Time Series and Cross-Sectional Momentum in Anomaly Returns

Feifei Wang, Xuemin (Sterling) Yan, and Lingling Zheng*

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* Feifei Wang is at Farmer College of Business, Miami University, Email: wangf10@miamioh.edu. Xuemin (Sterling) Yan is at the Robert J. Trulaske, Sr. College of Business, University of Missouri, Columbia, MO 65211-2600, U.S.A. Phone: 1-573-884-9708, Email: yanx@missouri.edu. Lingling Zheng is at School of Business, Renmin University of China, Beijing 100872, China. Phone: 86-10-82500431, Email: zhenglingling@rbs.ruc.edu.cn. We thank seminar participants at Renmin University of China for helpful comments.

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Abstract

We find strong evidence of time-series and cross-sectional momentum in the long-short returns of a comprehensive sample of anomalies. Strategies that exploit such persistence deliver significant abnormal returns that are robust to the stock momentum effect, cannot be explained by time-varying factor exposures, and are more pronounced when arbitrage capital is scarcer and market liquidity is lower. Our findings are inconsistent with the view that anomalies result from data mining. Although we cannot completely rule out risk-based explanations, our results are more consistent with behavioral explanations in which limits to arbitrage and slow-moving capital allow mispricing to persist.

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1. Introduction

Finance researchers have documented hundreds of cross-sectional return anomalies, i.e., stock return patterns that cannot be explained by traditional asset pricing models (Harvey, Liu, and Zhu (2016) and Hou, Xue, and Zhang (2017)). An important debate in this literature is whether the significant long-short returns are compensation for systematic risk, evidence of market inefficiency, or the result of data mining. Historically, much of the debate centered on risk- versus mispricing-based explanations. More recently, data mining has attracted considerable attention (Harvey, Liu, and Zhu (2016), McLean and Pontiff (2016), and Yan and Zheng (2017)).

We provide new evidence on this debate by examining the persistence of absolute and relative performance of a large sample of cross-sectional return anomalies. Intuitively, if anomalies result from data mining, i.e., they are spurious, then any superior long-short performance would be due to random chance, and hence should not persist. On the other hand, if the superior long-short returns represent compensation for risk, then they should continue. However, such persistence should weaken when we remove the mean long-short return (an estimate of the expected return). In the special case where the expected returns for anomalies are constant, we would expect the superior long-short performance to persist indefinitely, but completely disappear once we demean each anomaly's long-short returns. Finally, if the anomaly returns are due to mispricing, and, to the extent that arbitrage capital is limited and slow-moving, we would expect superior long-short performance to persist in the short run but dissipate in the long-run. Therefore, the data mining-, risk-, and mispricing-based explanations offer diametrically opposed predictions on whether superior anomaly returns should persist and whether such persistence should be short-lived or long-lived.

We compile a comprehensive list of cross-sectional return anomalies by merging the samples of Hou, Xue, and Zhang (2015) and McLean and Pontiff (2016). We restrict our sample to continuous anomaly variables that can be constructed from the CRSP, Compustat, or IBES data. Our final sample includes 90 anomalies, most of which exhibit significant CAPM alphas during our sample period from July 1963 to December 2015. We do not exclude anomalies with insignificant alphas from our analyses because doing so would introduce a selection bias. We perform our analyses at the weekly frequency because we want to examine both short- and long-term persistence in anomaly returns.

We begin by examining time-series momentum in our sample anomalies. We follow Moskowitz, Ooi, and Pedersen (2012) and estimate univariate regressions of anomaly returns on lagged anomaly returns. We find strong evidence of persistence. Almost all of the auto-regression coefficients from lagged 1 week to lagged 52 weeks are positive, with 14 (10) of them statistically significant at the 5 percent level for equal- (value-) weighted anomaly returns. We also follow Moskowitz, Ooi, and Pedersen (2012) and construct a diversified portfolio of time-series momentum strategies across all anomalies in our sample. This portfolio delivers significant abnormal returns that are robust to different look-back period and holding period (both of which ranging from 1 to 52 weeks). For example, the CAPM alpha for the time-series momentum strategy with a look-back period of 4 weeks and a holding period of 4 weeks is 0.29% per week (15% annualized) for equal-weighted anomaly returns. The corresponding number for value-weighted returns is 0.21% per week (11% annualized). These returns are economically and statistically significant. Although the time-series momentum profits are significant up to 52 weeks, they are most pronounced during the first 4 to 8 weeks, suggesting the persistence of anomaly returns is relatively short-lived.

Next, we examine whether anomaly returns exhibit cross-sectional momentum, i.e., whether the relative performance of anomalies persists. The cross-sectional momentum is related to, but distinct from the time-series momentum discussed above, which focuses entirely on an anomaly's own past returns. We find strong evidence of cross-sectional momentum among our sample of anomalies. Anomalies that performed relatively well (poorly) during the past 1 to 52 weeks continue to perform well (poorly) for the next 1 to 52 weeks. For example, the CAPM alpha for the cross-sectional momentum strategy with a formation period of 4 weeks and a holding period of 4 weeks is 0.37% per week (0.32% per week) for equal-weighted (value-weighted) anomaly returns, and highly statistically significant. Similar to time-series momentum, we find that the cross-sectional momentum is most pronounced during the first 4 to 8 weeks, confirming that the persistence of relative anomaly returns is also short-lived.

Momentum in anomaly returns is not merely a reflection of the momentum effect in stock returns (Jegadeesh and Titman (1993)). Profits to our time-series and cross-sectional momentum strategies are slightly reduced but remain highly significant after controlling for the momentum factor. In addition, our findings are not driven by small, illiquid stocks. In constructing anomaly returns, we remove all stocks with a price less than $5 or with a market capitalization ranked in the lowest NYSE decile. Moreover, when we form anomaly decile portfolios, we use NYSE breakpoints to further minimize the impact of micro-cap stocks (Hou, Xue, and Zhang (2015, 2017)). Also, our results remain significant when we skip a week after portfolio formation, eliminating a concern that our results are driven by microstructure biases. Finally, we find that the persistence in anomaly returns is attributable to both long and short legs.

Our finding of significant momentum in anomaly returns is inconsistent with the view that stock return anomalies are a product of data mining or statistical biases. We follow McLean and

Pontiff (2016) and use the term "statistical biases" to describe a wide range of biases that are inherent in academic research. These biases may lead to discoveries of "reliable" return predictability that is in fact spurious. If the anomalies in our sample are spurious, then any superior long-short performance would be a chance result, and therefore should not persist.

Momentum in anomaly returns could be due to cross-sectional differences in *unconditional* expected returns (Conrad and Kaul (1998) and Jegadeesh and Titman (2001)). We test this possibility in two ways. First, we examine whether the persistence in anomaly returns extends beyond the initial holding period. Intuitively, if anomaly A performs better than anomaly B because anomaly A is unconditionally riskier, then, everything else equal, we would expect the relative performance of these two anomalies to persist for a long time. Our evidence is inconsistent with this prediction. We find that the profits to the time-series and cross-sectional momentum strategies are indistinguishable from zero during the year after our initial holding period.

Second, we calculate the average long-short return for each anomaly and use it as a proxy for unconditional expected return. We subtract the mean long-short return from each anomaly and then examine whether momentum exists in demeaned anomaly returns. If momentum in anomaly returns is due to cross-sectional differences in unconditional expected returns, then it should disappear when we use demeaned long-short returns to construct our momentum strategies. We do not find such evidence. In fact, we find that both the time-series and cross-sectional momentum in anomaly returns are essentially unchanged when we use demeaned long-short returns. This evidence is inconsistent with explanations based on constant expected returns. Moreover, it casts doubts on risk-based explanations in general, because, to the extent that the average long-short return contains information about the riskiness of an anomaly, one would expect momentum in anomaly returns to be weaker in demeaned long-short returns.

Although our results on demeaned long-short returns are not supportive of risk-based explanations, we cannot rule out time-varying risk premium as an explanation for momentum in anomaly returns. To provide evidence on this possibility, we estimate rolling CAPM, Fama and French 3-factor, and Carhart 4-factor regressions of anomaly returns and remove the time-varying expected returns from each anomaly's long-short returns. We then test whether time-series and cross-sectional momentum exists in the residual anomaly returns. If the persistence in anomaly returns solely result from the persistence in factor exposures to the market, size, value, and momentum factors, then we would expect the residual anomaly returns to exhibit no persistence. Our results are inconsistent with this prediction—both the time-series and cross-sectional momentum remain highly significant in residual anomaly returns. In summary, although we cannot completely rule out risk-based explanations, we have shown several results that present significant challenges to any risk-based theories.

We argue that momentum in anomaly returns is more consistent with behavioral explanations in which the arbitrage capital is limited and slow-moving. Although textbook arbitrage requires no capital and entails no risk, arbitrage in practice requires capital and is risky (Shleifer and Vishny (1997)). In addition, arbitrage incurs transaction cost and holding cost (Pontiff (2006)). In the presence of costly arbitrage, mispricing will not be completely eliminated. Such incomplete or partial arbitrage will lead to persistence in anomaly returns in the short run. In the long run, the arrival of new information or additional arbitrage capital brings mispricing toward zero. Therefore, behavioral arguments predict that anomaly returns will be persistent in the short-run, but dissipate in the long run. Our evidence of short-term (but not long-term) persistence of anomaly returns is consistent with this prediction.

If momentum in anomaly returns is related to time-varying arbitrage capital, as predicted by behavioral explanations, then it should be more pronounced when the arbitrage capital is scarcer. To test this hypothesis, we construct two proxies for the amount of arbitrage capital, i.e., hedge fund total assets under management and aggregate short interest ratio. Consistent with the prediction of the behavioral explanations, we find that the persistence in anomaly returns is negatively related to our proxies for arbitrage capital. Behavioral explanations also predict that momentum in anomaly returns should be more pronounced when the market is less liquid. We find evidence consistent with this prediction. Our results provide additional support for behavioral explanations.

The objective of our study is not necessarily to advocate a new profitable trading strategy. Rather, our primary goal is to understand the dynamics of anomaly returns and thus shed new light on the underlying drivers of cross-sectional return anomalies. Even though we remove low-priced, small stocks from our sample and use NYSE breakpoints to construct portfolios, we acknowledge that the short-term nature of our strategy (rebalancing every week) likely implies high trading cost. Nevertheless, our results are valuable for money managers who face the decision of which anomalies to trade on. Specifically, we show that the recent performance of an anomaly could be used as an important input into such a decision.

Our paper is closely related to McLean and Pontiff (2016), who examine the post-publication performance of 95 anomalies. They find an average decline of 58% of long-short returns after the original papers are published. Our paper is also related to Chordia, Subrahmanyam, and Tong (2014), who document that the performance of a number of well documented anomalies decline over time as a result of increasing market liquidity and trading activity. A key difference between our paper and McLean and Pontiff (2016) and Chordia, Subrahmanyam, and Tong (2014) is that the above two papers examine changes in anomaly performances that are deterministic in time, whereas we focus on stochastic changes in anomaly returns.

Our paper adds to the growing literature examining the time-series variation of anomaly returns. Earlier studies in the anomaly literature typically focused on evaluating whether the average performance of an anomaly is economically and statistically significant. Several recent papers have recognized that anomaly returns vary considerably over time and such variation is linked to time-varying arbitrage capital. Hanson and Sunderam (2014) infer the amount of arbitrage capital allocated to quantitative equity strategies from the time-series variation in the cross-section of short interest. They provide evidence that an increase in arbitrage capital has led to a decline of strategy profits. Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) find that anomaly returns vary positively with aggregate mutual fund lows and negatively with aggregate hedge fund flows. They interpret mutual fund flows as dumb money, exacerbating the cross-sectional market mispricing, and hedge fund flows as smart money, correcting market mispricing. Akbas, Armstrong, Sorescu, and Subrahmanyam (2016) use flows to quant funds as a proxy for arbitrage capital and show that the degree of cross-sectional market efficiency varies with the availability of arbitrage capital. Our paper adds to this literature by providing new evidence on the link between arbitrage capital and market mispricing.

Our paper contributes to the recent debate on the effect of data mining. Harvey, Liu, and Zhu (2016) evaluate the impact of data mining among 315 published anomalies using a multiple testing framework and conclude that most claimed findings are likely false. McLean and Pontiff (2016) show that the post-publication performance of 95 anomalies declines only partially, suggesting that they are not entirely explained by data mining. Yan and Zheng (2017) evaluate the data mining bias by constructing a "universe" of fundamental signals and show that superior performances exist even after accounting for data mining. Hou, Xue, and Zhang (2017) find that 64% of the 447 anomalies are insignificant, concluding that this is evidence of extensive *p*-hacking. Our paper adds to this debate by examining the persistence of anomaly returns. Our finding suggests that the documented anomalies are not solely driven by data mining.

The rest of the paper proceeds as follows. Section 2 presents the data, sample, and descriptive statistics. Section 3 presents a simple behavioral model. Section 4 presents the empirical results. Section 5 concludes.

2. Data, Sample, and Descriptive Statistics

2.1. Data and Sample

To compile a comprehensive list of stock return anomalies, we start with the samples of anomalies from Hou, Xue, and Zhang (2015) and McLean and Pontiff (2016). We require that the anomaly variable be continuous (rather than an indicator variable) and can be constructed using the CRSP, COMPUSTAT, and IBES data. Our final list includes 90 anomalies covering six major categories.[1] The detailed list and definitions of these 90 anomalies are contained in the Appendix.

We obtain stock data including returns, share price, SIC code, and shares outstanding from the Center for Research in Security Prices (CRSP), quarterly and annual accounting data from Compustat, and analyst forecast data from IBES. We obtain Fama and French (1996) three factors and the momentum factor from Kenneth French's website.[2] Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11) with data necessary to compute anomaly variables and subsequent stock returns. Our sample period is from July 1963 to

[1] Harvey, Liu, and Zhu (2016) consider 315 return predictors, but many of them are macroeconomic variables or predictors of market returns. Hou, Xue, and Zhang (2017) replicate 447 anomalies, many of which share the same underlying anomaly variable and differ only in the length of the holding period.
[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

December 2015.

We exclude financial stocks and stocks with a price lower than $5 at the portfolio formation date. We also remove stocks whose market capitalization is ranked in the lowest NYSE decile at the portfolio formation date. We use NYSE breakpoints to sort all sample stocks into deciles. We remove low-priced and micro-cap stocks and use NYSE breakpoints to form portfolios to ensure that our results are not driven by small, illiquid stocks that comprise a tiny fraction of the market.

2.2. Long-short Returns

We sort all sample stocks into deciles based on each anomaly variable and construct equal-weighted as well as value-weighted portfolios. We examine the strategy that goes long on stocks in the top decile and short those stocks in the bottom decile, where the top (bottom) decile includes the stocks that are expected to outperform (underperform) based on prior literature. Taking the momentum anomaly as an example, we sort past winners into the top decile and past losers into the bottom decile. In contrast, for the asset growth anomaly, we sort low-asset growth stocks into the top decile and high-asset growth stocks into the bottom decile because prior studies (Cooper, Gulen, and Schill (2008)) have shown that low-asset growth firms earn significantly higher returns than high-asset growth firms. We examine both equal-weighted returns and value-weighted returns to demonstrate robustness and to mitigate concerns associated with each weighting scheme.

We follow the previous literature in forming portfolios and determining the rebalancing frequency and holding period. Specifically, for anomalies constructed using annual Compustat data, we form portfolios at the end of each June in year t by using accounting data from the fiscal year ending in calendar year t-1 and compute returns from July in year t to June in year t+1. For anomalies constructed using quarterly Compustat data, we form portfolios at the end of each quarter t by using accounting data from the fiscal quarter ending in calendar quarter t-1 and compute returns over the calendar quarter t+1. To ensure that the quarterly accounting data are publicly available before the portfolio formation date, we also require that the quarterly earnings announcement date fall in calendar quarter t-1 or t. Finally, for anomalies constructed using monthly CRSP data, we form portfolios every month and hold the portfolio for one month.

To focus on short-term as well as long-term persistence in anomaly returns, we compute long-short returns at the weekly frequency. We estimate CAPM 1-factor alpha, Fama-French 3-factor alpha, and Carhart 4-factor alpha of long-short returns by running the following time-series regressions:

$$r_{i,t} = \alpha_i + \beta_i MKT_t + e_{i,t}$$

$$r_{i,t} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + e_{i,t} \tag{1}$$

$$r_{i,t} = \alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t + u_i UMD_t + e_{i,t}$$

Where $r_{i,t}$ is the long-short hedge return for fundamental signal i in week t, *MKT*, *SMB*, *HML*, and *UMD* are market, size, value, and momentum factors (Fama and French (1996) and Carhart (1997)), and $e_{i,t}$ is the regression residual.

Although we estimate CAPM 1-factor, Fama and French 3-factor, and Carhart 4-factor alphas, we note that the CAPM 1-factor alpha likely provides the cleanest results. This is because traditionally anomalies are defined relative to the CAPM model and many anomalies in our sample are closely related to the *SMB*, *HML*, and *UMD* factors. As such, including these factors in estimating abnormal returns would bias against us finding any significant results.

2.3. Descriptive Statistics

Table 1 reports the average long-short performance of our sample of anomalies. We divide our sample of anomalies into six categories, Growth/Value, Intangibles, Investment, Momentum, Profitability, and Trading, and report the results in six panels. In each panel, we present 1-, 3-, and 4-factor alphas for both equal-weighted and valued-weighted long-short returns. We find that the majority of the anomalies in our sample exhibit significant 1-factor alphas. Specifically, 74 of the 90 anomalies have an equal-weighted 1-factor alpha that is positive and statistically significant at the 5 percent level. For value-weighted returns, the number is 62. Not surprisingly, the 3- and 4-factor alphas are generally less significant than the 1-factor alphas. 70 (54) of the 90 anomalies exhibit significant 3-factor alphas for equal- (value-) weighted returns. The corresponding numbers for 4-factor alphas are 63 and 31. We do not exclude anomalies that have insignificant alphas from our analyses because doing so would introduce a look-ahead bias.

3. A Simple Behavioral Model

To illustrate how limits to arbitrage and slow-moving arbitrage capital can lead to momentum in anomaly returns, we present a simple stylized model in this section. The setup of the model is as follows. There are N arbitrageurs, where $N >> 0$. All arbitrageurs are price takers. Each arbitrageur allocates his wealth among the risk-free asset, the market portfolio, and n long-short portfolios (i.e., anomalies). For simplicity, we assume the risk-free rate is 0. The market return follows:

$$r_m = \alpha_m + e_m \qquad \text{where } var(e_m) = \sigma_m^2 \tag{2}$$

The long-short return of each anomaly is given by:

$$r_i = \alpha_i + e_i \tag{3}$$

Where

$$var(e_i) = \sigma_i^2 \equiv \sigma^2 \qquad \forall\, i$$

$$cov\,(e_i, e_m) = 0 \qquad \forall\, i$$

$$cov\left(e_i, e_j\right) = 0 \qquad \forall\ i\ \neq\ j$$

For simplicity, we assume all anomalies have the same idiosyncratic volatility. We also assume that anomaly returns are uncorrelated with each other and uncorrelated with the market returns. In addition, we assume that the arbitrageurs do not have access to short sale proceeds. That is, the arbitrageurs have to expend capital in order to exploit market mispricing.

