from one-month stocks total returns (Lehmann, 1990; Jegadeesh, 1990). The following five rows present results for pure short-term residual reversal to only one risk factor (MKT, SMB HML, ST REV, UMD). The following five rows present results for pure short-term residual reversal to several subsets of risk factors, from the 3 factors of Fama & French (1993) to a large subset of 16 factors, described in Section 2.3. It´s reported the annualized excess return; Sharpe ratio; maximum drawdown in 3 months horizons; average monthly turnover; net of costs annualized excess returns and Sharpe ratio, using trading costs estimates of Frazzini *et al.* (2015); the break even trading cost, that is the cost per unit of turnover that would erode all the performance; the annualized alphas of time-series regressions to several risk factors (Fama & French (2015) - MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD) and one-day factor momentum (introduced by Garcia *et al.* (2020a), and the loading value to one-day factor momentum. We use daily returns from Jul/1/1963 to Dec/31/2018.

Table E.6: Components of return from Losers and Winners stocks in the sorting period

Panel A: Sort on return

	Formation period 1-month	Excess return	Loading do Mkt Univariate	Loading do Mkt Plus facmom	Loading to Fact momentum Univariate	Loading to Fact momentum Plus Mkt	Loading to Fact momentum Plus 6 factors
Long side	Total return	-67.9%	1.08	1.04	-1.99	-0.70	-0.64
	t-stat	-44.9	123.1	136.7	-17.5	-11.9	-12.7
	Systematic	-21.2%	1.07	1.04	-1.85	-0.57	-0.50
	t-stat	-9.1	134.7	151.3	-16.6	-10.1	-10.7
	idiosyncratic	-58.2%	-0.01	-0.01	-0.09	-0.11	-0.12
	t-stat	-221.4	-3.5	-5.7	-7.5	-9.0	-9.7
Short side	Total return	240.6%	1.01	1.03	-0.83	0.44	0.54
	t-stat	53.3	106.1	112.4	-7.2	6.5	10.6
	Systematic	41.4%	0.98	1.00	-0.79	0.44	0.54
	t-stat	16.0	106.7	114.7	-7.0	6.8	11.3
	idiosyncratic	135.5%	0.01	0.01	-0.02	-0.01	-0.01
	t-stat	237.4	6.10	5.97	-1.6	-0.5	-0.5
Total	Total return	-90.7%	0.07	0.02	-1.16	-1.14	-1.18
	t-stat	-170.4	4.9	1.2	-9.7	-9.7	-12.0
	Systematic	-44.4%	0.09	0.04	-1.07	-1.02	-1.05
	t-stat	-47.6	6.6	3.5	-9.2	-8.9	-11.2
	idiosyncratic	-82.4%	-0.02	-0.03	-0.07	-0.10	-0.11
	t-stat	-258.2	-5.3	-6.6	-2.9	-4.3	-4.6

Panel B: Sort on residuals

	Formation period 1-month	Excess return	Loading do Mkt Univariate	Loading do Mkt Plus facmom	Loading to Fact momentum Univariate	Loading to Fact momentum Plus Mkt	Loading to Fact momentum Plus 6 factors
Long side	Total return	-60.6%	1.02	1.01	-1.33	-0.09	0.01
	t-stat	-40.0	114.6	116.7	-13.7	-2.8	0.6
	Systematic	16.5%	1.03	1.04	-1.24	0.03	0.14
	t-stat	7.3	140.3	142.6	-12.6	1.2	8.9
	idiosyncratic	-66.2%	-0.02	-0.02	-0.09	-0.13	-0.13
	t-stat	-255.6	-6.1	-8.5	-5.2	-7.1	-7.3
Short side	Total return	173.3%	1.08	1.07	-1.49	-0.17	-0.07
	t-stat	42.5	212.3	214.8	-14.3	-6.0	-3.4
	Systematic	-3.4%	1.06	1.05	-1.48	-0.19	-0.10
	t-stat	-0.8	240.5	239.4	-14.8	-8.4	-6.8
	idiosyncratic	182.9%	0.02	0.02	-0.01	0.02	0.02
	t-stat	269.9	7.6	8.1	-0.4	1.1	1.3
Total	Total return	-85.7%	-0.06	-0.06	0.15	0.08	0.09
	t-stat	-226.1	-6.2	-6.1	3.3	1.9	2.1
	Systematic	20.4%	-0.02	-0.01	0.24	0.23	0.24
	t-stat	43.1	-3.3	-1.9	7.5	7.5	9.1
	idiosyncratic	-88.2%	-0.04	-0.04	-0.09	-0.14	-0.15
	t-stat	-285.1	-7.3	-8.9	-2.7	-4.5	-4.7

Notes: This table reports the decomposition of the return of recent winner and loser stocks (respective the short and long sides of the short-term reversal strategies), in their formation period. The return of these groups of stocks is decomposed into their systematic component of return, measured by their factor betas multiplied by its respective factor returns, and their idiosyncratic components of return, represented by the estimated residuals. To compute the systematic and idiosyncratic components of returns, we use a broad sample of 16 factors. Paneal A presents the results for stocks sorted on the their total returns (conventional short-term residual, as in Lehmann (1990) and Jegadeesh (1990)), and Panel B presents the results for stocks sorted on the their residual returns. It´s reported the annualized excess return and the loading values to Market and to the one-day factor momentum (introduced by Garcia *et al.* (2020a)), from time-series regressions. We use daily returns from Jul/1/1963 to Dec/31/2018. Better details of the procedures used can be found in subsection 4.4.1.

Table E.7: Short-term reversals hedged to factors: one-week and one-month look-back windows

Short-term reversals (1-month)	**Excess return**	**Sharpe ratio**	**Max DD**	**Average Turnover**	**Net of costs Exc ret**	**Net of costs SR**	**Break-even trading cost**	**Alpha 3 factors**	**Alpha 6 factors**	**Alpha 6f + facmom**	**Loading to Fact mom Univariate**	**Loading to Fact mom Plus 6 factors**
Regular 1-month	**5.7%**	0.59	-33%	3.6	1.2%	0.12	0.13%	**5.0%**	**7.4%**	**14.6%**	**-1.76**	**-1.65**
t-stat	**4.6**				1.0			**3.9**	**5.8**	**12.7**	**-33.8**	**-31.9**
Regular 1-week	**11.3%**	1.40	-16%	3.6	**6.6%**	0.82	0.25%	**11.9%**	**12.5%**	**15.9%**	**-0.81**	**-0.78**
t-stat	**10.1**				**6.0**			**10.2**	**10.4**	**13.0**	**-12.2**	**-12.6**
Hedged (FF3f) 1-month	**10.1%**	1.58	-22%	4.0	**4.9%**	0.77	0.20%	**9.5%**	**11.5%**	**13.7%**	**-0.51**	**-0.50**
t-stat	**11.3**				**5.7**			**10.5**	**13.1**	**15.5**	**-11.9**	**-13.7**
Hedged (FF3f) 1-week	**13.8%**	2.52	-8%	4.0	**8.4%**	1.54	0.27%	**13.6%**	**14.3%**	**15.4%**	**-0.25**	**-0.24**
t-stat	**17.6**				**11.0**			**17.3**	**18.1**	**19.2**	**-8.0**	**-8.1**
Hedged (16f) 1-month	**14.2%**	3.12	-11%	4.7	**7.9%**	1.74	0.23%	**13.9%**	**15.1%**	**14.8%**	0.02	**0.07**
t-stat	**21.7**				**12.4**			**21.2**	**23.4**	**22.6**	0.8	**2.8**
Hedged (16f) 1-week	**14.8%**	3.37	-7%	4.8	**8.4%**	1.91	0.24%	**14.6%**	**15.5%**	**15.4%**	-0.04	0.02
t-stat	**23.3**				**13.6**			**23.0**	**24.4**	**24.0**	-1.5	0.8

Notes: This table reports the performance of Hedged Short-term reversal strategies, in which each stock is hedged to its risk factor exposures, as better described in Section 2.3. It is used to different look-back windows do define winner and loser stocks, 1 week and 1 month, and the portfolio is rebalanced in the end of each month. The first two rows presents results for conventional short-term reversal, constructed from one-month and one-week stocks total returns. The next two rows present results for Hedged Short-term reversal strategies to the 3 Fama-French factors (Fama & French, 1993), and the last two rows the results for a large subset of 16 factors, described in Section 2.3. It´s reported the annualized excess return; Sharpe ratio; maximum drawdown in 3 months horizons; average monthly turnover; net of costs annualized excess returns and Sharpe ratio, using trading costs estimates of Frazzini *et al.* (2015); the break even trading cost, that is, the cost per unit of turnover that would erode all the performance; the annualized alphas of time-series regressions to several risk factors (Fama & French (2015) - MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD) and one-day factor momentum, introduced by Garcia *et al.* (2020a), and the loading value to one-day factor momentum. We use daily returns from Jul/1/1963 to Dec/31/2018.