The return and variance of the arbitrageur's portfolio are given by:

$$r_p = \omega_m r_m + \sum_{i=1}^{n} \omega_i r_i \tag{4}$$

$$\sigma_p^2 = \omega_m^2 \sigma_m^2 + \sum_{i=1}^{n} \omega_i^2\, \sigma_i^2 \tag{5}$$

All arbitrageurs have identical mean-variance utility function as follows:

$$U = E\left(r_p\right) - \frac{\lambda}{2}\sigma_p^2 \tag{6}$$

Plugging (4) and (5) into (6) and maximizing the arbitrageur's utility,

$$\max_{\omega_m, \omega_i} \quad \omega_m \alpha_m + \sum_{i=1}^{n} \omega_i \alpha_i - \frac{\lambda}{2}\left(\omega_m^2 \sigma_m^2 + \sum_{i=1}^{n} \omega_i^2\, \sigma^2\right) \tag{7}$$

Solving the first order conditions results in the following optimal weights:

$$\omega_m = \frac{\alpha_m}{\lambda \sigma_m^2} \tag{8}$$

$$\omega_i = \frac{\alpha_i}{\lambda \sigma^2} \quad \forall\ i \tag{9}$$

The optimal weight on the risk-free asset is 1 minus the weight on the market portfolio and the sum of the weights on the long-short portfolios.

Our model is a one-period model with two dates. At the beginning of the period (t=0), initial mispricing arises:

$$\alpha_{i,0} > 0 \quad \forall\ i$$

To capture slow-moving arbitrage capital, we assume that there is a probability p<1 that each arbitrageur becomes aware of these mispricings and trades against them. Ex post, the fraction of all arbitrageurs who become aware of the mispricings is denoted by ρ. For ease of exposition, we assume that each arbitrageur has an initial wealth of \$1. For each \$1 employed by the arbitrageurs to trade against an anomaly, the alpha of the anomaly will be reduced by γ. Denote the total arbitrage capital devoted to anomaly i as AC_i, we can express the changes in alpha as follows:

$$\Delta\alpha_i = \alpha_{i,1} - \alpha_{i,0} = -\gamma AC_i \tag{10}$$

From (8), the expected total arbitrage capital on anomaly i is given as follows:

$$E(AC_i) = \frac{Np\alpha_{i,0}}{\lambda\sigma^2} \tag{11}$$

The expected changes and percentage changes in α are then as follows:

$$E(\Delta\alpha_i) = -\frac{\gamma Np\alpha_{i,0}}{\lambda\sigma^2} \tag{12}$$

$$E(\%\Delta\alpha_i) = \frac{\gamma Np}{\lambda\sigma^2} \tag{13}$$

And the expected α at t=1 is as follows:

$$E(\alpha_{i,1}) = \alpha_{i,0}\left(1 - \frac{\gamma Np}{\lambda\sigma^2}\right) \tag{14}$$

We further assume that:

$$\gamma < \frac{\lambda\sigma^2}{Np} \tag{15}$$

The inequality in (15) implies that the initial mispricing will not completely go away if the expected number of arbitrageurs show up and trade against the anomaly.

Equation (11) indicates that the expected arbitrage capital devoted to anomaly i is increasing in N, p, and $\alpha_{i,0}$, and decreasing in λ and σ^2. Equation (12) indicates that the expected reduction in mispricing is increasing in γ, N, p, and $\alpha_{i,0}$, and decreasing in λ and σ^2. Equation (14) indicates that the expected mispricing at t=1 is increasing in $\alpha_{i,0}$, λ and σ^2, and decreasing in γ, N, and p.

Equation (14), combined with the assumptions in equation (15), indicate that there exists time-series momentum in anomaly returns. That is, positive anomaly returns tend to be followed by positive anomaly returns. To show the existence of cross-sectional momentum, consider anomalies i and j, and, without loss of generality, assume $\alpha_{i,0}>\alpha_{j,0}$. Using (14), we can show that

$$E(\alpha_{i,1}) - E(\alpha_{j,1}) = (\alpha_{i,0} - \alpha_{j,0})\left(1 - \frac{\gamma Np}{\lambda\sigma^2}\right) \tag{16}$$

Therefore, if $\alpha_{i,0}>\alpha_{j,0}$, then $E(\alpha_{i,1})>E(\alpha_{j,1})$. That is, the relative performance among anomalies also persists. This result arises because the percentage decline in alpha is the same for both anomalies. Therefore, the anomaly with the higher initial alpha will continue to have a higher alpha at the end of the period. Moreover, we can show that

$$E(\alpha_{i,1}) - E(\alpha_{j,1}) < (\alpha_{i,0} - \alpha_{j,0}) \tag{17}$$

That is, the performance gap between anomalies shrinks over time. This result is due to the fact that anomalies with higher initial mispricing attract greater amount of arbitrage capital and therefore experience a greater decline in alpha. In the long run, as more arbitrageurs become aware of the mispricing, i.e., more arbitrage capital become available, the mispricing will shrink to zero. As a result, superior alphas persist in the short run but dissipate in the long run.

4. Empirical Results

4.1. Time-series Momentum

We begin our empirical analysis by examining time-series momentum in anomaly returns. Because volatility varies greatly across anomalies, we follow Moskowitz, Ooi, and Pedersen (2012) and scale anomaly returns by their ex-ante volatilities. Specifically, we use the realized volatility during the previous month (estimated from daily anomaly returns) to scale each anomaly's long-short returns.

To study the persistence of anomaly returns, we estimate the following univariate regressions of anomaly returns on lagged anomaly returns.

$$\frac{r_{i,t}}{\sigma_{i,t-1}} = \alpha + \beta \frac{r_{i,t-m}}{\sigma_{i,t-m-1}} + e_{i,t} \tag{19}$$

We follow Moskowitz, Ooi, and Pedersen (2012) and stack all anomalies and dates and run a pooled panel regression and compute *t*-statistics that account for clustering by time. The regression are run using lags of *m*=1, 2, …, 104 weeks.

Panel A of Figure 1 plots the *t*-statistics from the regression (19) by for equal-weighted anomaly returns. We find strong evidence of persistence during the first 52 lags. Forty eight of the 52 auto-regression coefficients are positive, and 14 of them are statistically significant at the 5 percent level. In contrast, only 4 coefficients are negative and none of them are statistically significant. The results for weeks 52 through 104 show a mix of positive and negative coefficients, and few of them are statistically significant.

Panel B presents the results for value-weighted anomaly returns. The results are qualitatively similar to those in Panel A. We find strong evidence of persistence during the first 52 weeks. 45 of the 52 auto-regression coefficients are positive, with 10 being statistically significant at the 5 percent level. In contrast, only 7 coefficients are negative and none of them are statistically significant. The results for weeks 52 through 104 are largely insignificant.

Next, we follow Moskowitz, Ooi, and Pedersen (2012) and create a diversified portfolio of anomalies based on time-series momentum. Specifically, for each anomaly and each week, we consider whether the long-short return over the past *k* weeks is positive or negative, and go long the anomaly if positive and "short" the anomaly if negative.[3] The holding period is *h* weeks. We vary both *k* (the length of the look-back period) and *h* (the length of the holding period). The possible values for *k* and *h* are: *k*, *h* = 1, 2, 3, 4, 8, 12, 26, and 52 weeks. Following Moskowitz, Ooi, and Pedersen (2012), we set the position size to be inversely proportional to the anomalies' ex ante volatility (estimated by the realized volatility in the previous month). Specifically, we size each position so that it has an ex ante volatility of 12%. The choice of 12% is based on the average volatility across all anomalies in our sample over the time sample period 1963-2015.

Table 2 presents the 1-, 3-, and 4-factor alphas for the above time-series momentum strategies. Panel A reports the results for equal-weighted returns. We find that the time-series momentum strategy delivers significant abnormal returns that are robust to different look-back periods and holding periods. For example, the CAPM alpha for the time-series momentum trading strategy with a look-back period of 4 weeks and a holding period of 4 weeks is 0.29% per week (15% annualized), and highly statistically significant. The 3- and 4-factor alphas are slightly lower at 0.26% and 0.24% per week, respectively, but they continue to be economically large and

[3] By "shorting" an anomaly, we mean that we take the opposite positions to the original long-short portfolio, i.e., long the original short portfolio and short the original long portfolio.

statistically significant. Moreover, the significant 4-factor alphas indicate that momentum in anomalies is not mechanically driven by the momentum effect in stocks.

Looking at the results across different look-back period and holding periods, we find that the results are most pronounced at shorter horizons, i.e., 1 to 8 weeks. Extending the look back period beyond 8 weeks reduces the alphas slightly, while extending the holding period beyond 4-8 weeks lead to significantly lower alphas, suggesting that the persistence of anomaly returns is relatively short-lived. For example, for the look-back period of 4 weeks, extending the holding period from 4 weeks to 8 weeks reduces the equal-weighted 1-factor alpha from 0.29% per week to 0.2% per week. Simple calculation indicates that the average 1-factor alpha for week 5 through week 8 is only 0.1% per week, which is only one third of the average return over the first 4 weeks.

The results reported in Panel B for value-weighted returns paint a similar picture. We continue to find that the time-series momentum strategy delivers significant abnormal returns that are robust across different look-back periods and holding periods. For example, the CAPM alpha for the trading strategy with a look-back period of 4 weeks and a holding period of 4 weeks is 0.21% per week (11% annualized). This number is somewhat lower than its counterpart for equal-weighted returns reported in Panel A, but is nevertheless economically meaningful and statistically significant. The return continues to be significant after controlling for the momentum factor, again indicating that momentum in anomalies is not mechanically driven by momentum in stocks. Similar to Panel A, we find that the results are most significant at shorter horizons, i.e., 1 to 8 weeks. Extending the holding period beyond 8 weeks lead to significantly lower alphas, suggesting that the persistence of anomaly returns is short-lived. Overall, Table 2 reveals strong evidence of time-series momentum.

4.2. Cross-sectional Momentum

In time-series momentum, the focus is on the predictive ability of an anomaly's own past returns. Next, we examine whether anomaly returns exhibit cross-sectional momentum, i.e., whether the relative performance of anomalies is persistent. We develop our cross-sectional momentum strategies similarly to the traditional stock momentum strategies (Jegadeesh and Titman (1993, 2001)). At each week, we sort all anomalies based on their cumulative long-short return over the past *k* weeks into quintile portfolios. The top quintile portfolio (i.e., the past winners) include the 18 anomalies that performed the best during the past *k* weeks. The bottom quintile portfolio (i.e., the past losers) include the 18 anomalies that performed the worst during the past *k* weeks. We then go long the past winners and "short" the past losers.[4] We hold the portfolios for *h* weeks. We vary both *k* (the length of the formation period) and *h* (the length of the holding period). As in the time series momentum, the possible values for *k* and *h* are: *k*, *h* = 1, 2, 3, 4, 8, 12, 26, and 52 weeks. We then evaluate the abnormal performance of the cross-sectional momentum strategies relative to the CAPM 1-factor, Fama and French 3-factor, and Carhart 4-factor models.

Panel A of Table 3 contains the results for equal-weighted anomaly returns. We find strong evidence of cross-sectional momentum among our sample of anomalies. Anomalies that performed relatively well (poorly) during the past 1 to 52 weeks continue to perform relatively well (poorly) for the next 1 to 52 weeks. For example, the CAPM alpha for the momentum strategy with a formation period of 4 weeks and a holding period of 4 weeks is 0.32% per week (16.6% annualized), and highly statistically significant. The 3- and 4-factor alphas are slightly lower at 0.28% and 0.24% per week, respectively, and continue to be economically and statistically significant. The significant 4-factor alpha again indicates that the cross-sectional momentum in

[4] Again, "shorting" here means we take the opposite positions to the original long-short portfolio, i.e., long the original short portfolio and short the original long portfolio.

anomalies is not repackaging the momentum effect in stocks. Examining across different look-back periods and holding periods, we find that results are most significant at shorter horizons, i.e., 1 to 8 weeks. In particular, extending the holding period beyond 4-8 weeks lead to significantly lower alphas, suggesting that the persistence of anomaly returns is relatively short-lived. This finding is quite different from that of the stock momentum literature, where momentum seems to be the strongest at the 3-12 month horizon.

The results reported in Panel B for value-weighted returns are qualitatively similar. We continue to find that the cross-sectional momentum strategy delivers significant abnormal returns that are robust across different look-back periods and holding periods. For example, the CAPM alpha for the trading strategy with a look-back period of 4 weeks and a holding period of 4 weeks is 0.31% per week (16% annualized). This number is almost identical to that in Panel A, suggesting that the cross-sectional momentum in anomaly returns are equally strong in value-weighted returns. Similar to Panel A, we find that the results are most significant at shorter horizons. Extending the holding period beyond 8 weeks lead to significantly lower alphas, suggesting that the persistence of anomaly returns is short-lived.

In summary, we find significant evidence of time-series as well as cross-sectional momentum in anomaly returns during our sample period. This finding is inconsistent with the view that market anomalies are a product of data mining or statistical biases. If the anomalies in our sample are spurious, then any superior long-short performance during any given period would simply be a chance result, and therefore should not persist. Given that we are able to rule out data mining, we will focus on the risk- and mispricing-based explanations in the sections below. Specifically, Section 4.3 investigates risk-based explanations based on constant expected returns.

Section 4.4 examines explanations based on the time-varying expected returns. Section 4.5 provides evidence on behavioral explanations.

4.3. Constant Expected Returns

Momentum in anomaly returns could be due to cross-sectional differences in unconditional expected returns. We test this possibility in two ways by following the previous literature on stock momentum.[5] First, we follow Jegadeesh and Titman (2001) and examine whether the persistence in anomaly returns extends beyond our initial holding period of 52 weeks. If, for example, the asset growth anomaly performs better than the gross profitability anomaly because the former is unconditionally riskier than the latter, then such outperformance will persist not only during our holding period, but also beyond the holding period. To test this prediction, we compute and plot the cumulative returns to our time series and cross-sectional momentum strategies up to 104 weeks in Figure 2. Panel A presents the results for time-series momentum strategies and Panel B plots the results for cross-sectional momentum strategies. If momentum in anomaly returns is due to differences in unconditional expected returns, then we would expect the cumulative returns to our momentum strategies to continue to increase after the end of our initial holding period. The evidence in Figure 2 is inconsistent with this prediction. We find that, for time-series momentum strategies, the cumulative returns stay essentially flat from week 52 to week 104. For cross-sectional momentum strategies, the cumulative returns actually decline somewhat after week 52.[6] Overall, our examination of post holding period returns to the momentum strategies suggests that our findings are not attributed to differences in unconditional expected returns.

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[5] The literature is ambiguous about whether stock momentum is due to cross-sectional differences in unconditional stock returns. Conrad and Kaul (1998) and Bulkley and Nawosah (2009) present evidence consistent with the hypothesis, while Jegadeesh and Titman (2001) find evidence inconsistent with the hypothesis.

[6] Unreported test indicates that this decline is statistically insignificant.

In the second test, we calculate the average long-short return for each anomaly and use it as a proxy for the unconditional expected return for the anomaly. We then subtract the mean long-short return from each anomaly and test whether the momentum exists in demeaned long-short returns. If momentum in anomaly returns is due to cross-sectional differences in unconditional expected returns, then it should disappear when we use demeaned long-short returns. Tables 4 and 5 report our results for time-series momentum and cross-sectional momentum, respectively. Overall, we find that both the time-series and cross-sectional momentum remain highly significant in demeaned anomaly returns. In fact, the quantitative results are nearly unchanged using demeaned long-short returns. For example, the CAPM alpha for the time-series momentum strategy with a look-back period of 4 weeks and a holding period of 4 weeks is 0.29% per week (0.21% per week) for equal-weighted (value-weighted) anomaly returns in Table 2, and 0.27% per week (0.2% per week) in Table 4. Similarly, the cross-sectional momentum strategies with a 4-week formation period and a 4-week holding period exhibit a 1-factor alpha of 0.32% per week (0.31% per week) for equal- (value-) weighted returns in Table 3. The corresponding numbers are 0.32% per week (0.3% per week) in Table 5.

The above result is inconsistent with risk explanations based on constant expected returns. We emphasize that this finding also casts doubts on risk-based explanations in general because, to the extent that the average long-short return contains some information about the riskiness of an anomaly, one would expect momentum in anomaly returns to be weaker in demeaned long-short returns.

4.4. Time-varying Expected Returns

Although our results on demeaned long-short returns are inconsistent with risk-based explanations with constant expected returns, we cannot rule out the possibility that our results are explained by time-varying risk premium. Indeed, it is impossible to rule out such an explanation without knowing what the correct asset-pricing model is. Nevertheless, in this section we provide evidence on the time-varying risk premium explanation based on several standard asset pricing models, namely, the CAPM, the Fama and French 3-factor model, and the Carhart 4-factor model.

Specifically, we estimate rolling regressions of anomaly returns on market, size, value, and momentum factors each week by using past 52 weeks of data. We calculate the expected return for each week using these rolling factor loadings along with the realized market, size, value, and momentum factors. Then we subtract the time-varying expected return from the anomaly returns to obtain the unexpected or residual anomaly returns. Finally, we repeat our time-series momentum and cross-sectional momentum analyses using these residual anomaly returns. If the persistence in anomaly returns result from the persistence in factor loadings in the market, size, value, and momentum factors, then we would expect the residual anomaly returns to exhibit no persistence.

Table 6 reports the results for time-series momentum strategies. The layout of the table is identical to Table 2 except that the strategies are implemented using residual anomaly returns. Overall, we continue to find significant returns to our time-series momentum strategies. Indeed, the magnitude of the profits is sometimes even larger in Table 6. For example, the profits for the strategy (after removing time-varying 1-factor returns) with a look-back period of 4 weeks and a holding period of 4 weeks is 0.46% per week (0.41% per week) for equal- (value-) weighted returns. The results are robust to alternative look-back periods and holding periods, and hold for both equal- and value-weighted returns.

Table 7 presents the results for cross-sectional momentum strategies. We find that removing time-varying expected returns associated with the market, size, value, and momentum factors have little impact on the profits of the cross-sectional momentum strategies. For example, the profits for the cross-sectional momentum strategy (after accounting for time-varying 1-factor returns) with a formation period of 4 weeks and a holding period of 4 weeks is 0.32% per week (0.31% per week) for equal- (value-) weighted returns, identical to their counterparts reported in Table 3. Overall, our results are inconsistent with the idea that momentum in anomaly returns is due to time-varying exposures to market, size, value, and momentum factors or the persistence in factor premiums.

Because there is no consensus on what the correct asset-pricing model is, we acknowledge that we cannot completely rule out risk-based explanations. We note, however, that we have uncovered several pieces of evidence that present significant challenges to risk-based theories. First, we show that removing the average long-short return from each anomaly does not weaken the momentum in anomaly returns. Second, we show that momentum in anomaly returns is short-lived, suggesting that any risk-based explanation would have to explain why risk (or risk premium) changes so quickly. Third, we show that time-varying factor loadings in standard CAPM, Fama and French 3-factor, and Carhart 4-factor models cannot explain the momentum in anomaly returns.

4.5. Arbitrage Capital

We argue that momentum in anomaly returns is more consistent with behavioral explanations in which arbitrage capital is limited and slow-moving. Arbitrage requires capital and is risky (Shleifer and Vishny (1997)). In addition, arbitrage incurs transaction cost and holding cost (Pontiff (2006)). Everything else equal, greater mispricing will attract a greater amount of arbitrage capital, which in turn eliminates a greater amount of mispricing. However, in the presence of costly arbitrage, mispricing will not be completely eliminated. Such incomplete or partial arbitrage generates persistence in anomaly returns. In the long run, the arrival of new information or additional arbitrage capital brings mispricing toward zero. Therefore, behavioral arguments predict that anomaly returns will be persistent in the short-run, but dissipate in the long run. Our evidence of short-term (and no long-term) persistence of anomaly returns is consistent with this prediction.

If momentum in anomaly returns is related to time-varying arbitrage capital, as predicted by behavioral explanations, then it should be more pronounced when arbitrage capital is scarcer. To test this hypothesis, we construct two proxies for the amount of arbitrage capital, i.e., aggregate hedge fund assets under management and aggregate short interest. We then regress the returns to our time-series and cross-sectional momentum strategies on our proxies for arbitrage capital. The behavioral explanation also predicts that momentum in anomaly returns is more significant when market liquidity is lower (i.e., when arbitrage is more limited). To proxy for market liquidity, we use the aggregate Amihud's illiquidity measure and a time trend. The use of a time trend as a proxy for market liquidity is motivated by Chordia, Subrahmanyam, and Tong (2014), who argue that market liquidity exhibits a secular trend. To the extent that arbitrage capital has increased over time, the time trend can also be thought of as a proxy for the amount of arbitrage capital. In either case, we would expect momentum profits to decline over time.

Table 8 reports the regression results. There are four panels in Table 8, corresponding to equal- and value-weighted time-series momentum strategies, and equal- and value-weighted cross-sectional momentum strategies, respectively. In each panel, we estimate four regressions, one for each of the proxies for arbitrage capital and market liquidity. Looking at Panel A, we find significant evidence that equal-weighted time-series momentum profits is decreasing in hedge fund assets under management and aggregate short interest, and is increasing in aggregate market liquidity. Furthermore, we find that time-series momentum profits decrease over time. These results are consistent with the prediction of the behavioral explanations, i.e., the persistence in anomaly returns is weaker when arbitrage capital is more abundant and when the market liquidity is lower.

Results presented in Panel B on value-weighted time-series momentum profits are similar to those in Panel A. We continue to find time-series momentum is more pronounced when hedge fund assets under management and aggregate short interest are lower and when aggregate Amihud's illiquidity is higher. Moreover, the momentum has attenuated over time. Panel C and Panel D reports the results for cross-sectional momentum. We find qualitatively similar results to those presented in Panels A and B. That is, we find that cross-sectional momentum profits are decreasing in hedge fund assets under management, aggregate short interest, and a time trend, and increasing in aggregate Amihud's illiquidity measure. While the results are still significant for aggregate short interest and time trend, they are statistically insignificant for hedge fund total assets under management and aggregate illiquidity. Overall, the results reported in Table 8 provide additional support for the behavioral explanations.

4.6. Robustness Tests

Our findings of significant time-series and cross-sectional momentum in anomaly returns are not due to small, illiquid stocks. In constructing anomaly returns, we remove all stocks with a price less than $5 or with a market capitalization ranked in the lowest NYSE decile. Moreover, when we form anomaly decile portfolios, we use NYSE breakpoints to further minimize the impact of micro-cap stocks (Hou, Xue, and Zhang (2015, 2017)). To further examine whether our results are due to possible market microstructure effect, we present two robustness tests. In the first test, we skip a week after portfolio formation (i.e., before we compute holding period returns). The results are presented in Table 9 and Table 10. We find that the results become weaker after we skip a week, but continue to be statistically significant. The weaker results after skipping a week is in line with our finding that momentum in anomaly returns is relatively short-lived. In the second test, we examine the extent to which our results are driven by the long versus short legs. If the persistence in long-short returns is attributable to the short leg, then it may not be implementable. The results in Table 11 indicate that the profits to our time-series and cross-sectional momentum strategies are attributable to both long and short legs.

5. Conclusions

We find strong evidence of time-series and cross-sectional momentum in the long-short returns of 90 anomalies. Anomalies that performed well during recent weeks continue to perform well for up to a year. Strategies that exploit such persistence deliver significant abnormal returns that are robust to the momentum effect of Jegadeesh and Titman (1993). Our evidence is inconsistent with the view that stock market anomalies are a product of data mining because if anomaly returns are spurious then they should not persist. Our results are also inconsistent with risk-based explanations with constant returns because the persistence in anomaly return does not extend beyond our initial holding period and the profits to our momentum strategies remain unchanged after we demean each anomaly's long-short returns. We also show that the momentum in anomaly returns cannot be explained by time-varying exposures to standard asset pricing factors such as CAPM, Fama and French 3-factor model, and the Carhart 4-factor model. Although we cannot completely rule out time-varying risk premium, our results are more consistent with behavioral explanations in which limits to arbitrage and slow-moving capital allow mispricing to persist. Consistent with this view, we find the profits to our momentum strategies are more pronounced when arbitrage capital is scarcer and market liquidity is lower.

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Appendix: List of anomalies

We compile a comprehensive list of anomalies by merging the samples of Hou, Xue, and Zhang (HXZ 2015) and McLean and Pontiff (MP 2016). We additionally require that the anomaly variable be continuous and can be constructed using the CRSP, COMPUSTAT, and IBES data.

Abbreviation	Anomaly	Authors	Source
Panel A: Growth/Value			
A/ME	Market leverage	Bhandari (1988)	HXZ
B/M	Book-to-market equity	Rosenberg et al. (1985)	HXZ
B/P-E	Enterprise component of book-to-price	Penman et al. (2007)	MP
B/P-Lev	Leverage component of book-to-price	Penman et al. (2007)	MP
CF/P	Cash flow-to-price	Lakonishok et al. (1994)	HXZ
D/P	Dividend yield	Litzenberger and Ramaswamy (1979)	HXZ
E/P	Earnings-to-price	Basu (1983)	HXZ
EF/P	Analysts' earnings forecasts-to-price	Elgers et al. (2001)	HXZ
Enter	Enterprise multiple	Loughran and Wellman (2012)	MP
LTG	Long-term growth forecasts of analysts	La Porta (1996)	HXZ
NO/P	Net payout yield	Boudoukh et al. (2007)	HXZ
O/P	Payout yield	Boudoukh et al. (2007)	HXZ
Rev	Long-term reversal	Bondt and Thaler (1985)	HXZ
SG	Sales growth	Lakonishok et al. (1994)	HXZ
σ(CF)	Cash flow variance	Haugen and Baker (1996)	MP
Panel B: Intangibles			
AccQ	Accrual quality	Francis et al. (2005)	HXZ
AD/M	Advertisement expense-to-market	Chan et al. (2001)	HXZ
Age	Firm Age	Barry and Brown (1984)	MP
BC/A	Brand capital-to-assets	Belo et al. (2014b)	HXZ
H/N	Hiring rate	Belo et al. (2014a)	HXZ
OC/A	Organizational capital-to-assets	Eisfeldt and Papanikolaou (2013)	HXZ
OL	Operating leverage	Novy-Marx (2011)	HXZ
RC/A	R&D capital-to-assets	Li (2011)	HXZ
RD/M	R&D-to-market	Chan et al. (2001)	HXZ
RD/S	R&D-to-sales	Chan et al. (2001)	HXZ
Panel C: Investment			
ACI	Abnormal corporate Investment	Titman et al. (2004)	HXZ
BeG	Growth in book equity	Lockwood and Prombutr (2010)	MP
CEI	Composite issuance	Daniel and Titman (2006)	HXZ
I/A	Growth in total assets	Cooper et al. (2008)	HXZ
I-ADJ	Investment growth-industry adjusted	Abarbanell and Bushee (1998)	MP
IG	Investment growth	Xing (2008)	HXZ
IvC	Inventory changes	Thomas and Zhang (2002)	HXZ
IvG	Inventory growth	Belo and Lin (2012)	HXZ
NCO	Changes in net noncurrent operating assets	Richardson et al. (2005)	MP
NOA	Net operating assets	Hirshleifer et al. (2004)	HXZ

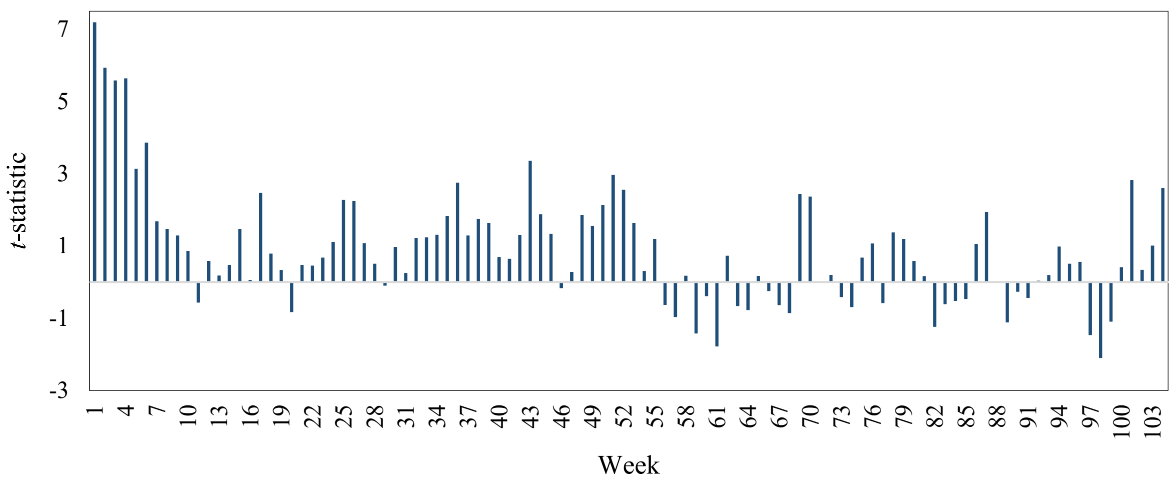
Abbreviation	Anomaly	Authors	Source
NoaG	Growth in long-term operating assets	Fairfield et al. (2003)	MP
NSI	Net stock issues	Pontiff and Woodgate (2008)	HXZ
NWC	Changes in net non-cash working capital	Richardson et al. (2005)	MP
NXF	Net external financing	Bradshaw et al. (2006)	HXZ
OA	Operating accruals	Sloan (1996)	HXZ
POA	Percent operating accrual	Hafzalla et al. (2011)	HXZ
PTA	Percent total accruals	Hafzalla et al. (2011)	HXZ
TA	Total accrual	Richardson et al. (2005)	HXZ
ΔPI/A	Changes in property, plant, and equipment plus changes in inventory	Lyandres et al. (2008)	HXZ
Panel D: Momentum			
Abr-1	Cumulative abnormal stock returns around earnings announcements	Chan et al. (1996)	HXZ
R11-1	Momentum (11-month prior returns)	Jegadeesh and Titman (1993)	HXZ
R6-1	Momentum (6-month prior returns)	Jegadeesh and Titman (1993)	HXZ
R6-Lag	Lagged momentum	Novy-Marx (2012)	MP
RE-1	Revisions in analysts' earnings forecasts	Chan et al. (1996)	HXZ
Season	Seasonality	Heston and Sadka (2008)	MP
SUE-1	Earnings surprise	Foster et al. (1984)	HXZ
W52	52-week high	George and Hwang (2004)	MP
Panel E: Profitability			
ATO	Asset turnover	Soliman (2008)	HXZ
CTO	Capital turnover	Haugen and Baker (1996)	HXZ
F	F-score	Piotroski (2000)	HXZ
FP	Financial distress	Campbell et al. (2008)	HXZ
GP/A	Gross profitability-to-assets	Novy-Marx (2013)	HXZ
O	O-score	Ohlson (1980)	HXZ
PM	Pro t margin	Soliman (2008)	HXZ
RNA	Return on net operating assets	Soliman (2008)	HXZ
ROA	Return on assets	Balakrishnan et al. (2010)	HXZ
ROE	Return on equity	Haugen and Baker (1996)	HXZ
RS	Revenue surprise	Jegadeesh and Livnat (2006)	HXZ
S/IV	ΔSales - Δinventory	Abarbanell and Bushee (1998)	MP
S/P	Sale-to-price	Barbee Jr et al. (1996)	MP
S/SG&A	ΔSales - ΔSG&A	Abarbanell and Bushee (1998)	MP
TES	Tax expense surprise	Thomas and Zhang (2011)	HXZ
TI/BI	Taxable income-to-book income	Green et al. (2014)	HXZ
Z	Z-score	Dichev (1998)	MP
ΔATO	Change in asset turnover	Soliman (2008)	MP
ΔPM	Change in profit margin	Soliman (2008)	MP

Abbreviation	Anomaly	Authors	Source
Panel F: Trading			
1/P	1/share price	Miller and Scholes (1982)	HXZ
B-A	Bid-ask spread	Amihud and Mendelson (1986)	MP
Disp	Dispersion of analysts' earnings forecasts	Diether et al. (2002)	HXZ
Dvol	Dollar trading volume	Brennan et al. (1998)	HXZ
Illiq	Illiquidity	Amihud (2002)	HXZ
Ivol	Idiosyncratic volatility	Ang et al. (2006)	HXZ
MDR	Maximum daily return	Bali et al. (2011)	HXZ
ME	Market equity	Banz (1981)	HXZ
S-Rev	Short-term reversal	Jegadeesh (1990)	HXZ
Skew	Coskewness	Harvey and Siddique (2000)	MP
Short	Short interest	Dechow et al. (2001)	MP
Svol	Systematic volatility	Ang et al. (2006)	HXZ
Turn	Share turnover	Datar et al. (1998)	HXZ
Tvol	Total volatility	Ang et al. (2006)	HXZ
Vol-T	Volume trend	Haugen and Baker (1996)	MP
β-M	Beta monthly	Fama and MacBeth (1973)	MP
β-D	Beta daily	Dimson (1979)	HXZ
β-FP	Beta FP	Frazzini and Pedersen (2014)	HXZ
σ(Dvol)	Dollar volume volatility	Chordia et al. (2001)	MP

Figure 1
Time series predictability

This figure plots the *t*-statistic of b in the regression $r_{i,t} = a + b\, r_{i,t-\tau} + e_{i,t}$, where $r_{i,t}$ is the long-short return of anomaly *i* in time *t* scaled by past-month realized volatility. Our sample of 90 anomalies is compiled from Hou, Xue, and Zhang (2015) and McLean and Pontiff (2016). The detailed list and definitions of these 90 anomalies are contained in the Appendix. We obtain monthly stock data from the CRSP, accounting data from Compustat, and analyst forecast data from IBES. We obtain Fama and French (1996) three factors and the momentum factor from Kenneth French's website. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks and stocks with a price lower than $5. We also remove stocks whose market capitalization is ranked in the lowest NYSE decile at the portfolio formation date. We use NYSE breakpoints to sort all sample stocks into deciles. We sort all sample stocks into deciles based on each anomaly variable and construct equal-weighted as well as value-weighted portfolios. Our sample period is from July 1963 to December 2015.

Time series predictability for equal-weighted anomaly returns



Time series predictability for value-weighted anomaly returns

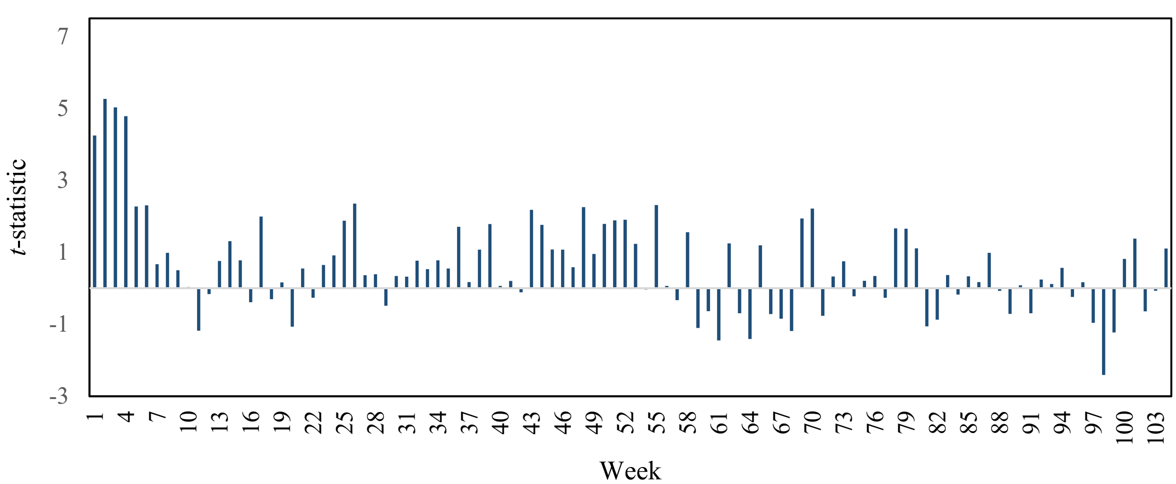
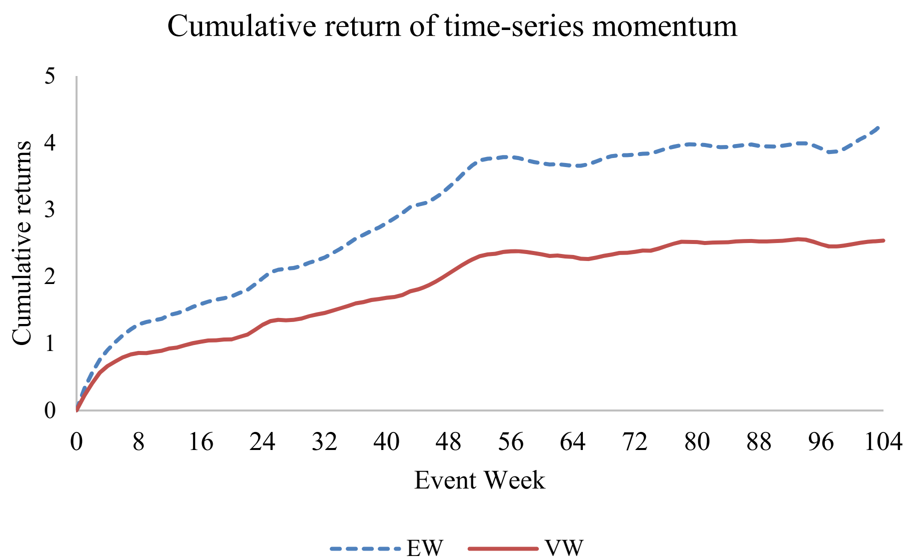


Figure 2
Cumulative returns of time-series and cross-sectional momentum strategies

This figure plots the cumulative returns of time-series and cross-sectional momentum strategies of anomalies by event week. Our sample of 90 anomalies is compiled from Hou, Xue, and Zhang (2015) and McLean and Pontiff (2016). The detailed list and definitions of these 90 anomalies are in the Appendix. We obtain monthly stock data from the CRSP, accounting data from Compustat, and analyst forecast data from IBES. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks and stocks with a price lower than $5. We also remove stocks whose market capitalization is ranked in the lowest NYSE decile at the portfolio formation date. We use NYSE breakpoints to sort all sample stocks into deciles. We sort all sample stocks into deciles based on each anomaly variable and construct equal-weighted as well as value-weighted portfolios. Our sample period is from July 1963 to December 2015. The time-series momentum strategies are described in Section 4.1. The cross-sectional momentum strategies are described in Section 4.2. The charts below correspond to a look-back period of 4 weeks and a holding-period of 4 weeks.