Table E.8: Hedged Short-term reversals

Panel A: Daily rebalance and one-month look-back window

Short-term reversals (1-month)	Excess return	Sharpe ratio	Max DD	Average Turnover	Net of costs Exc ret	Net of costs SR	Break-even trading cost	Alpha 3 factors	Alpha 6 factors	Alpha 6f + facmom	Loading to Fact mom Univariate	Loading to Fact mom Plus 6 factors
Regular	**29.6%**	2.69	-24%	15.6	**7.5%**	0.68	0.14%	**28.9%**	**30.4%**	**44.4%**	**-2.71**	**-2.61**
t-stat	**17.8**				**4.9**			**18.1**	**18.8**	**37.1**	**-42.1**	**-44.3**
Hedged to FF3f	**40.1%**	5.42	-16%	18.3	**12.5%**	1.69	0.15%	**39.5%**	**41.2%**	**47.0%**	**-1.03**	**-1.02**
t-stat	**33.9**				**11.8**			**33.6**	**34.8**	**40.8**	**-19.9**	**-21.8**
Hedged to 6 factors	**44.7%**	6.78	-16%	20.2	**13.6%**	2.06	0.15%	**43.9%**	**45.6%**	**50.0%**	**-0.81**	**-0.76**
t-stat	**41.6**				**14.3**			**41.5**	**43.3**	**48.4**	**-18.9**	**-20.1**
Hedged to 9 factors	**44.1%**	7.74	-10%	21.2	**11.8%**	2.07	0.14%	**43.4%**	**45.1%**	**47.5%**	**-0.49**	**-0.43**
t-stat	**47.5**				**14.5**			**47.5**	**49.5**	**51.9**	**-14.2**	**-14.1**
Hedged to 12 factors	**44.4%**	8.11	-8%	21.8	**11.2%**	2.04	0.14%	**43.9%**	**45.4%**	**47.6%**	**-0.45**	**-0.38**
t-stat	**49.7**				**14.3**			**49.7**	**51.5**	**53.6**	**-13.8**	**-13.0**
Hedged to 16 factors	**46.3%**	8.63	-8%	22.8	**11.3%**	2.11	0.14%	**45.8%**	**47.2%**	**49.1%**	**-0.38**	**-0.32**
t-stat	**52.5**				**14.8**			**52.6**	**54.3**	**55.5**	**-11.5**	**-10.6**

Panel B: Daily rebalance and one-week look-back window

Short-term reversals (1-week)	Excess return	Sharpe ratio	Max DD	Average Turnover	Net of costs Exc ret	Net of costs SR	Break-even trading cost	Alpha 3 factors	Alpha 6 factors	Alpha 6f + facmom	Loading to Fact mom Univariate	Loading to Fact mom Plus 6 factors
Regular	**35.4%**	3.34	-18%	29.5	**-5.0%**	-0.47	0.09%	**35.1%**	**34.9%**	**42.8%**	**-1.53**	**-1.44**
t-stat	**21.5**				**-3.6**			**21.5**	**21.1**	**26.4**	**-20.1**	**-20.0**
Hedged to FF3F	**47.4%**	6.56	-9%	32.8	-0.5%	-0.07	0.10%	**47.2%**	**47.6%**	**51.7%**	**-0.72**	**-0.71**
t-stat	**39.9**				-0.5			**40.0**	**39.5**	**42.6**	**-14.3**	**-15.3**
Hedged to 6 factors	**52.1%**	7.93	-10%	34.8	0.3%	0.04	0.10%	**51.8%**	**52.3%**	**56.0%**	**-0.63**	**-0.60**
t-stat	**47.3**				0.3			**47.4**	**46.9**	**49.5**	**-14.0**	**-14.6**
Hedged to 9 factors	**51.3%**	8.74	-7%	35.5	-1.1%	-0.19	0.10%	**51.0%**	**51.6%**	**54.4%**	**-0.49**	**-0.46**
t-stat	**52.3**				-1.4			**52.9**	**52.5**	**54.7**	**-13.7**	**-14.0**
Hedged to 12 factors	**51.7%**	9.00	-7%	36.0	-1.5%	-0.26	0.10%	**51.5%**	**52.1%**	**54.7%**	**-0.48**	**-0.44**
t-stat	**53.7**				-1.9			**54.2**	**54.2**	**56.3**	**-13.8**	**-13.8**
Hedged to 16 factors	**53.0%**	9.40	-7%	34.6	1.1%	0.19	0.10%	**52.7%**	**53.4%**	**55.9%**	**-0.45**	**-0.41**
t-stat	**55.9**				1.4			**56.4**	**56.3**	**58.3**	**-13.4**	**-13.5**