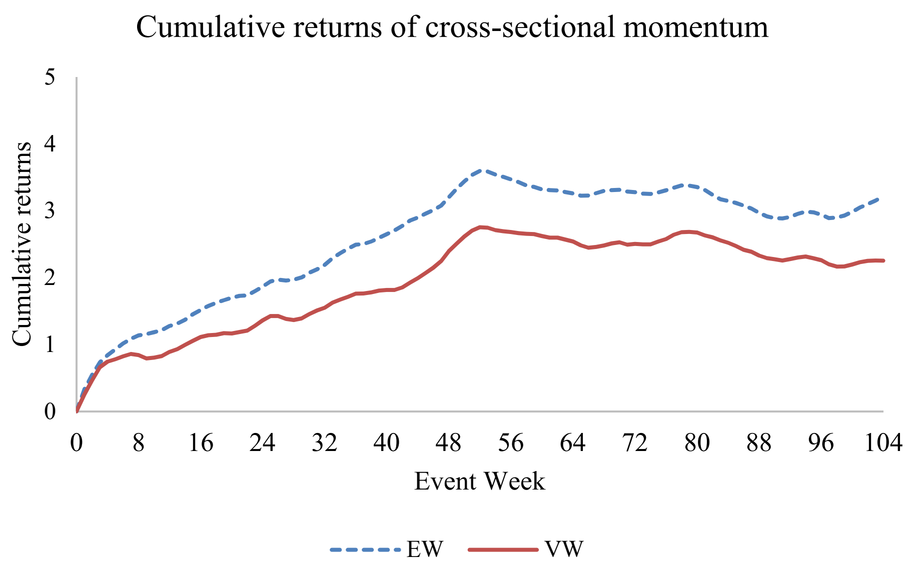


Table 1
Summary statistics

This table reports the summary statistics for anomaly returns. Our sample of 90 anomalies is compiled from Hou, Xue, and Zhang (2015) and McLean and Pontiff (2016). The detailed list and definitions of these 90 anomalies are contained in the Appendix. We obtain monthly stock data from the CRSP, accounting data from Compustat, and analyst forecast data from IBES. We obtain Fama and French (1996) three factors and the momentum factor from Kenneth French's website. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks and stocks with a price lower than $5. We also remove stocks whose market capitalization is ranked in the lowest NYSE decile at the portfolio formation date. We use NYSE breakpoints to sort all sample stocks into deciles. We sort all sample stocks into deciles based on each anomaly variable and construct equal-weighted as well as value-weighted portfolios. Our sample period is from July 1963 to December 2015. For each anomaly variable, we construct long-short strategies based on the two extreme deciles, with the long position being the higher-performing decile and the short position being the lower-performing decile (according to prior literature). We then compute 1-, 3-, and 4-factor alphas by regressing anomaly returns on the market, size, value, and momentum factors as defined in Fama and French (1996) and Carhart (1997). All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Growth/Value

	EW			VW		
Anomaly	α1	α3	α4	α1	α3	α4
A/ME	0.12 (2.49)	0.02 (0.55)	0.09 (2.24)	0.08 (1.60)	-0.04 (-0.95)	0.04 (0.86)
B/M	0.18 (4.14)	0.08 (2.01)	0.12 (3.05)	0.10 (2.10)	-0.03 (-0.74)	0.03 (0.73)
B/P-E	0.05 (2.05)	0.03 (1.28)	0.04 (1.61)	0.03 (0.56)	-0.01 (-0.32)	0.03 (0.72)
B/P-Lev	0.09 (2.92)	0.08 (2.78)	0.02 (0.93)	0.05 (1.35)	0.04 (0.91)	0.04 (0.90)
CF/P	0.18 (4.76)	0.10 (2.86)	0.13 (3.38)	0.12 (2.92)	0.02 (0.40)	0.05 (1.34)
D/P	0.10 (2.07)	0.02 (0.39)	0.03 (0.62)	0.15 (2.55)	0.04 (0.62)	0.00 (0.01)
E/P	0.17 (4.72)	0.09 (2.70)	0.11 (3.02)	0.13 (2.95)	0.02 (0.52)	0.06 (1.33)
EF/P	0.21 (3.32)	0.21 (3.73)	0.26 (4.61)	0.23 (3.57)	0.21 (3.67)	0.22 (3.75)
Enter	0.07 (2.57)	0.02 (0.80)	0.04 (1.66)	0.09 (2.40)	0.03 (1.00)	0.05 (1.52)
LTG	0.22 (2.67)	0.20 (3.10)	0.17 (2.50)	0.19 (2.25)	0.15 (2.18)	0.09 (1.27)
NO/P	0.15 (4.02)	0.13 (3.75)	0.13 (3.45)	0.14 (3.21)	0.12 (2.89)	0.11 (2.55)
O/P	0.13 (3.72)	0.09 (2.61)	0.09 (2.80)	0.16 (3.33)	0.08 (1.64)	0.09 (1.78)
Rev	0.17 (5.14)	0.10 (2.99)	0.07 (2.13)	0.13 (2.91)	0.02 (0.40)	-0.03 (-0.55)
SG	0.08 (3.37)	0.05 (1.95)	0.05 (2.08)	0.04 (1.29)	-0.00 (-0.06)	0.01 (0.17)

Panel B: Intangibles

	EW			VW		
Anomaly	α1	α3	α4	α1	α3	α4
AD/M	0.12 (2.31)	0.05 (1.09)	0.10 (2.04)	0.13 (2.28)	0.04 (0.66)	0.11 (1.87)
AccQ	0.02 (0.55)	-0.05 (-1.48)	-0.04 (-1.07)	-0.03 (-0.62)	-0.08 (-1.97)	-0.05 (-1.14)
Age	0.08 (1.65)	0.10 (1.95)	0.06 (1.21)	0.03 (0.53)	0.06 (1.20)	0.01 (0.24)
BC/A	0.16 (3.38)	0.15 (3.70)	0.12 (2.73)	0.19 (3.27)	0.19 (3.56)	0.16 (2.94)
H/N	0.11 (4.28)	0.07 (2.88)	0.07 (2.85)	0.09 (2.67)	0.05 (1.46)	0.03 (0.91)
OC/A	0.14 (3.42)	0.12 (3.05)	0.08 (1.89)	0.13 (2.55)	0.14 (2.73)	0.09 (1.75)
OL	0.09 (2.48)	0.07 (2.01)	0.06 (1.63)	0.07 (1.98)	0.10 (2.75)	0.06 (1.61)
RC/A	0.07 (1.02)	0.06 (1.11)	0.01 (0.16)	0.07 (1.10)	0.07 (1.53)	0.04 (0.82)
RD/M	0.14 (3.06)	0.09 (2.12)	0.07 (1.66)	0.05 (0.82)	-0.01 (-0.23)	0.00 (0.03)
RD/S	-0.02 (-0.29)	-0.02 (-0.45)	-0.06 (-1.12)	-0.06 (-0.93)	-0.04 (-0.80)	-0.04 (-0.78)

Panel C: Investment						
	EW			VW		
Anomaly	α1	α3	α4	α1	α3	α4
ACI	0.10 (4.95)	0.09 (4.65)	0.07 (3.65)	0.09 (2.91)	0.09 (2.89)	0.04 (1.46)
BeG	0.11 (4.94)	0.07 (3.01)	0.06 (2.68)	0.11 (3.16)	0.05 (1.31)	0.02 (0.47)
CEI	0.06 (3.03)	0.06 (2.85)	0.05 (2.56)	0.06 (2.19)	0.07 (2.29)	0.06 (1.95)
D_NCO	0.13 (6.44)	0.10 (4.89)	0.07 (3.64)	0.12 (4.52)	0.10 (3.65)	0.07 (2.55)
D_NWC	0.09 (5.42)	0.09 (5.51)	0.09 (5.00)	0.13 (4.17)	0.13 (4.33)	0.12 (4.25)
I-ADJ	-0.00 (-0.01)	0.02 (0.95)	0.05 (1.97)	0.01 (0.24)	0.03 (0.75)	0.03 (0.93)
I/A	0.15 (6.23)	0.10 (4.18)	0.09 (3.73)	0.13 (3.48)	0.08 (2.11)	0.07 (1.70)
IG	0.10 (5.86)	0.08 (4.54)	0.07 (3.99)	0.13 (4.66)	0.09 (3.23)	0.07 (2.54)
IvC	0.12 (5.92)	0.10 (5.26)	0.10 (5.33)	0.14 (4.51)	0.11 (3.44)	0.08 (2.43)
IvG	0.12 (5.74)	0.10 (4.69)	0.09 (4.46)	0.11 (3.71)	0.08 (2.46)	0.05 (1.43)
NOA	0.16 (4.86)	0.15 (4.64)	0.10 (3.09)	0.12 (3.56)	0.13 (3.76)	0.08 (2.49)
NoaG	0.15 (6.78)	0.12 (5.59)	0.09 (4.40)	0.10 (3.26)	0.08 (2.70)	0.06 (2.08)
NSI	0.16 (5.02)	0.15 (4.49)	0.11 (3.52)	0.10 (2.56)	0.12 (3.22)	0.10 (2.61)
NXF	0.19 (5.07)	0.18 (4.80)	0.13 (3.56)	0.13 (2.25)	0.16 (2.74)	0.07 (1.35)
OA	0.07 (3.56)	0.07 (3.84)	0.08 (4.14)	0.08 (2.67)	0.08 (2.77)	0.07 (2.42)
PI/A	0.17 (7.14)	0.14 (5.72)	0.10 (4.40)	0.14 (4.42)	0.12 (3.50)	0.08 (2.34)
POA	0.07 (3.30)	0.07 (3.40)	0.09 (4.04)	0.10 (3.12)	0.06 (2.24)	0.08 (2.53)
PTA	0.06 (4.03)	0.05 (3.29)	0.05 (3.07)	0.09 (3.63)	0.08 (3.13)	0.06 (2.32)
TA	0.11 (5.63)	0.08 (4.29)	0.06 (3.44)	0.08 (2.86)	0.05 (1.60)	0.03 (1.02)

Panel D: Momentum						
	EW			VW		
Anomaly	α1	α3	α4	α1	α3	α4
Abr-1	0.30 (14.28)	0.30 (14.21)	0.28 (13.53)	0.21 (6.18)	0.21 (6.10)	0.18 (5.42)
R11-1	0.38 (8.17)	0.43 (9.14)	0.27 (6.23)	0.36 (5.99)	0.40 (6.90)	0.20 (3.72)
R6-1	0.35 (7.91)	0.36 (8.07)	0.21 (5.20)	0.27 (5.23)	0.28 (5.34)	0.11 (2.33)
R6-Lag	0.25 (7.12)	0.29 (8.14)	0.22 (5.66)	0.30 (5.82)	0.34 (6.69)	0.22 (4.18)
RE-1	0.20 (6.04)	0.23 (6.88)	0.17 (5.06)	0.17 (3.20)	0.20 (3.75)	0.10 (1.87)
SUE	0.28 (9.16)	0.30 (10.38)	0.25 (9.15)	0.16 (4.41)	0.17 (4.65)	0.10 (3.02)
Season	0.08 (4.13)	0.09 (5.06)	0.09 (4.85)	0.15 (4.65)	0.18 (5.81)	0.17 (5.65)
W52	0.28 (4.15)	0.32 (4.75)	0.15 (2.27)	0.23 (3.10)	0.27 (3.56)	0.08 (1.03)

Panel E: Profitability						
	EW			VW		
Anomaly	α1	α3	α4	α1	α3	α4
ATO	0.01 (0.19)	0.08 (2.20)	0.05 (1.40)	0.03 (0.60)	0.10 (1.97)	0.05 (0.96)
CTO	0.05 (1.47)	0.05 (1.50)	0.05 (1.39)	0.03 (0.86)	0.07 (1.95)	0.04 (1.13)
D_ATO	0.02 (0.89)	-0.02 (-1.18)	0.00 (0.05)	0.01 (0.58)	-0.01 (-0.31)	0.01 (0.42)
D_PM	0.02 (0.91)	0.04 (2.26)	0.01 (0.80)	0.03 (0.86)	0.06 (1.93)	0.02 (0.68)
F	0.16 (5.46)	0.18 (6.08)	0.14 (5.13)	0.10 (2.93)	0.10 (2.85)	0.09 (2.57)
FP	0.28 (4.97)	0.33 (5.81)	0.17 (3.95)	0.30 (3.76)	0.38 (4.74)	0.17 (2.91)
GP/A	0.12 (3.99)	0.14 (4.70)	0.11 (3.78)	0.05 (1.53)	0.10 (3.02)	0.07 (2.03)
O	0.07 (2.73)	0.12 (4.40)	0.07 (3.08)	0.03 (0.82)	0.12 (2.97)	0.06 (1.81)
PM	0.06 (1.31)	0.10 (2.40)	0.07 (1.74)	0.02 (0.43)	0.08 (1.56)	0.04 (0.90)
RNA	0.03 (0.65)	0.13 (2.52)	0.07 (1.54)	0.03 (0.50)	0.12 (1.99)	0.05 (0.95)
ROA	0.23 (5.14)	0.29 (6.81)	0.22 (5.90)	0.13 (2.31)	0.22 (4.02)	0.11 (2.48)
ROE	0.27 (5.53)	0.34 (7.59)	0.27 (6.78)	0.15 (2.43)	0.24 (4.19)	0.13 (2.66)
RS	0.19 (4.41)	0.24 (6.25)	0.17 (5.52)	0.11 (2.21)	0.15 (3.26)	0.07 (1.73)
S/IV	0.04 (2.91)	0.04 (2.87)	0.04 (2.64)	0.09 (3.08)	0.08 (2.86)	0.04 (1.23)
S/P	0.13 (2.91)	0.04 (1.02)	0.10 (2.54)	0.11 (2.23)	-0.01 (-0.21)	0.05 (1.20)
S/SGA	0.01 (0.77)	0.00 (0.18)	-0.00 (-0.06)	-0.00 (-0.11)	-0.01 (-0.41)	0.01 (0.19)
TES	0.07 (2.67)	0.10 (4.06)	0.08 (3.24)	0.01 (0.25)	0.06 (1.37)	0.02 (0.39)
TI/BI	0.07 (2.71)	0.08 (2.80)	0.06 (2.24)	0.06 (1.61)	0.08 (2.42)	0.04 (1.24)
Z	0.02 (0.48)	-0.02 (-0.75)	0.00 (0.12)	0.05 (1.27)	-0.05 (-1.13)	-0.02 (-0.39)

Panel F: Trading						
	EW			VW		
Anomaly	α1	α3	α4	α1	α3	α4
1/P	0.06 (1.23)	0.17 (3.40)	0.05 (1.07)	0.06 (0.99)	0.19 (3.23)	0.04 (0.69)
B-A	0.13 (2.09)	0.19 (3.33)	0.10 (1.79)	0.13 (1.78)	0.18 (2.63)	0.08 (1.15)
BETA_D	0.21 (3.61)	0.19 (3.19)	0.10 (1.57)	0.16 (2.44)	0.12 (1.79)	0.04 (0.61)
BETA_FP	0.31 (3.48)	0.32 (3.60)	0.19 (2.16)	0.27 (3.01)	0.23 (2.52)	0.11 (1.24)
BETA_M	0.22 (2.86)	0.23 (3.03)	0.13 (1.66)	0.19 (2.13)	0.19 (2.09)	0.08 (0.91)
Disp	0.24 (5.50)	0.28 (6.64)	0.21 (5.22)	0.24 (3.87)	0.29 (4.83)	0.18 (3.01)
Dvol	0.17 (4.65)	0.04 (1.07)	0.07 (1.88)	0.13 (3.73)	-0.01 (-0.17)	0.05 (1.55)
Illiq	0.12 (3.19)	-0.02 (-0.63)	0.03 (0.99)	0.11 (2.70)	-0.04 (-0.93)	0.03 (0.88)
Ivol	0.24 (3.53)	0.27 (3.92)	0.18 (2.71)	0.19 (2.51)	0.23 (3.05)	0.12 (1.81)
MDR	0.27 (4.22)	0.29 (4.55)	0.22 (3.47)	0.19 (2.55)	0.20 (2.70)	0.11 (1.56)
ME	0.08 (1.78)	-0.06 (-1.40)	-0.01 (-0.27)	0.08 (1.66)	-0.07 (-1.57)	-0.02 (-0.39)
S-Rev	0.07 (1.61)	0.07 (1.66)	0.14 (3.16)	-0.05 (-0.92)	-0.04 (-0.76)	0.04 (0.81)
STD_DVOL	0.22 (5.24)	0.10 (2.45)	0.11 (2.49)	0.16 (4.73)	0.03 (0.72)	0.07 (2.04)
Short	0.27 (5.62)	0.28 (5.54)	0.23 (4.70)	0.15 (2.84)	0.17 (3.08)	0.11 (2.07)
Skew	0.06 (2.43)	0.04 (1.56)	0.05 (1.98)	0.07 (1.94)	0.03 (0.86)	0.04 (1.21)
Svol	0.09 (2.84)	0.10 (3.38)	0.09 (2.82)	0.15 (3.00)	0.20 (3.88)	0.13 (2.56)
Turn	0.25 (3.96)	0.22 (3.54)	0.19 (2.87)	0.16 (2.19)	0.14 (1.98)	0.09 (1.23)
Tvol	0.28 (3.61)	0.30 (3.91)	0.20 (2.58)	0.23 (2.84)	0.24 (2.93)	0.13 (1.53)
Vol-T	0.02 (0.63)	0.04 (1.38)	0.04 (1.19)	-0.09 (-2.49)	-0.03 (-0.69)	-0.02 (-0.47)

Table 2
Alphas of time-series momentum strategies

Table 2 reports the alphas of time-series momentum strategies. We calculate each anomaly's prior returns during formation period ranging from one week to 52 weeks. The time-series strategies are constructed by going long the anomalies with positive past returns and short those with negative returns. Portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Equal-weighted returns

Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.37 (12.5)	0.28 (12.2)	0.25 (12.3)	0.23 (12.0)	0.16 (9.99)	0.12 (8.05)	0.07 (6.44)	0.05 (6.29)
	α3	0.33 (11.3)	0.26 (11.2)	0.24 (11.3)	0.21 (11.2)	0.15 (9.36)	0.11 (7.54)	0.06 (6.10)	0.05 (5.90)
	α4	0.32 (10.8)	0.25 (10.8)	0.23 (10.9)	0.20 (10.5)	0.13 (8.39)	0.10 (6.63)	0.05 (4.86)	0.04 (4.83)
2	α1	0.39 (13.5)	0.34 (12.5)	0.30 (12.0)	0.26 (11.3)	0.18 (9.45)	0.14 (7.58)	0.08 (6.52)	0.07 (6.32)
	α3	0.36 (12.3)	0.31 (11.4)	0.27 (11.1)	0.24 (10.5)	0.17 (8.96)	0.13 (7.15)	0.08 (6.22)	0.07 (6.04)
	α4	0.34 (11.8)	0.30 (11.1)	0.26 (10.5)	0.23 (9.76)	0.16 (7.92)	0.11 (6.24)	0.06 (4.98)	0.05 (5.00)
3	α1	0.42 (13.5)	0.36 (12.4)	0.32 (11.4)	0.29 (10.7)	0.20 (8.81)	0.14 (6.99)	0.09 (5.99)	0.07 (5.93)
	α3	0.39 (12.3)	0.34 (11.4)	0.30 (10.5)	0.26 (9.85)	0.18 (8.23)	0.13 (6.57)	0.08 (5.70)	0.07 (5.68)
	α4	0.37 (11.8)	0.32 (10.8)	0.28 (9.76)	0.24 (8.96)	0.17 (7.16)	0.12 (5.65)	0.06 (4.50)	0.06 (4.65)
4	α1	0.42 (13.7)	0.37 (12.2)	0.32 (10.9)	0.29 (10.2)	0.20 (8.24)	0.15 (6.54)	0.09 (5.60)	0.07 (5.66)
	α3	0.39 (12.5)	0.34 (11.2)	0.30 (9.97)	0.26 (9.34)	0.19 (7.69)	0.14 (6.11)	0.09 (5.35)	0.07 (5.48)
	α4	0.37 (11.8)	0.32 (10.4)	0.27 (9.12)	0.24 (8.38)	0.17 (6.61)	0.12 (5.15)	0.07 (4.12)	0.06 (4.35)
8	α1	0.37 (12.1)	0.33 (10.9)	0.30 (9.79)	0.26 (8.77)	0.19 (6.37)	0.14 (5.13)	0.09 (4.49)	0.08 (4.96)
	α3	0.35 (11.3)	0.31 (10.2)	0.28 (9.10)	0.25 (8.19)	0.17 (6.01)	0.13 (4.71)	0.09 (4.32)	0.08 (4.91)
	α4	0.32 (10.3)	0.29 (9.22)	0.25 (8.05)	0.22 (7.10)	0.15 (4.96)	0.10 (3.71)	0.06 (3.09)	0.06 (3.65)
12	α1	0.31 (10.0)	0.28 (8.92)	0.25 (8.06)	0.23 (7.22)	0.17 (5.34)	0.13 (4.25)	0.10 (4.03)	0.09 (4.60)
	α3	0.29 (9.42)	0.26 (8.39)	0.24 (7.62)	0.21 (6.84)	0.16 (5.00)	0.12 (3.95)	0.09 (3.94)	0.09 (4.57)
	α4	0.26 (8.36)	0.23 (7.32)	0.21 (6.46)	0.18 (5.66)	0.12 (3.93)	0.09 (2.92)	0.06 (2.71)	0.06 (3.25)
26	α1	0.27 (8.44)	0.25 (7.63)	0.23 (6.94)	0.21 (6.36)	0.17 (5.09)	0.14 (4.29)	0.13 (3.93)	0.10 (3.99)
	α3	0.25 (7.73)	0.23 (7.06)	0.21 (6.47)	0.20 (6.00)	0.17 (4.92)	0.14 (4.21)	0.13 (3.96)	0.11 (4.04)
	α4	0.20 (6.25)	0.18 (5.58)	0.17 (4.98)	0.15 (4.51)	0.12 (3.50)	0.10 (2.87)	0.08 (2.64)	0.07 (2.72)
52	α1	0.26 (8.42)	0.25 (7.77)	0.24 (7.13)	0.23 (6.71)	0.20 (5.49)	0.17 (4.78)	0.14 (4.07)	0.10 (3.37)
	α3	0.25 (8.29)	0.25 (7.73)	0.23 (7.12)	0.23 (6.72)	0.20 (5.55)	0.17 (4.86)	0.15 (4.17)	0.11 (3.59)
	α4	0.19 (6.24)	0.19 (5.79)	0.17 (5.25)	0.17 (4.91)	0.14 (3.90)	0.12 (3.31)	0.10 (2.80)	0.07 (2.46)

Panel B: Value-weighted returns

Past Returns		Holding period (weeks) 1	2	3	4	8	12	26	52
1	α1	0.21 (7.99)	0.19 (9.14)	0.17 (9.77)	0.15 (9.56)	0.11 (9.07)	0.07 (6.93)	0.05 (5.84)	0.03 (5.16)
	α3	0.19 (7.17)	0.18 (8.46)	0.16 (9.03)	0.14 (8.83)	0.10 (8.43)	0.07 (6.35)	0.04 (5.33)	0.03 (4.85)
	α4	0.18 (6.67)	0.17 (8.16)	0.16 (8.70)	0.13 (8.31)	0.09 (7.54)	0.06 (5.47)	0.03 (4.27)	0.02 (3.84)
2	α1	0.25 (9.30)	0.24 (9.84)	0.21 (9.74)	0.19 (9.56)	0.13 (8.41)	0.09 (6.37)	0.05 (5.34)	0.04 (4.86)
	α3	0.24 (8.51)	0.22 (9.08)	0.20 (9.00)	0.18 (8.96)	0.12 (7.98)	0.09 (5.97)	0.05 (4.91)	0.04 (4.71)
	α4	0.23 (8.17)	0.22 (8.89)	0.19 (8.65)	0.17 (8.46)	0.11 (7.07)	0.07 (5.13)	0.04 (3.92)	0.03 (3.61)
3	α1	0.28 (10.1)	0.26 (10.1)	0.24 (9.69)	0.21 (9.22)	0.14 (7.66)	0.10 (5.88)	0.06 (5.00)	0.04 (4.68)
	α3	0.26 (9.07)	0.24 (9.18)	0.22 (8.88)	0.19 (8.51)	0.13 (7.17)	0.09 (5.51)	0.06 (4.66)	0.05 (4.57)
	α4	0.25 (8.72)	0.24 (8.81)	0.21 (8.39)	0.18 (7.84)	0.12 (6.21)	0.08 (4.63)	0.04 (3.59)	0.03 (3.37)
4	α1	0.29 (10.4)	0.27 (10.1)	0.24 (9.33)	0.21 (8.76)	0.14 (7.01)	0.10 (5.37)	0.06 (4.52)	0.04 (4.35)
	α3	0.27 (9.33)	0.25 (9.28)	0.22 (8.61)	0.20 (8.16)	0.13 (6.58)	0.09 (5.01)	0.06 (4.18)	0.05 (4.24)
	α4	0.26 (8.80)	0.24 (8.72)	0.21 (7.93)	0.18 (7.35)	0.11 (5.57)	0.08 (4.09)	0.04 (3.09)	0.03 (3.01)
8	α1	0.26 (9.54)	0.24 (9.10)	0.22 (8.36)	0.19 (7.51)	0.12 (4.95)	0.09 (3.83)	0.05 (3.38)	0.05 (3.95)
	α3	0.25 (9.01)	0.23 (8.64)	0.21 (7.81)	0.18 (7.05)	0.12 (4.71)	0.08 (3.57)	0.05 (3.21)	0.05 (3.90)
	α4	0.23 (7.99)	0.21 (7.59)	0.18 (6.68)	0.16 (5.88)	0.09 (3.58)	0.06 (2.48)	0.03 (1.94)	0.03 (2.49)
12	α1	0.22 (7.83)	0.19 (6.91)	0.17 (6.14)	0.15 (5.48)	0.10 (3.66)	0.07 (2.68)	0.05 (2.67)	0.05 (3.63)
	α3	0.21 (7.45)	0.18 (6.61)	0.16 (5.91)	0.15 (5.27)	0.09 (3.46)	0.07 (2.55)	0.05 (2.66)	0.05 (3.70)
	α4	0.18 (6.43)	0.16 (5.55)	0.14 (4.78)	0.12 (4.09)	0.06 (2.28)	0.04 (1.39)	0.02 (1.30)	0.03 (2.20)
26	α1	0.17 (6.19)	0.16 (5.74)	0.15 (5.24)	0.13 (4.76)	0.10 (3.58)	0.08 (3.04)	0.07 (2.87)	0.06 (3.15)
	α3	0.15 (5.59)	0.15 (5.26)	0.14 (4.87)	0.12 (4.46)	0.10 (3.48)	0.08 (3.04)	0.07 (2.98)	0.06 (3.29)
	α4	0.11 (4.04)	0.10 (3.76)	0.09 (3.36)	0.08 (2.94)	0.05 (1.97)	0.04 (1.63)	0.04 (1.50)	0.03 (1.75)
52	α1	0.18 (6.64)	0.18 (6.14)	0.17 (5.64)	0.16 (5.33)	0.14 (4.43)	0.12 (3.91)	0.10 (3.15)	0.07 (2.71)
	α3	0.18 (6.69)	0.17 (6.23)	0.17 (5.77)	0.16 (5.47)	0.14 (4.65)	0.13 (4.11)	0.10 (3.35)	0.08 (3.08)
	α4	0.13 (4.72)	0.12 (4.32)	0.11 (3.90)	0.11 (3.62)	0.09 (2.88)	0.07 (2.44)	0.06 (1.93)	0.05 (1.91)

Table 3
Alphas of cross-sectional momentum strategies

Table 3 reports the alphas of cross sectional momentum strategies. We sort 90 anomalies into quintile portfolios based on prior returns during the formation period ranging from one week to 52 weeks. The cross-sectional strategies are constructed based on two extreme quintiles, with the long position being the high past performance quintile and the short position being the low past performance quintile. Portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Equal-weighted returns

Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.35 (8.17)	0.26 (7.67)	0.24 (8.19)	0.21 (7.59)	0.14 (6.31)	0.10 (4.51)	0.07 (4.06)	0.06 (4.13)
	α3	0.44 (8.78)	0.34 (8.65)	0.32 (8.40)	0.27 (8.82)	0.19 (7.08)	0.14 (5.94)	0.09 (5.16)	0.06 (5.11)
	α4	0.37 (7.17)	0.31 (7.22)	0.29 (7.14)	0.24 (7.88)	0.17 (5.96)	0.11 (4.99)	0.07 (4.19)	0.06 (4.43)
2	α1	0.32 (6.63)	0.28 (7.30)	0.26 (7.37)	0.21 (6.81)	0.13 (4.75)	0.09 (3.64)	0.04 (2.26)	0.03 (2.30)
	α3	0.36 (8.59)	0.30 (7.87)	0.26 (7.43)	0.23 (6.84)	0.16 (5.61)	0.11 (4.08)	0.08 (3.97)	0.07 (4.18)
	α4	0.47 (10.0)	0.40 (9.01)	0.34 (8.91)	0.30 (8.45)	0.21 (6.73)	0.15 (5.48)	0.10 (4.96)	0.08 (4.96)
3	α1	0.42 (8.42)	0.37 (7.65)	0.31 (8.01)	0.26 (7.78)	0.19 (5.92)	0.13 (4.67)	0.08 (3.96)	0.07 (4.41)
	α3	0.38 (8.27)	0.34 (8.11)	0.30 (7.29)	0.25 (6.73)	0.16 (4.73)	0.10 (3.54)	0.05 (2.21)	0.04 (2.50)
	α4	0.40 (9.10)	0.32 (7.94)	0.27 (6.98)	0.24 (6.51)	0.16 (5.00)	0.12 (3.78)	0.09 (3.61)	0.07 (4.03)
4	α1	0.50 (9.62)	0.43 (9.23)	0.37 (8.07)	0.32 (7.58)	0.23 (6.32)	0.16 (5.25)	0.11 (4.62)	0.09 (4.84)
	α3	0.45 (7.94)	0.38 (7.76)	0.33 (6.98)	0.28 (6.56)	0.21 (5.32)	0.14 (4.39)	0.08 (3.73)	0.08 (4.39)
	α4	0.39 (7.73)	0.34 (7.21)	0.29 (6.23)	0.24 (5.48)	0.16 (4.09)	0.10 (3.11)	0.05 (1.88)	0.04 (2.35)
8	α1	0.39 (8.72)	0.31 (7.37)	0.28 (6.82)	0.24 (6.10)	0.16 (4.46)	0.12 (3.54)	0.08 (3.27)	0.08 (3.74)
	α3	0.50 (10.3)	0.43 (8.95)	0.37 (7.66)	0.33 (7.06)	0.24 (5.92)	0.17 (4.94)	0.11 (4.37)	0.09 (4.62)
	α4	0.45 (8.70)	0.38 (7.61)	0.33 (6.59)	0.29 (6.05)	0.21 (5.00)	0.14 (4.06)	0.09 (3.57)	0.08 (4.20)
12	α1	0.40 (7.91)	0.33 (6.91)	0.27 (5.69)	0.23 (5.01)	0.16 (3.73)	0.10 (2.75)	0.04 (1.68)	0.04 (2.07)
	α3	0.32 (6.90)	0.27 (5.92)	0.24 (5.31)	0.20 (4.59)	0.13 (3.10)	0.11 (2.82)	0.09 (2.72)	0.09 (3.27)
	α4	0.43 (8.33)	0.38 (7.29)	0.34 (6.64)	0.31 (6.03)	0.21 (4.63)	0.15 (3.88)	0.11 (3.66)	0.10 (4.02)
26	α1	0.39 (7.25)	0.35 (6.43)	0.32 (5.75)	0.28 (5.21)	0.18 (3.90)	0.12 (3.05)	0.09 (2.96)	0.09 (3.80)
	α3	0.33 (6.37)	0.29 (5.51)	0.25 (4.66)	0.21 (4.02)	0.13 (2.60)	0.07 (1.72)	0.03 (1.06)	0.04 (1.61)
	α4	0.26 (5.64)	0.22 (4.76)	0.20 (4.37)	0.18 (3.98)	0.13 (2.94)	0.10 (2.48)	0.09 (2.57)	0.09 (3.18)
52	α1	0.37 (7.25)	0.32 (6.37)	0.30 (5.89)	0.27 (5.40)	0.19 (4.25)	0.14 (3.33)	0.11 (3.41)	0.11 (3.83)
	α3	0.33 (6.29)	0.29 (5.55)	0.26 (5.08)	0.23 (4.51)	0.15 (3.36)	0.10 (2.51)	0.09 (2.88)	0.10 (3.68)
	α4	0.27 (5.19)	0.23 (4.37)	0.20 (3.75)	0.16 (3.12)	0.09 (1.87)	0.04 (0.88)	0.03 (0.83)	0.04 (1.42)

Panel B: Value-weighted returns									
Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.20 (4.16)	0.16 (4.56)	0.17 (5.54)	0.15 (5.47)	0.10 (5.12)	0.06 (3.33)	0.05 (3.81)	0.04 (4.11)
	α3	0.31 (5.73)	0.27 (6.46)	0.26 (6.89)	0.22 (7.49)	0.15 (6.27)	0.10 (5.18)	0.07 (4.83)	0.04 (4.43)
	α4	0.28 (4.99)	0.26 (5.71)	0.25 (6.02)	0.21 (6.79)	0.14 (5.23)	0.09 (4.09)	0.06 (3.81)	0.05 (3.95)
2	α1	0.22 (4.18)	0.22 (5.46)	0.22 (6.19)	0.18 (5.68)	0.10 (4.19)	0.06 (2.89)	0.03 (1.92)	0.02 (1.87)
	α3	0.26 (5.26)	0.24 (5.42)	0.22 (5.77)	0.20 (5.98)	0.13 (5.26)	0.08 (3.42)	0.06 (3.97)	0.05 (4.20)
	α4	0.38 (7.21)	0.36 (7.47)	0.31 (7.94)	0.28 (8.01)	0.19 (6.32)	0.13 (5.16)	0.08 (4.70)	0.06 (4.44)
3	α1	0.36 (6.58)	0.34 (6.80)	0.29 (7.34)	0.26 (7.56)	0.18 (5.56)	0.12 (4.25)	0.07 (3.60)	0.06 (3.91)
	α3	0.33 (6.41)	0.33 (7.27)	0.28 (6.87)	0.24 (6.75)	0.14 (4.60)	0.08 (3.19)	0.04 (1.89)	0.03 (1.95)
	α4	0.29 (5.76)	0.27 (5.88)	0.24 (5.87)	0.22 (6.06)	0.13 (4.68)	0.09 (3.37)	0.07 (3.53)	0.06 (3.92)
4	α1	0.42 (7.62)	0.38 (8.03)	0.35 (7.65)	0.31 (7.25)	0.21 (5.70)	0.14 (4.80)	0.09 (4.24)	0.06 (4.04)
	α3	0.39 (6.70)	0.36 (7.14)	0.32 (6.88)	0.28 (6.53)	0.20 (4.89)	0.13 (3.85)	0.07 (3.23)	0.06 (3.66)
	α4	0.36 (6.64)	0.33 (6.69)	0.29 (6.28)	0.24 (5.64)	0.15 (3.88)	0.08 (2.81)	0.03 (1.43)	0.03 (1.62)
8	α1	0.30 (5.93)	0.27 (5.84)	0.25 (5.99)	0.21 (5.52)	0.12 (3.81)	0.08 (2.83)	0.06 (2.92)	0.06 (3.62)
	α3	0.43 (8.07)	0.39 (7.84)	0.35 (7.09)	0.30 (6.54)	0.20 (5.13)	0.14 (4.31)	0.08 (3.77)	0.06 (3.84)
	α4	0.39 (7.16)	0.36 (7.06)	0.32 (6.39)	0.28 (5.93)	0.19 (4.43)	0.12 (3.49)	0.07 (2.95)	0.07 (3.49)
12	α1	0.35 (6.26)	0.32 (6.34)	0.27 (5.49)	0.23 (4.82)	0.13 (3.19)	0.07 (2.17)	0.02 (0.99)	0.02 (1.29)
	α3	0.26 (5.27)	0.23 (4.84)	0.20 (4.37)	0.17 (3.76)	0.09 (2.20)	0.07 (1.90)	0.06 (2.21)	0.07 (3.25)
	α4	0.39 (7.08)	0.35 (6.53)	0.32 (5.95)	0.28 (5.39)	0.18 (3.79)	0.12 (3.07)	0.08 (2.76)	0.07 (3.34)
26	α1	0.37 (6.39)	0.34 (5.94)	0.30 (5.27)	0.26 (4.70)	0.16 (3.18)	0.10 (2.34)	0.07 (2.16)	0.08 (3.22)
	α3	0.29 (5.30)	0.26 (4.85)	0.22 (4.02)	0.18 (3.37)	0.09 (1.75)	0.03 (0.77)	0.00 (0.12)	0.02 (0.80)
	α4	0.18 (3.70)	0.16 (3.30)	0.15 (3.11)	0.14 (2.87)	0.09 (1.95)	0.06 (1.54)	0.07 (2.15)	0.07 (3.28)
52	α1	0.31 (5.75)	0.28 (5.21)	0.26 (4.88)	0.23 (4.41)	0.16 (3.21)	0.11 (2.37)	0.08 (2.51)	0.08 (3.28)
	α3	0.29 (5.14)	0.26 (4.60)	0.24 (4.30)	0.21 (3.74)	0.13 (2.46)	0.08 (1.72)	0.07 (2.06)	0.08 (3.13)
	α4	0.22 (3.96)	0.18 (3.34)	0.16 (2.93)	0.12 (2.33)	0.04 (0.88)	-0.00 (-0.08)	-0.00 (-0.07)	0.02 (0.63)