Notes: This table reports the performance of Hedged Short-term reversal strategies, in which each stock is hedged to its risk factor exposures, as better described in Section 2.3. It is used to different look-back windows do define winner and loser stocks, 1 week and 1 month, and a daily rebalance frequencies, that is, winner and loser stocks are defined every day and then the portfolios are rebalanced. The first two rows presents results for conventional short-term reversal and the following rows the results for Hedged Short-term reversal strategies, to several subsets of risk factors, from the 3 factors of Fama & French (1993) to a large subset of 16 factors, described in Section 2.3. Panel A presents results for the one-month look-back window and Panel B presents results for the one-week look-back window. It´s reported the annualized excess return; Sharpe ratio; maximum drawdown in 3 months horizons; average monthly turnover; net of costs annualized excess returns and Sharpe ratio, using trading costs estimates of Frazzini *et al.* (2015); the break even trading cost, that is, the cost per unit of turnover that would erode all the performance; the annualized alphas of time-series regressions to several risk factors (Fama & French (2015) - MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD) and one-day factor momentum, introduced by Garcia *et al.* (2020a), and the loading value to one-day factor momentum. We use daily returns from Jul/1/1963 to Dec/31/2018.

Table E.9: Short-term reversals returns per calendar month

Panel A: To 16 factors

	Conventional Reversal			Hedged Reversal			Residual Reversal		
Month	**Return**	**t-stat**	**% return**	**Return**	**t-stat**	**% return**	**Return**	**t-stat**	**% return**
January	**2.0%**	**5.8**	**34%**	**2.4%**	**10.7**	**18%**	**1.9%**	**7.9**	**20%**
February	0.2%	0.5	4%	**1.4%**	**7.6**	**10%**	**0.7%**	**3.8**	**8%**
March	0.8%	1.9	13%	**1.1%**	**6.2**	**8%**	**0.8%**	**4.8**	**9%**
April	-0.1%	-0.2	-1%	**1.0%**	**5.9**	**7%**	**0.6%**	**3.2**	**6%**
May	-0.1%	-0.3	-2%	**0.9%**	**5.9**	**7%**	**0.5%**	**3.1**	**6%**
June	0.5%	1.7	9%	**0.6%**	**4.0**	**4%**	**0.5%**	**3.2**	**6%**
July	**1.1%**	**3.0**	**19%**	**1.2%**	**6.6**	**9%**	**1.0%**	**5.9**	**11%**
August	0.3%	0.9	4%	**1.0%**	**6.1**	**7%**	**0.6%**	**3.5**	**6%**
Septemper	0.0%	0.1	0%	**1.0%**	**5.5**	**7%**	**0.4%**	**2.5**	**5%**
October	0.7%	1.5	11%	**0.8%**	**4.4**	**6%**	**0.5%**	**2.9**	**6%**
November	-0.3%	-0.5	-4%	**1.0%**	**5.0**	**7%**	**0.6%**	**2.7**	**7%**
December	0.8%	1.9	13%	**1.1%**	**6.9**	**8%**	**0.9%**	**5.2**	**10%**