Table 4

Alphas of time-series momentum strategies – using demeaned long-short returns

Table 4 reports the alphas of time-series momentum strategies based on demeaned anomaly returns. For each anomaly, we compute the demeaned anomaly returns by subtracting the average returns from the weekly anomaly returns. We then calculate each anomaly's prior returns based on demeaned anomaly returns during formation period ranging from one week to 52 weeks. The time-series strategies are constructed by going long the anomalies with positive past returns and short those with negative returns. Portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Equal-weighted returns

Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.36 (12.3)	0.28 (12.2)	0.25 (12.1)	0.22 (11.8)	0.15 (9.78)	0.11 (7.86)	0.06 (6.21)	0.05 (5.79)
	α3	0.33 (11.1)	0.26 (11.2)	0.23 (11.2)	0.21 (11.0)	0.14 (9.13)	0.10 (7.30)	0.06 (5.76)	0.05 (5.30)
	α4	0.32 (10.6)	0.25 (10.8)	0.22 (10.7)	0.20 (10.2)	0.13 (8.13)	0.09 (6.33)	0.05 (4.42)	0.04 (4.16)
2	α1	0.38 (13.1)	0.33 (12.3)	0.29 (11.7)	0.26 (11.0)	0.18 (9.16)	0.13 (7.28)	0.08 (6.14)	0.06 (5.74)
	α3	0.35 (12.0)	0.30 (11.3)	0.27 (10.9)	0.24 (10.3)	0.17 (8.70)	0.12 (6.87)	0.07 (5.81)	0.06 (5.40)
	α4	0.34 (11.5)	0.29 (11.0)	0.26 (10.2)	0.22 (9.49)	0.15 (7.64)	0.11 (5.90)	0.06 (4.50)	0.05 (4.30)
3	α1	0.40 (12.8)	0.34 (11.8)	0.30 (10.7)	0.27 (9.97)	0.19 (8.41)	0.13 (6.60)	0.08 (5.56)	0.06 (5.44)
	α3	0.37 (11.7)	0.32 (10.8)	0.28 (9.83)	0.25 (9.19)	0.17 (7.84)	0.12 (6.21)	0.08 (5.25)	0.07 (5.21)
	α4	0.35 (11.2)	0.31 (10.2)	0.26 (9.12)	0.23 (8.31)	0.16 (6.76)	0.11 (5.25)	0.06 (4.01)	0.05 (4.11)
4	α1	0.41 (13.2)	0.35 (11.7)	0.31 (10.4)	0.27 (9.71)	0.19 (7.86)	0.14 (6.27)	0.08 (5.22)	0.07 (5.24)
	α3	0.38 (12.0)	0.32 (10.7)	0.28 (9.58)	0.25 (8.93)	0.18 (7.36)	0.13 (5.91)	0.08 (5.01)	0.07 (5.05)
	α4	0.36 (11.4)	0.30 (10.0)	0.26 (8.73)	0.23 (7.99)	0.16 (6.28)	0.11 (4.91)	0.06 (3.74)	0.05 (3.89)
8	α1	0.36 (11.5)	0.32 (10.4)	0.28 (9.30)	0.25 (8.38)	0.18 (6.10)	0.13 (4.86)	0.08 (4.11)	0.07 (4.54)
	α3	0.34 (10.9)	0.30 (9.87)	0.27 (8.76)	0.24 (7.92)	0.17 (5.83)	0.12 (4.54)	0.08 (4.04)	0.07 (4.53)
	α4	0.31 (9.89)	0.28 (8.87)	0.24 (7.71)	0.21 (6.83)	0.14 (4.77)	0.09 (3.53)	0.06 (2.78)	0.05 (3.22)
12	α1	0.30 (9.63)	0.26 (8.54)	0.24 (7.54)	0.21 (6.80)	0.15 (4.89)	0.11 (3.78)	0.08 (3.60)	0.07 (4.10)
	α3	0.28 (9.03)	0.25 (8.04)	0.22 (7.14)	0.20 (6.47)	0.14 (4.60)	0.10 (3.56)	0.08 (3.62)	0.08 (4.15)
	α4	0.25 (7.99)	0.22 (7.00)	0.19 (6.02)	0.17 (5.31)	0.11 (3.53)	0.07 (2.52)	0.05 (2.33)	0.05 (2.78)
26	α1	0.23 (7.49)	0.21 (6.71)	0.20 (6.11)	0.18 (5.60)	0.15 (4.45)	0.12 (3.86)	0.10 (3.47)	0.08 (3.31)
	α3	0.21 (6.90)	0.20 (6.25)	0.19 (5.77)	0.17 (5.37)	0.14 (4.40)	0.12 (3.91)	0.11 (3.64)	0.09 (3.52)
	α4	0.17 (5.40)	0.15 (4.77)	0.14 (4.27)	0.13 (3.88)	0.10 (2.99)	0.08 (2.56)	0.07 (2.29)	0.05 (2.17)
52	α1	0.24 (8.10)	0.23 (7.53)	0.21 (6.96)	0.21 (6.49)	0.17 (5.16)	0.15 (4.37)	0.11 (3.34)	0.08 (2.61)
	α3	0.24 (8.22)	0.23 (7.72)	0.22 (7.14)	0.21 (6.69)	0.18 (5.36)	0.15 (4.57)	0.12 (3.60)	0.09 (3.03)
	α4	0.18 (6.11)	0.17 (5.74)	0.16 (5.23)	0.15 (4.86)	0.12 (3.70)	0.10 (2.99)	0.07 (2.19)	0.05 (1.80)

Panel B: Value-weighted returns

Past Returns		Holding period (weeks) 1	2	3	4	8	12	26	52
1	α1	0.21 (7.88)	0.18 (9.04)	0.17 (9.56)	0.15 (9.30)	0.10 (8.84)	0.07 (6.75)	0.04 (5.60)	0.03 (4.81)
	α3	0.19 (7.14)	0.17 (8.40)	0.16 (8.86)	0.14 (8.58)	0.10 (8.24)	0.07 (6.23)	0.04 (5.18)	0.03 (4.53)
	α4	0.18 (6.65)	0.17 (8.11)	0.15 (8.54)	0.13 (8.06)	0.09 (7.32)	0.06 (5.31)	0.03 (4.06)	0.02 (3.47)
2	α1	0.25 (9.31)	0.24 (9.77)	0.21 (9.54)	0.18 (9.34)	0.12 (8.30)	0.08 (6.26)	0.05 (5.16)	0.04 (4.71)
	α3	0.24 (8.58)	0.22 (9.07)	0.20 (8.87)	0.17 (8.80)	0.12 (7.88)	0.08 (5.89)	0.05 (4.78)	0.04 (4.49)
	α4	0.23 (8.26)	0.22 (8.90)	0.19 (8.52)	0.17 (8.30)	0.11 (6.95)	0.07 (5.02)	0.04 (3.74)	0.03 (3.37)
3	α1	0.29 (10.1)	0.26 (9.97)	0.23 (9.54)	0.21 (8.99)	0.13 (7.60)	0.09 (5.79)	0.06 (4.80)	0.04 (4.45)
	α3	0.26 (9.22)	0.24 (9.15)	0.22 (8.81)	0.19 (8.37)	0.13 (7.16)	0.09 (5.45)	0.06 (4.48)	0.04 (4.29)
	α4	0.26 (8.88)	0.24 (8.79)	0.21 (8.33)	0.18 (7.70)	0.12 (6.19)	0.08 (4.55)	0.04 (3.39)	0.03 (3.10)
4	α1	0.28 (10.1)	0.26 (9.98)	0.23 (9.13)	0.20 (8.52)	0.13 (6.84)	0.09 (5.26)	0.06 (4.44)	0.04 (4.29)
	α3	0.26 (9.10)	0.24 (9.24)	0.22 (8.46)	0.19 (7.98)	0.13 (6.50)	0.09 (4.99)	0.06 (4.19)	0.05 (4.17)
	α4	0.25 (8.59)	0.23 (8.69)	0.20 (7.79)	0.18 (7.18)	0.11 (5.49)	0.07 (4.05)	0.04 (3.06)	0.03 (2.92)
8	α1	0.26 (9.61)	0.24 (9.07)	0.21 (8.28)	0.18 (7.38)	0.12 (4.84)	0.08 (3.67)	0.05 (3.12)	0.04 (3.70)
	α3	0.25 (9.11)	0.23 (8.66)	0.20 (7.79)	0.18 (6.98)	0.11 (4.65)	0.08 (3.48)	0.05 (3.03)	0.05 (3.64)
	α4	0.23 (8.11)	0.21 (7.63)	0.18 (6.68)	0.15 (5.82)	0.09 (3.54)	0.06 (2.41)	0.03 (1.77)	0.03 (2.24)
12	α1	0.21 (7.54)	0.19 (6.81)	0.17 (6.01)	0.15 (5.28)	0.09 (3.46)	0.06 (2.41)	0.04 (2.42)	0.05 (3.35)
	α3	0.20 (7.27)	0.18 (6.58)	0.16 (5.84)	0.14 (5.11)	0.09 (3.34)	0.06 (2.36)	0.05 (2.50)	0.05 (3.38)
	α4	0.18 (6.24)	0.16 (5.54)	0.13 (4.73)	0.11 (3.96)	0.06 (2.18)	0.03 (1.22)	0.02 (1.14)	0.03 (1.92)
26	α1	0.16 (5.78)	0.14 (5.25)	0.13 (4.66)	0.11 (4.20)	0.08 (3.08)	0.07 (2.60)	0.06 (2.49)	0.05 (2.89)
	α3	0.15 (5.42)	0.14 (4.98)	0.12 (4.46)	0.11 (4.08)	0.09 (3.17)	0.07 (2.78)	0.06 (2.74)	0.06 (3.04)
	α4	0.11 (3.86)	0.09 (3.45)	0.08 (2.93)	0.07 (2.54)	0.04 (1.63)	0.03 (1.32)	0.03 (1.20)	0.03 (1.55)
52	α1	0.17 (6.44)	0.17 (6.18)	0.16 (5.74)	0.15 (5.36)	0.13 (4.44)	0.11 (3.92)	0.09 (3.07)	0.06 (2.61)
	α3	0.17 (6.63)	0.17 (6.43)	0.16 (6.02)	0.16 (5.65)	0.14 (4.76)	0.12 (4.21)	0.09 (3.34)	0.08 (3.03)
	α4	0.12 (4.63)	0.12 (4.51)	0.11 (4.12)	0.10 (3.78)	0.08 (2.95)	0.07 (2.49)	0.05 (1.84)	0.05 (1.83)

Table 5
Alphas of cross-sectional momentum strategies – using demeaned long-short returns

Table 5 reports the alphas of cross sectional momentum strategies based on demeaned anomaly returns. For each anomaly, we calculate the demeaned anomaly returns by subtracting the average returns from the weekly anomaly returns. We then sort 90 anomalies into quintile portfolios based on the demeaned returns during formation period ranging from one week to 52 weeks. The cross-sectional strategies are constructed based on two extreme quintiles, with the long position being the high past performance quintile and the short position being the low past performance quintile. Portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Equal-weighted returns

Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.35 (8.11)	0.25 (7.55)	0.24 (8.08)	0.20 (7.44)	0.13 (6.15)	0.10 (4.43)	0.07 (3.88)	0.05 (3.86)
	α3	0.44 (8.88)	0.34 (8.64)	0.31 (8.37)	0.27 (8.73)	0.19 (6.95)	0.14 (5.89)	0.09 (4.99)	0.06 (4.79)
	α4	0.38 (7.27)	0.31 (7.23)	0.29 (7.11)	0.24 (7.80)	0.16 (5.84)	0.11 (4.94)	0.07 (4.05)	0.06 (4.13)
2	α1	0.32 (6.69)	0.28 (7.30)	0.25 (7.36)	0.21 (6.75)	0.13 (4.64)	0.09 (3.59)	0.04 (2.14)	0.03 (2.09)
	α3	0.36 (8.62)	0.30 (7.95)	0.26 (7.44)	0.23 (6.79)	0.15 (5.53)	0.11 (3.97)	0.08 (3.81)	0.06 (3.91)
	α4	0.47 (10.0)	0.40 (9.14)	0.35 (8.92)	0.30 (8.37)	0.21 (6.63)	0.15 (5.39)	0.10 (4.76)	0.07 (4.62)
3	α1	0.42 (8.36)	0.37 (7.71)	0.32 (8.00)	0.27 (7.68)	0.19 (5.80)	0.13 (4.60)	0.08 (3.78)	0.07 (4.11)
	α3	0.38 (8.19)	0.35 (8.12)	0.30 (7.25)	0.25 (6.61)	0.16 (4.62)	0.10 (3.42)	0.05 (2.07)	0.04 (2.29)
	α4	0.40 (9.18)	0.32 (7.95)	0.27 (6.93)	0.24 (6.40)	0.16 (4.86)	0.11 (3.65)	0.08 (3.42)	0.07 (3.78)
4	α1	0.50 (9.79)	0.43 (9.28)	0.37 (8.05)	0.32 (7.47)	0.23 (6.16)	0.16 (5.15)	0.10 (4.43)	0.08 (4.56)
	α3	0.46 (8.12)	0.39 (7.87)	0.33 (7.04)	0.28 (6.54)	0.21 (5.24)	0.14 (4.35)	0.08 (3.59)	0.08 (4.10)
	α4	0.40 (7.96)	0.35 (7.30)	0.29 (6.25)	0.24 (5.44)	0.16 (4.02)	0.10 (3.07)	0.05 (1.79)	0.04 (2.17)
8	α1	0.39 (8.75)	0.32 (7.35)	0.28 (6.78)	0.24 (6.04)	0.16 (4.35)	0.11 (3.40)	0.08 (3.09)	0.07 (3.45)
	α3	0.51 (10.3)	0.43 (8.89)	0.37 (7.65)	0.33 (7.02)	0.24 (5.81)	0.17 (4.86)	0.11 (4.25)	0.09 (4.34)
	α4	0.46 (8.75)	0.39 (7.67)	0.33 (6.66)	0.29 (6.08)	0.22 (4.97)	0.14 (4.05)	0.09 (3.51)	0.09 (3.97)
12	α1	0.41 (7.94)	0.34 (6.94)	0.28 (5.72)	0.24 (5.01)	0.16 (3.69)	0.10 (2.71)	0.04 (1.62)	0.04 (1.92)
	α3	0.31 (6.78)	0.26 (5.80)	0.23 (5.24)	0.20 (4.52)	0.13 (2.98)	0.10 (2.66)	0.08 (2.54)	0.08 (3.01)
	α4	0.43 (8.26)	0.38 (7.21)	0.34 (6.56)	0.30 (5.93)	0.21 (4.54)	0.15 (3.78)	0.11 (3.51)	0.10 (3.78)
26	α1	0.39 (7.24)	0.35 (6.39)	0.32 (5.71)	0.28 (5.16)	0.18 (3.86)	0.12 (3.02)	0.09 (2.88)	0.10 (3.59)
	α3	0.32 (6.29)	0.29 (5.44)	0.25 (4.61)	0.21 (3.96)	0.13 (2.55)	0.07 (1.65)	0.03 (0.98)	0.04 (1.49)
	α4	0.26 (5.58)	0.22 (4.68)	0.20 (4.24)	0.18 (3.82)	0.12 (2.69)	0.09 (2.20)	0.08 (2.28)	0.08 (2.85)
52	α1	0.37 (7.20)	0.32 (6.30)	0.29 (5.80)	0.26 (5.29)	0.19 (4.07)	0.14 (3.15)	0.11 (3.23)	0.10 (3.56)
	α3	0.34 (6.31)	0.29 (5.54)	0.27 (5.06)	0.23 (4.48)	0.15 (3.24)	0.10 (2.40)	0.09 (2.73)	0.10 (3.42)
	α4	0.27 (5.21)	0.23 (4.37)	0.20 (3.74)	0.16 (3.09)	0.09 (1.77)	0.03 (0.79)	0.02 (0.69)	0.03 (1.24)

Panel B: Value-weighted returns

Past Returns		Holding period (weeks) 1	2	3	4	8	12	26	52
1	α1	0.20 (4.03)	0.16 (4.44)	0.17 (5.38)	0.15 (5.30)	0.09 (4.94)	0.05 (3.14)	0.04 (3.54)	0.03 (3.76)
	α3	0.30 (5.60)	0.26 (6.36)	0.26 (6.76)	0.22 (7.31)	0.15 (6.08)	0.10 (5.04)	0.06 (4.57)	0.04 (4.06)
	α4	0.27 (4.88)	0.26 (5.64)	0.25 (5.94)	0.20 (6.64)	0.14 (5.05)	0.09 (3.92)	0.06 (3.57)	0.04 (3.61)
2	α1	0.22 (4.09)	0.22 (5.42)	0.21 (6.09)	0.18 (5.57)	0.10 (4.05)	0.06 (2.74)	0.03 (1.74)	0.02 (1.62)
	α3	0.25 (5.12)	0.23 (5.30)	0.21 (5.63)	0.19 (5.83)	0.12 (5.09)	0.07 (3.23)	0.06 (3.67)	0.05 (3.86)
	α4	0.38 (7.12)	0.35 (7.31)	0.31 (7.77)	0.28 (7.82)	0.19 (6.11)	0.12 (5.02)	0.08 (4.42)	0.05 (4.09)
3	α1	0.36 (6.54)	0.34 (6.66)	0.29 (7.18)	0.26 (7.38)	0.18 (5.36)	0.11 (4.11)	0.07 (3.42)	0.06 (3.64)
	α3	0.32 (6.30)	0.32 (7.11)	0.28 (6.71)	0.24 (6.59)	0.14 (4.47)	0.08 (3.08)	0.03 (1.75)	0.03 (1.76)
	α4	0.29 (5.75)	0.26 (5.84)	0.24 (5.85)	0.22 (6.03)	0.13 (4.59)	0.08 (3.18)	0.06 (3.27)	0.05 (3.66)
4	α1	0.42 (7.56)	0.38 (7.95)	0.34 (7.59)	0.30 (7.20)	0.20 (5.64)	0.14 (4.68)	0.08 (4.04)	0.06 (3.85)
	α3	0.39 (6.59)	0.35 (7.03)	0.32 (6.76)	0.28 (6.46)	0.20 (4.83)	0.13 (3.77)	0.07 (3.11)	0.06 (3.47)
	α4	0.35 (6.49)	0.33 (6.55)	0.29 (6.17)	0.24 (5.56)	0.15 (3.81)	0.08 (2.70)	0.03 (1.34)	0.03 (1.51)
8	α1	0.29 (5.86)	0.27 (5.75)	0.25 (5.87)	0.21 (5.37)	0.12 (3.69)	0.08 (2.68)	0.06 (2.71)	0.05 (3.35)
	α3	0.43 (8.01)	0.39 (7.76)	0.35 (7.00)	0.30 (6.42)	0.20 (5.07)	0.14 (4.22)	0.08 (3.62)	0.06 (3.64)
	α4	0.39 (7.09)	0.37 (6.98)	0.32 (6.32)	0.28 (5.83)	0.19 (4.41)	0.12 (3.45)	0.07 (2.89)	0.07 (3.34)
12	α1	0.35 (6.21)	0.32 (6.25)	0.27 (5.42)	0.23 (4.75)	0.13 (3.17)	0.07 (2.11)	0.02 (0.93)	0.02 (1.20)
	α3	0.26 (5.25)	0.23 (4.79)	0.20 (4.40)	0.17 (3.75)	0.09 (2.14)	0.07 (1.79)	0.05 (1.99)	0.06 (3.02)
	α4	0.39 (7.14)	0.35 (6.53)	0.32 (6.02)	0.28 (5.43)	0.18 (3.81)	0.12 (3.05)	0.07 (2.63)	0.07 (3.21)
26	α1	0.37 (6.40)	0.34 (5.89)	0.30 (5.29)	0.26 (4.70)	0.16 (3.18)	0.10 (2.32)	0.07 (2.06)	0.08 (3.04)
	α3	0.30 (5.34)	0.27 (4.85)	0.22 (4.06)	0.18 (3.39)	0.09 (1.78)	0.03 (0.77)	0.00 (0.06)	0.02 (0.70)
	α4	0.18 (3.63)	0.16 (3.21)	0.15 (3.01)	0.13 (2.80)	0.08 (1.83)	0.06 (1.35)	0.06 (1.86)	0.06 (2.98)
52	α1	0.31 (5.67)	0.27 (5.13)	0.25 (4.79)	0.23 (4.37)	0.15 (3.18)	0.10 (2.30)	0.07 (2.33)	0.08 (3.07)
	α3	0.29 (5.07)	0.26 (4.56)	0.24 (4.21)	0.21 (3.70)	0.13 (2.46)	0.08 (1.68)	0.07 (1.96)	0.09 (2.91)
	α4	0.22 (3.92)	0.18 (3.35)	0.16 (2.88)	0.12 (2.31)	0.04 (0.90)	-0.00 (-0.09)	-0.01 (-0.16)	0.01 (0.52)

Table 6

Alphas of time-series momentum strategies – Removing time-varying expected returns

Table 6 reports the alphas of time-series momentum strategies. We calculate each anomaly's prior returns during formation period ranging from one week to 52 weeks. The time-series strategies are constructed by going long the anomalies with positive past returns and short those with negative returns. Portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Equal-weighted returns

Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.47 (10.2)	0.39 (10.3)	0.38 (11.0)	0.34 (10.5)	0.26 (8.07)	0.22 (6.86)	0.16 (6.54)	0.12 (5.93)
	α3	0.28 (6.98)	0.25 (8.00)	0.25 (9.62)	0.23 (9.12)	0.19 (8.20)	0.18 (7.08)	0.15 (6.87)	0.12 (5.65)
	α4	0.23 (6.26)	0.23 (8.21)	0.24 (9.70)	0.21 (9.18)	0.16 (8.02)	0.15 (7.77)	0.12 (7.77)	0.08 (5.54)
2	α1	0.53 (11.5)	0.48 (10.9)	0.44 (10.5)	0.40 (9.72)	0.32 (7.94)	0.26 (6.71)	0.20 (6.69)	0.16 (6.03)
	α3	0.33 (8.70)	0.31 (9.09)	0.30 (9.68)	0.28 (9.36)	0.24 (8.44)	0.22 (7.21)	0.19 (7.12)	0.16 (5.90)
	α4	0.28 (8.05)	0.30 (9.41)	0.28 (9.86)	0.26 (9.20)	0.21 (8.34)	0.19 (7.86)	0.15 (7.94)	0.11 (5.64)
3	α1	0.58 (12.3)	0.53 (11.5)	0.48 (10.6)	0.44 (9.57)	0.35 (7.79)	0.29 (6.66)	0.22 (6.66)	0.18 (6.16)
	α3	0.39 (10.1)	0.36 (9.80)	0.35 (9.72)	0.32 (9.06)	0.28 (8.12)	0.25 (7.09)	0.22 (7.24)	0.18 (6.00)
	α4	0.37 (10.2)	0.34 (10.3)	0.32 (9.77)	0.29 (8.94)	0.24 (8.26)	0.22 (7.70)	0.18 (7.97)	0.13 (5.76)
4	α1	0.60 (12.0)	0.54 (10.9)	0.49 (10.0)	0.46 (9.23)	0.37 (7.62)	0.31 (6.56)	0.24 (6.52)	0.20 (6.05)
	α3	0.42 (10.2)	0.39 (9.81)	0.37 (9.50)	0.34 (8.77)	0.30 (7.85)	0.27 (6.90)	0.24 (7.15)	0.19 (5.94)
	α4	0.36 (9.79)	0.35 (9.89)	0.32 (9.27)	0.29 (8.29)	0.26 (7.84)	0.23 (7.31)	0.19 (7.76)	0.13 (5.59)
8	α1	0.56 (10.9)	0.52 (9.85)	0.49 (9.17)	0.46 (8.50)	0.37 (6.78)	0.32 (6.21)	0.27 (6.07)	0.23 (5.80)
	α3	0.44 (10.8)	0.41 (10.3)	0.39 (9.75)	0.37 (9.13)	0.34 (7.62)	0.32 (7.30)	0.29 (7.26)	0.23 (5.81)
	α4	0.37 (10.2)	0.35 (9.71)	0.33 (9.09)	0.32 (8.62)	0.28 (7.43)	0.25 (6.91)	0.21 (7.42)	0.15 (5.11)
12	α1	0.52 (10.2)	0.48 (9.21)	0.46 (8.52)	0.43 (7.97)	0.38 (6.76)	0.34 (6.12)	0.29 (5.97)	0.25 (5.57)
	α3	0.41 (9.95)	0.40 (9.64)	0.39 (9.39)	0.38 (8.84)	0.37 (8.00)	0.36 (7.58)	0.32 (7.55)	0.26 (5.75)
	α4	0.35 (9.65)	0.34 (9.24)	0.32 (8.77)	0.31 (8.07)	0.28 (7.12)	0.27 (6.88)	0.22 (7.31)	0.16 (4.85)
26	α1	0.52 (9.81)	0.50 (9.14)	0.49 (8.70)	0.47 (8.24)	0.42 (7.03)	0.39 (6.45)	0.34 (5.88)	0.29 (5.10)
	α3	0.47 (11.0)	0.46 (10.6)	0.46 (10.3)	0.45 (10.0)	0.44 (8.96)	0.42 (8.42)	0.36 (7.19)	0.30 (5.45)
	α4	0.37 (9.73)	0.36 (9.46)	0.35 (8.98)	0.34 (8.63)	0.32 (7.63)	0.29 (7.13)	0.23 (5.80)	0.16 (3.82)
52	α1	0.49 (9.34)	0.48 (8.80)	0.47 (8.32)	0.46 (7.92)	0.42 (6.83)	0.40 (6.21)	0.34 (5.28)	0.29 (4.73)
	α3	0.47 (10.6)	0.46 (10.3)	0.46 (9.94)	0.45 (9.52)	0.42 (8.16)	0.40 (7.34)	0.36 (5.90)	0.32 (5.19)
	α4	0.30 (8.05)	0.30 (7.69)	0.29 (7.23)	0.28 (6.88)	0.26 (5.75)	0.24 (5.05)	0.20 (3.76)	0.16 (3.04)

Panel B: Value-weighted returns

Past Returns		Holding period (weeks) 1	2	3	4	8	12	26	52
1	α1	0.33 (6.66)	0.30 (7.58)	0.30 (8.69)	0.27 (8.75)	0.20 (7.34)	0.16 (6.31)	0.12 (6.32)	0.09 (5.51)
	α3	0.18 (3.86)	0.17 (5.30)	0.20 (7.06)	0.20 (7.13)	0.17 (7.38)	0.16 (6.43)	0.14 (6.62)	0.11 (5.37)
	α4	0.14 (3.33)	0.17 (5.67)	0.18 (6.84)	0.18 (7.06)	0.14 (6.96)	0.13 (6.47)	0.11 (7.35)	0.07 (5.22)
2	α1	0.40 (8.04)	0.39 (8.53)	0.37 (9.08)	0.35 (8.92)	0.26 (7.49)	0.21 (6.29)	0.16 (6.36)	0.12 (5.66)
	α3	0.25 (5.88)	0.26 (6.81)	0.27 (7.59)	0.27 (7.91)	0.24 (7.69)	0.21 (6.50)	0.19 (6.60)	0.15 (5.69)
	α4	0.22 (5.34)	0.25 (7.10)	0.25 (7.53)	0.24 (7.67)	0.19 (7.40)	0.17 (6.69)	0.14 (7.24)	0.09 (5.42)
3	α1	0.46 (9.08)	0.45 (9.27)	0.43 (9.16)	0.39 (8.73)	0.30 (7.21)	0.24 (6.20)	0.18 (6.18)	0.14 (5.58)
	α3	0.31 (7.25)	0.32 (7.70)	0.33 (8.20)	0.31 (8.23)	0.27 (7.77)	0.25 (6.74)	0.23 (6.83)	0.18 (5.86)
	α4	0.30 (7.36)	0.31 (7.78)	0.29 (7.91)	0.28 (7.97)	0.23 (7.65)	0.20 (6.98)	0.17 (7.58)	0.11 (5.57)
4	α1	0.51 (9.79)	0.47 (9.45)	0.45 (9.21)	0.41 (8.66)	0.32 (7.00)	0.25 (6.11)	0.20 (6.05)	0.15 (5.45)
	α3	0.37 (7.85)	0.37 (8.13)	0.37 (8.41)	0.35 (8.25)	0.30 (7.49)	0.28 (6.61)	0.25 (6.70)	0.19 (5.69)
	α4	0.32 (7.50)	0.33 (7.90)	0.31 (7.87)	0.29 (7.60)	0.25 (7.25)	0.22 (6.64)	0.18 (7.22)	0.12 (5.40)
8	α1	0.49 (9.18)	0.47 (8.75)	0.44 (8.20)	0.41 (7.62)	0.31 (5.91)	0.26 (5.29)	0.22 (5.29)	0.18 (4.96)
	α3	0.43 (9.20)	0.42 (9.13)	0.40 (8.89)	0.39 (8.48)	0.35 (7.15)	0.33 (6.70)	0.30 (6.74)	0.24 (5.52)
	α4	0.36 (8.49)	0.35 (8.57)	0.33 (8.32)	0.32 (8.13)	0.27 (6.95)	0.25 (6.38)	0.21 (6.80)	0.14 (4.89)
12	α1	0.45 (8.38)	0.43 (7.90)	0.40 (7.39)	0.38 (6.86)	0.31 (5.61)	0.27 (5.05)	0.24 (5.19)	0.20 (4.84)
	α3	0.41 (8.54)	0.41 (8.65)	0.41 (8.52)	0.40 (8.14)	0.38 (7.23)	0.38 (6.85)	0.34 (6.97)	0.26 (5.45)
	α4	0.32 (7.74)	0.33 (8.28)	0.32 (8.05)	0.31 (7.63)	0.27 (6.56)	0.26 (6.39)	0.22 (6.55)	0.14 (4.56)
26	α1	0.47 (8.50)	0.46 (8.16)	0.45 (7.81)	0.43 (7.43)	0.37 (6.30)	0.34 (5.77)	0.29 (5.26)	0.24 (4.56)
	α3	0.51 (9.76)	0.50 (9.60)	0.50 (9.34)	0.49 (9.07)	0.48 (8.12)	0.46 (7.71)	0.39 (6.64)	0.31 (4.96)
	α4	0.37 (9.01)	0.36 (8.91)	0.36 (8.62)	0.35 (8.37)	0.31 (7.27)	0.29 (6.60)	0.22 (5.08)	0.15 (3.60)
52	α1	0.44 (8.10)	0.44 (7.72)	0.43 (7.40)	0.42 (7.13)	0.39 (6.18)	0.36 (5.67)	0.31 (4.90)	0.25 (4.29)
	α3	0.50 (9.17)	0.50 (8.94)	0.49 (8.65)	0.49 (8.37)	0.46 (7.38)	0.44 (6.66)	0.39 (5.40)	0.34 (4.61)
	α4	0.32 (7.35)	0.31 (7.25)	0.30 (6.91)	0.30 (6.69)	0.27 (5.75)	0.25 (4.96)	0.20 (3.70)	0.17 (3.17)

Table 7
Alphas of cross-sectional momentum strategies– Removing time-varying expected returns

Table 7 reports the alphas of cross sectional momentum strategies. We sort 90 anomalies into quintile portfolios based on prior returns during the formation period ranging from one week to 52 weeks. The cross-sectional strategies are constructed based on two extreme quintiles, with the long position being the high past performance quintile and the short position being the low past performance quintile. Portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Equal-weighted returns

Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.35 (8.17)	0.26 (7.67)	0.24 (8.19)	0.21 (7.59)	0.14 (6.31)	0.10 (4.51)	0.07 (4.06)	0.06 (4.13)
	α3	0.44 (8.78)	0.34 (8.65)	0.32 (8.40)	0.27 (8.82)	0.19 (7.08)	0.14 (5.94)	0.09 (5.16)	0.06 (5.11)
	α4	0.37 (7.17)	0.31 (7.22)	0.29 (7.14)	0.24 (7.88)	0.17 (5.96)	0.11 (4.99)	0.07 (4.19)	0.06 (4.43)
2	α1	0.32 (6.63)	0.28 (7.30)	0.26 (7.37)	0.21 (6.81)	0.13 (4.75)	0.09 (3.64)	0.04 (2.26)	0.03 (2.30)
	α3	0.36 (8.59)	0.30 (7.87)	0.26 (7.43)	0.23 (6.84)	0.16 (5.61)	0.11 (4.08)	0.08 (3.97)	0.07 (4.18)
	α4	0.47 (10.0)	0.40 (9.01)	0.34 (8.91)	0.30 (8.45)	0.21 (6.73)	0.15 (5.48)	0.10 (4.96)	0.08 (4.96)
3	α1	0.42 (8.42)	0.37 (7.65)	0.31 (8.01)	0.26 (7.78)	0.19 (5.92)	0.13 (4.67)	0.08 (3.96)	0.07 (4.41)
	α3	0.38 (8.27)	0.34 (8.11)	0.30 (7.29)	0.25 (6.73)	0.16 (4.73)	0.10 (3.54)	0.05 (2.21)	0.04 (2.50)
	α4	0.40 (9.10)	0.32 (7.94)	0.27 (6.98)	0.24 (6.51)	0.16 (5.00)	0.12 (3.78)	0.09 (3.61)	0.07 (4.03)
4	α1	0.50 (9.62)	0.43 (9.23)	0.37 (8.07)	0.32 (7.58)	0.23 (6.32)	0.16 (5.25)	0.11 (4.62)	0.09 (4.84)
	α3	0.45 (7.94)	0.38 (7.76)	0.33 (6.98)	0.28 (6.56)	0.21 (5.32)	0.14 (4.39)	0.08 (3.73)	0.08 (4.39)
	α4	0.39 (7.73)	0.34 (7.21)	0.29 (6.23)	0.24 (5.48)	0.16 (4.09)	0.10 (3.11)	0.05 (1.88)	0.04 (2.35)
8	α1	0.39 (8.72)	0.31 (7.37)	0.28 (6.82)	0.24 (6.10)	0.16 (4.46)	0.12 (3.54)	0.08 (3.27)	0.08 (3.74)
	α3	0.50 (10.3)	0.43 (8.95)	0.37 (7.66)	0.33 (7.06)	0.24 (5.92)	0.17 (4.94)	0.11 (4.37)	0.09 (4.62)
	α4	0.45 (8.70)	0.38 (7.61)	0.33 (6.59)	0.29 (6.05)	0.21 (5.00)	0.14 (4.06)	0.09 (3.57)	0.08 (4.20)
12	α1	0.40 (7.91)	0.33 (6.91)	0.27 (5.69)	0.23 (5.01)	0.16 (3.73)	0.10 (2.75)	0.04 (1.68)	0.04 (2.07)
	α3	0.32 (6.90)	0.27 (5.92)	0.24 (5.31)	0.20 (4.59)	0.13 (3.10)	0.11 (2.82)	0.09 (2.72)	0.09 (3.27)
	α4	0.43 (8.33)	0.38 (7.29)	0.34 (6.64)	0.31 (6.03)	0.21 (4.63)	0.15 (3.88)	0.11 (3.66)	0.10 (4.02)
26	α1	0.39 (7.25)	0.35 (6.43)	0.32 (5.75)	0.28 (5.21)	0.18 (3.90)	0.12 (3.05)	0.09 (2.96)	0.09 (3.80)
	α3	0.33 (6.37)	0.29 (5.51)	0.25 (4.66)	0.21 (4.02)	0.13 (2.60)	0.07 (1.72)	0.03 (1.06)	0.04 (1.61)
	α4	0.26 (5.64)	0.22 (4.76)	0.20 (4.37)	0.18 (3.98)	0.13 (2.94)	0.10 (2.48)	0.09 (2.57)	0.09 (3.18)
52	α1	0.37 (7.25)	0.32 (6.37)	0.30 (5.89)	0.27 (5.40)	0.19 (4.25)	0.14 (3.33)	0.11 (3.41)	0.11 (3.83)
	α3	0.33 (6.29)	0.29 (5.55)	0.26 (5.08)	0.23 (4.51)	0.15 (3.36)	0.10 (2.51)	0.09 (2.88)	0.10 (3.68)
	α4	0.27 (5.19)	0.23 (4.37)	0.20 (3.75)	0.16 (3.12)	0.09 (1.87)	0.04 (0.88)	0.03 (0.83)	0.04 (1.42)