Panel B: To 3 Fama-French factors

	Regular Reversal			Hedged Reversal			Residual Reversal		
Month	**Return**	**t-stat**	**% return**	**Return**	**t-stat**	**% return**	**Return**	**t-stat**	**% return**
January	**2.0%**	**5.8**	**34%**	**2.3%**	**8.3**	**23%**	**2.1%**	**7.2**	**29%**
February	0.2%	0.5	4%	**0.9%**	**3.6**	**9%**	**0.6%**	**2.5**	**8%**
March	0.8%	1.9	13%	**1.1%**	**4.0**	**11%**	**0.7%**	**2.7**	**10%**
April	-0.1%	-0.2	-1%	**0.6%**	**2.6**	**6%**	0.3%	1.7	5%
May	-0.1%	-0.3	-2%	**0.5%**	**2.6**	**5%**	0.2%	1.0	3%
June	0.5%	1.7	9%	**0.5%**	**2.3**	**5%**	0.1%	0.7	2%
July	**1.1%**	**3.0**	**19%**	**1.1%**	**4.3**	**11%**	**0.9%**	**3.4**	**12%**
August	0.3%	0.9	4%	**0.5%**	**2.7**	**5%**	**0.5%**	**2.6**	**7%**
Septemper	0.0%	0.1	0%	**0.6%**	**2.3**	**6%**	0.3%	1.3	4%
October	0.7%	1.5	11%	0.5%	1.7	5%	0.5%	1.4	6%
November	-0.3%	-0.5	-4%	0.2%	0.8	2%	0.0%	0.1	0%
December	0.8%	1.9	13%	**1.1%**	**4.5**	**11%**	**1.0%**	**4.4**	**14%**

Notes: This table reports the performance per calendar month for the conventional short-term reversal, Hedged Short-term reversal strategies and Short-term residual reversal. In Hedged Short-term reversal strategies, each stock is hedged to its risk factor exposures. In Short-term residual reversal strategies, winner and loser stocks are defined according to their residual returns. Section 2.3 and 2.4 give more details on how each strategy is constructed. The upper table reports results for the strategies using 16 factors, and the lower table reports results for the strategies using the 3 Fama-French factors (Fama & French, 1993). We use daily returns from Jul/1/1963 to Dec/31/2018.

Table E.10: Hedged short-term reversals

Panel A - Hedged short-term reversals to Large stocks: long and short sides

Short-term reversals Large stocks - (1-month)	Excess return	Sharpe ratio	Max DD	Average Turnover	Net of costs Exc ret	SR	Break-even trading cost	Alpha to 6f + facmom	Loading to Fact mom Univariate	Plus 6 factors
Regular	**2.8%**	0.25	-35%	3.3	-1.3%	-	0.07%	**12.3%**	**-1.87**	**-1.81**
t-stat	**2.2**				-1.0			**8.8**	**-29.1**	**-28.6**
Long side	**5.9%**	0.32	-59%	1.7	3.8%	0.20	0.29%	**6.2%**	**-2.28**	**-0.96**
t-stat	**3.0**				1.9			**8.0**	**-22.7**	**-26.1**
Short side	-5.4%	-	-39%	1.7	**-7.3%**	-	-0.28%	**5.7%**	**0.41**	**-0.85**
t-stat	-1.8				**-2.5**			**8.2**	**4.0**	**-26.5**
Hedged to FF3f	**7.6%**	0.95	-19%	4.5	2.0%	0.25	0.14%	**11.6%**	**-0.62**	**-0.60**
t-stat	**7.1**				1.9			**10.4**	**-13.2**	**-14.1**
Long side	**3.2%**	0.67	-14%	2.4	0.3%	0.05	0.11%	**6.3%**	**-0.49**	**-0.46**
t-stat	**5.0**				0.4			**9.8**	**-15.1**	**-16.7**
Short side	**4.4%**	1.05	-10%	2.4	**1.4%**	0.33	0.15%	**4.9%**	**-0.14**	**-0.14**
t-stat	**7.7**				**2.4**			**8.4**	**-6.0**	**-6.6**
Hedged to FF16F	**11.4%**	1.99	-10%	5.5	**4.3%**	0.76	0.16%	**12.5%**	**-0.08**	-0.01
t-stat	**14.1**				**5.5**			**14.9**	**-2.3**	-0.4
Long side	**5.3%**	1.52	-7%	3.2	**1.4%**	0.39	0.14%	**6.7%**	**-0.17**	**-0.14**
t-stat	**11.1**				**2.9**			**13.8**	**-7.9**	**-7.5**
Short side	**5.9%**	1.73	-9%	3.2	**1.9%**	0.56	0.15%	**5.4%**	**0.10**	**0.13**
t-stat	**12.5**				**4.1**			**11.1**	**4.5**	**6.5**

Panel B – Hedged short-term reversals: long and short sides

Short-term reversals (1-month)	Excess return	Sharpe ratio	Max DD	Average Turnover	Net of costs Exc ret	SR	Break-even trading cost	Alpha 3 factors	6 factors	Plus FACMOM	Loading to Fact mom Univariate	Plus 6 factors
Regular	**5.7%**	0.59	-33%	3.6	1.2%	0.12	0.13%	**5.0%**	**7.4%**	**14.6%**	**-1.76**	**-1.65**
t-stat	**4.6**				1.0			**3.9**	**5.8**	**12.7**	**-33.8**	**-31.9**
Long side	**8.9%**	0.47	-60%	1.8	**6.6%**	0.35	0.39%	**1.7%**	**3.5%**	**7.2%**	**-2.34**	**-0.91**
t-stat	**4.0**				**3.0**			**2.2**	**4.8**	**11.0**	**-22.5**	**-29.3**
Short side	**-5.6%**	-0.34	-43%	1.8	**-7.6%**	-0.46	-0.27%	**3.3%**	**3.8%**	**6.9%**	**0.57**	**-0.74**
t-stat	**-2.0**				**-2.7**			**5.3**	**6.2**	**12.2**	**5.8**	**-29.3**
Hedged to FF3f	**10.1%**	1.58	-22%	4.0	**4.9%**	0.77	0.20%	**9.5%**	**11.5%**	**13.7%**	**-0.51**	**-0.50**
t-stat	**11.3**				**5.7**			**10.5**	**13.1**	**15.5**	**-11.9**	**-13.7**
Long side	**4.1%**	1.00	-16%	2.4	**1.2%**	0.29	0.14%	**3.7%**	**5.3%**	**6.9%**	**-0.41**	**-0.39**
t-stat	**7.4**				**2.2**			**6.6**	**9.8**	**13.0**	**-14.3**	**-16.0**
Short side	**5.9%**	1.87	-8%	2.3	**3.0%**	0.97	0.21%	**5.6%**	**5.9%**	**6.4%**	**-0.10**	**-0.11**
t-stat	**13.5**				**7.1**			**12.9**	**13.7**	**14.5**	**-5.1**	**-6.4**
Hedged to FF16F	**14.2%**	3.12	-11%	4.7	**7.9%**	1.74	0.23%	**13.9%**	**15.1%**	**14.8%**	0.02	**0.07**
t-stat	**21.7**				**12.4**			**21.2**	**23.4**	**22.6**	0.8	**2.8**
Long side	**6.7%**	2.41	-8%	2.9	**3.0%**	1.09	0.19%	**6.4%**	**7.3%**	**7.5%**	**-0.08**	**-0.06**
t-stat	**17.3**				**8.0**			**16.7**	**19.3**	**19.8**	**-4.8**	**-3.6**
Short side	**7.1%**	2.83	-5%	2.8	**3.5%**	1.39	0.20%	**7.0%**	**7.3%**	**6.7%**	**0.11**	**0.13**
t-stat	**20.3**				**10.2**			**20.0**	**20.7**	**18.9**	**6.8**	**8.8**

Notes: This table reports the performance of both long and short sides of Hedged Short-term reversal strategies. Panel A presents results for strategies constructed only with large-cap stocks, whose market value is above the NYSE median breakpoint, represented by the largest 800 stocks on average over time. Panel B presents results for strategies constructed with all size stocks. In hedged Short-term reversal strategies, each stock is hedged to its risk factor exposures, as better described in Section 2.3. The first row presents results for conventional short-term reversal, constructed from one-month stocks total returns (Lehmann, 1990; Jegadeesh, 1990). The following three rows present results for hedged strategies for the 3 factors of Fama & French (1993), and the next three rows the results for a large subset of 16 factors, described in Section 2.3. It´s reported the annualized excess return; Sharpe ratio; maximum drawdown in 3 months horizons; average monthly turnover; net of costs annualized excess returns and Sharpe ratio, using trading costs estimates of Frazzini *et al.* (2015); the break even trading cost, that is, the cost per unit of turnover that would erode all the performance; the annualized alphas of time-series regressions to several risk factors (Fama & French (2015) - MKT, SMB, HML, RMW, CMA) plus stock momentum (UMD) and one-day factor momentum, introduced by Garcia *et al.* (2020a), and the loading value to one-day factor momentum. We use daily returns from Jul/1/1963 to Dec/31/2018.