Panel B: Value-weighted returns

Past Returns		Holding period (weeks) 1	2	3	4	8	12	26	52
1	α1	0.20 (4.16)	0.16 (4.56)	0.17 (5.54)	0.15 (5.47)	0.10 (5.12)	0.06 (3.33)	0.05 (3.81)	0.04 (4.11)
	α3	0.31 (5.73)	0.27 (6.46)	0.26 (6.89)	0.22 (7.49)	0.15 (6.27)	0.10 (5.18)	0.07 (4.83)	0.04 (4.43)
	α4	0.28 (4.99)	0.26 (5.71)	0.25 (6.02)	0.21 (6.79)	0.14 (5.23)	0.09 (4.09)	0.06 (3.81)	0.05 (3.95)
2	α1	0.22 (4.18)	0.22 (5.46)	0.22 (6.19)	0.18 (5.68)	0.10 (4.19)	0.06 (2.89)	0.03 (1.92)	0.02 (1.87)
	α3	0.26 (5.26)	0.24 (5.42)	0.22 (5.77)	0.20 (5.98)	0.13 (5.26)	0.08 (3.42)	0.06 (3.97)	0.05 (4.20)
	α4	0.38 (7.21)	0.36 (7.47)	0.31 (7.94)	0.28 (8.01)	0.19 (6.32)	0.13 (5.16)	0.08 (4.70)	0.06 (4.44)
3	α1	0.36 (6.58)	0.34 (6.80)	0.29 (7.34)	0.26 (7.56)	0.18 (5.56)	0.12 (4.25)	0.07 (3.60)	0.06 (3.91)
	α3	0.33 (6.41)	0.33 (7.27)	0.28 (6.87)	0.24 (6.75)	0.14 (4.60)	0.08 (3.19)	0.04 (1.89)	0.03 (1.95)
	α4	0.29 (5.76)	0.27 (5.88)	0.24 (5.87)	0.22 (6.06)	0.13 (4.68)	0.09 (3.37)	0.07 (3.53)	0.06 (3.92)
4	α1	0.42 (7.62)	0.38 (8.03)	0.35 (7.65)	0.31 (7.25)	0.21 (5.70)	0.14 (4.80)	0.09 (4.24)	0.06 (4.04)
	α3	0.39 (6.70)	0.36 (7.14)	0.32 (6.88)	0.28 (6.53)	0.20 (4.89)	0.13 (3.85)	0.07 (3.23)	0.06 (3.66)
	α4	0.36 (6.64)	0.33 (6.69)	0.29 (6.28)	0.24 (5.64)	0.15 (3.88)	0.08 (2.81)	0.03 (1.43)	0.03 (1.62)
8	α1	0.30 (5.93)	0.27 (5.84)	0.25 (5.99)	0.21 (5.52)	0.12 (3.81)	0.08 (2.83)	0.06 (2.92)	0.06 (3.62)
	α3	0.43 (8.07)	0.39 (7.84)	0.35 (7.09)	0.30 (6.54)	0.20 (5.13)	0.14 (4.31)	0.08 (3.77)	0.06 (3.84)
	α4	0.39 (7.16)	0.36 (7.06)	0.32 (6.39)	0.28 (5.93)	0.19 (4.43)	0.12 (3.49)	0.07 (2.95)	0.07 (3.49)
12	α1	0.35 (6.26)	0.32 (6.34)	0.27 (5.49)	0.23 (4.82)	0.13 (3.19)	0.07 (2.17)	0.02 (0.99)	0.02 (1.29)
	α3	0.26 (5.27)	0.23 (4.84)	0.20 (4.37)	0.17 (3.76)	0.09 (2.20)	0.07 (1.90)	0.06 (2.21)	0.07 (3.25)
	α4	0.39 (7.08)	0.35 (6.53)	0.32 (5.95)	0.28 (5.39)	0.18 (3.79)	0.12 (3.07)	0.08 (2.76)	0.07 (3.34)
26	α1	0.37 (6.39)	0.34 (5.94)	0.30 (5.27)	0.26 (4.70)	0.16 (3.18)	0.10 (2.34)	0.07 (2.16)	0.08 (3.22)
	α3	0.29 (5.30)	0.26 (4.85)	0.22 (4.02)	0.18 (3.37)	0.09 (1.75)	0.03 (0.77)	0.00 (0.12)	0.02 (0.80)
	α4	0.18 (3.70)	0.16 (3.30)	0.15 (3.11)	0.14 (2.87)	0.09 (1.95)	0.06 (1.54)	0.07 (2.15)	0.07 (3.28)
52	α1	0.31 (5.75)	0.28 (5.21)	0.26 (4.88)	0.23 (4.41)	0.16 (3.21)	0.11 (2.37)	0.08 (2.51)	0.08 (3.28)
	α3	0.29 (5.14)	0.26 (4.60)	0.24 (4.30)	0.21 (3.74)	0.13 (2.46)	0.08 (1.72)	0.07 (2.06)	0.08 (3.13)
	α4	0.22 (3.96)	0.18 (3.34)	0.16 (2.93)	0.12 (2.33)	0.04 (0.88)	-0.00 (-0.08)	-0.00 (-0.07)	0.02 (0.63)

Table 8

Arbitrage capital, market liquidity, and the performance of the time-series and cross-sectional momentum strategies

Table 8 presents the estimates of b in the regression: $R_{i,t} = a + bX_t + e_t$. X_t includes HFAUM, SI, Aggilliq, and a time trend. $R_{i,t}$ is the return to the following four momentum strategies: equal-weighted and valued-weighted time-series momentum strategies, and equal-weighted and valued-weighted cross-sectional momentum strategies, where both the formation and holding period is four weeks. HFAUM is the total asset under management by hedge funds scaled by the total market capitalization of all common stocks. SI is the aggregate short interest of NYSE/AMEX stocks scaled by total market capitalization of all NYSE/AMEX stocks. Aggilliq is the aggregate Amihud's illiquidity measure. Numbers in parentheses are the t-statistics, adjusted for heteroscedasticity and autocorrelations. The time-series momentum strategies are described in Section 4.1. The cross-sectional momentum strategies are described in Section 4.2. The results below are based on strategies with a look-back period of 4 weeks and a holding-period of 4 weeks.

Panel A: Time Series Momentum - EW

	Intercept	HFAUM	SI	Aggilliq	Trend
(1)	0.28	-5.16			
	(7.08)	(-2.86)			
(2)	0.36		-11.61		
	(8.30)		(-3.92)		
(3)	0.19			0.37	
	(5.22)			(2.27)	
(4)	0.39				-0.29
	(8.51)				(-3.78)

Panel B: Time Series Momentum – VW

	Intercept	HFAUM	SI	Aggilliq	Trend
(1)	0.17	-3.84			
	(5.01)	(-2.45)			
(2)	0.27		-10.41		
	(6.49)		(-3.82)		
(3)	0.13			0.30	
	(4.06)			(1.96)	
(4)	0.35				-0.33
	(7.70)				(-4.56)

Panel C: Cross-sectional Momentum – EW					
	Intercept	HFAUM	SI	Aggilliq	Trend
(1)	0.29	-5.25			
	(4.66)	(-1.35)			
(2)	0.39		-8.49		
	(5.33)		(-1.68)		
(3)	0.21			0.18	
	(3.25)			(0.70)	
(4)	0.36				-0.24
	(5.67)				(-1.90)

Panel D: Cross-sectional Momentum – VW					
	Intercept	HFAUM	SI	Aggilliq	Trend
(1)	0.24	-5.64			
	(3.42)	(-1.36)			
(2)	0.31		-11.21		
	(4.48)		(-2.04)		
(3)	0.17			0.30	
	(2.36)			(1.01)	
(4)	0.40				-0.36
	(5.65)				(-2.62)

Table 9
Alphas of time series momentum strategies – skipping one week

Table 9 reports the alphas of time-series momentum strategies, where there is one week gap between the formation and holding periods. We calculate each anomaly's prior returns during formation period ranging from one week to 52 weeks. The time-series strategies are constructed by going long the anomalies with positive past returns and short those with negative returns. Skipping one week, portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Equal-weighted returns

Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.22 (8.26)	0.21 (9.43)	0.19 (9.65)	0.17 (9.13)	0.12 (8.25)	0.09 (6.38)	0.06 (5.63)	0.05 (5.93)
	α3	0.21 (7.89)	0.20 (8.98)	0.18 (9.19)	0.16 (8.65)	0.12 (7.81)	0.08 (6.01)	0.05 (5.39)	0.05 (5.68)
	α4	0.21 (7.67)	0.19 (8.56)	0.17 (8.47)	0.15 (7.92)	0.10 (6.79)	0.07 (5.07)	0.04 (4.09)	0.04 (4.52)
2	α1	0.29 (9.81)	0.26 (9.58)	0.23 (9.26)	0.20 (8.72)	0.15 (7.81)	0.11 (6.09)	0.07 (5.65)	0.06 (5.86)
	α3	0.28 (9.14)	0.24 (9.04)	0.21 (8.73)	0.19 (8.30)	0.14 (7.43)	0.10 (5.77)	0.07 (5.45)	0.06 (5.71)
	α4	0.27 (8.84)	0.23 (8.44)	0.20 (7.99)	0.17 (7.37)	0.12 (6.35)	0.08 (4.84)	0.05 (4.17)	0.05 (4.58)
3	α1	0.32 (10.7)	0.28 (9.70)	0.25 (9.02)	0.22 (8.34)	0.16 (6.99)	0.11 (5.63)	0.07 (5.13)	0.07 (5.48)
	α3	0.29 (9.83)	0.26 (9.01)	0.23 (8.38)	0.20 (7.75)	0.15 (6.60)	0.11 (5.28)	0.07 (4.93)	0.07 (5.32)
	α4	0.28 (9.21)	0.24 (8.26)	0.21 (7.46)	0.18 (6.77)	0.13 (5.59)	0.09 (4.35)	0.05 (3.70)	0.05 (4.21)
4	α1	0.32 (10.3)	0.28 (9.17)	0.25 (8.55)	0.22 (8.03)	0.16 (6.47)	0.12 (5.22)	0.08 (4.80)	0.07 (5.20)
	α3	0.29 (9.42)	0.25 (8.45)	0.22 (7.86)	0.21 (7.46)	0.15 (6.11)	0.11 (4.86)	0.07 (4.62)	0.07 (5.10)
	α4	0.27 (8.60)	0.23 (7.51)	0.20 (6.86)	0.18 (6.44)	0.13 (5.09)	0.08 (3.89)	0.05 (3.37)	0.05 (3.92)
8	α1	0.30 (9.84)	0.26 (8.69)	0.23 (7.67)	0.21 (6.82)	0.15 (5.02)	0.11 (4.10)	0.08 (3.93)	0.07 (4.64)
	α3	0.28 (9.42)	0.25 (8.18)	0.22 (7.21)	0.19 (6.45)	0.14 (4.73)	0.10 (3.73)	0.08 (3.82)	0.07 (4.65)
	α4	0.26 (8.34)	0.22 (7.09)	0.19 (6.09)	0.16 (5.34)	0.11 (3.71)	0.07 (2.72)	0.05 (2.58)	0.05 (3.35)
12	α1	0.25 (8.16)	0.23 (7.30)	0.21 (6.47)	0.19 (5.82)	0.14 (4.33)	0.11 (3.61)	0.09 (3.67)	0.08 (4.37)
	α3	0.23 (7.70)	0.21 (6.98)	0.19 (6.15)	0.17 (5.50)	0.13 (4.02)	0.10 (3.34)	0.08 (3.63)	0.08 (4.38)
	α4	0.20 (6.54)	0.18 (5.76)	0.16 (4.92)	0.14 (4.30)	0.09 (2.96)	0.07 (2.31)	0.05 (2.37)	0.05 (3.02)
26	α1	0.23 (7.28)	0.21 (6.56)	0.20 (5.96)	0.18 (5.51)	0.15 (4.46)	0.13 (3.87)	0.12 (3.79)	0.10 (3.80)
	α3	0.21 (6.81)	0.20 (6.21)	0.19 (5.68)	0.17 (5.29)	0.15 (4.38)	0.13 (3.86)	0.12 (3.85)	0.10 (3.87)
	α4	0.16 (5.19)	0.15 (4.62)	0.14 (4.12)	0.13 (3.76)	0.10 (2.96)	0.08 (2.49)	0.08 (2.53)	0.06 (2.55)
52	α1	0.24 (7.81)	0.23 (7.04)	0.22 (6.59)	0.21 (6.15)	0.18 (5.07)	0.16 (4.47)	0.14 (3.90)	0.10 (3.22)
	α3	0.24 (7.83)	0.23 (7.10)	0.22 (6.64)	0.21 (6.23)	0.18 (5.17)	0.16 (4.59)	0.14 (4.02)	0.11 (3.48)
	α4	0.18 (5.74)	0.16 (5.13)	0.16 (4.75)	0.15 (4.41)	0.12 (3.53)	0.11 (3.03)	0.09 (2.66)	0.07 (2.35)

Panel B: Value-weighted returns

Past Returns		Holding period (weeks) 1	2	3	4	8	12	26	52
1	α1	0.18 (7.05)	0.16 (8.21)	0.14 (8.34)	0.13 (8.60)	0.09 (7.80)	0.06 (5.77)	0.04 (5.26)	0.03 (4.97)
	α3	0.17 (6.92)	0.16 (7.81)	0.13 (7.79)	0.12 (8.02)	0.09 (7.38)	0.06 (5.40)	0.04 (4.86)	0.03 (4.77)
	α4	0.17 (6.80)	0.15 (7.59)	0.12 (7.37)	0.11 (7.51)	0.08 (6.45)	0.05 (4.46)	0.03 (3.80)	0.02 (3.70)
2	α1	0.23 (8.74)	0.20 (8.33)	0.17 (8.24)	0.15 (7.73)	0.10 (6.87)	0.07 (5.18)	0.05 (4.60)	0.04 (4.51)
	α3	0.22 (8.26)	0.18 (7.80)	0.16 (7.79)	0.14 (7.40)	0.10 (6.58)	0.07 (4.97)	0.05 (4.34)	0.04 (4.48)
	α4	0.22 (8.19)	0.18 (7.54)	0.15 (7.31)	0.13 (6.72)	0.09 (5.59)	0.06 (4.08)	0.03 (3.29)	0.03 (3.31)
3	α1	0.25 (9.35)	0.22 (8.71)	0.19 (8.06)	0.16 (7.32)	0.10 (5.89)	0.07 (4.58)	0.05 (4.14)	0.04 (4.28)
	α3	0.23 (8.67)	0.20 (8.04)	0.17 (7.50)	0.15 (6.99)	0.10 (5.67)	0.07 (4.39)	0.05 (3.97)	0.04 (4.28)
	α4	0.23 (8.31)	0.19 (7.53)	0.16 (6.78)	0.14 (6.16)	0.08 (4.66)	0.06 (3.46)	0.03 (2.84)	0.03 (3.02)
4	α1	0.25 (9.29)	0.22 (8.36)	0.19 (7.65)	0.16 (7.13)	0.10 (5.29)	0.08 (4.13)	0.05 (3.75)	0.04 (4.04)
	α3	0.23 (8.67)	0.20 (7.82)	0.18 (7.23)	0.15 (6.82)	0.10 (5.11)	0.07 (3.90)	0.05 (3.58)	0.04 (4.02)
	α4	0.22 (8.04)	0.19 (7.04)	0.16 (6.36)	0.14 (5.87)	0.08 (4.11)	0.05 (2.93)	0.03 (2.45)	0.03 (2.74)
8	α1	0.23 (8.39)	0.20 (7.49)	0.17 (6.50)	0.14 (5.53)	0.09 (3.62)	0.07 (2.90)	0.05 (2.81)	0.05 (3.68)
	α3	0.22 (8.11)	0.19 (7.02)	0.16 (6.16)	0.14 (5.34)	0.09 (3.46)	0.06 (2.70)	0.04 (2.73)	0.05 (3.68)
	α4	0.20 (7.06)	0.16 (5.89)	0.13 (4.98)	0.11 (4.19)	0.06 (2.36)	0.04 (1.60)	0.02 (1.43)	0.03 (2.24)
12	α1	0.17 (6.06)	0.15 (5.34)	0.13 (4.67)	0.11 (4.00)	0.07 (2.69)	0.05 (2.06)	0.04 (2.27)	0.05 (3.40)
	α3	0.16 (5.91)	0.15 (5.20)	0.13 (4.53)	0.11 (3.88)	0.07 (2.53)	0.05 (1.96)	0.04 (2.34)	0.05 (3.50)
	α4	0.14 (4.78)	0.11 (4.01)	0.09 (3.30)	0.07 (2.65)	0.04 (1.34)	0.02 (0.79)	0.02 (0.93)	0.03 (1.98)
26	α1	0.15 (5.45)	0.13 (4.90)	0.12 (4.37)	0.11 (3.99)	0.08 (3.07)	0.07 (2.72)	0.07 (2.72)	0.06 (3.01)
	α3	0.14 (5.10)	0.13 (4.64)	0.12 (4.18)	0.11 (3.85)	0.08 (3.06)	0.07 (2.77)	0.07 (2.87)	0.06 (3.18)
	α4	0.10 (3.56)	0.09 (3.11)	0.07 (2.62)	0.06 (2.29)	0.04 (1.57)	0.04 (1.36)	0.03 (1.40)	0.03 (1.66)
52	α1	0.17 (6.08)	0.16 (5.47)	0.15 (5.16)	0.15 (4.81)	0.13 (4.11)	0.12 (3.64)	0.09 (3.00)	0.07 (2.58)
	α3	0.17 (6.19)	0.16 (5.61)	0.15 (5.31)	0.15 (5.01)	0.13 (4.34)	0.12 (3.84)	0.10 (3.20)	0.08 (2.97)
	α4	0.11 (4.16)	0.10 (3.66)	0.10 (3.40)	0.09 (3.14)	0.08 (2.58)	0.07 (2.18)	0.05 (1.80)	0.05 (1.81)

Table 10
Alphas of cross sectional momentum strategies – skipping one week

Table 10 reports the alphas of cross sectional momentum strategies, where there is one week gap between the formation and holding periods. We sort 90 anomalies into quintile portfolios based on prior returns during formation period ranging from one week to 52 weeks. The cross-sectional strategies are constructed based on two extreme quintiles, with the long position being the high past performance quintile and the short position being the low past performance quintile. Skipping one week, portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations.

Panel A: Equal-weighted returns

Past		Holding period (weeks)							
Returns		1	2	3	4	8	12	26	52
1	α1	0.17 (4.08)	0.19 (5.64)	0.16 (5.54)	0.14 (5.08)	0.10 (4.51)	0.07 (3.32)	0.06 (3.47)	0.05 (3.86)
	α3	0.25 (5.82)	0.26 (6.52)	0.21 (7.09)	0.19 (6.20)	0.14 (5.59)	0.10 (4.42)	0.08 (4.51)	0.06 (4.77)
	α4	0.25 (5.46)	0.25 (6.00)	0.20 (6.73)	0.17 (5.78)	0.13 (4.76)	0.08 (3.59)	0.06 (3.62)	0.06 (4.26)
2	α1	0.23 (5.70)	0.22 (6.24)	0.18 (5.76)	0.14 (4.93)	0.10 (3.60)	0.05 (2.29)	0.03 (1.65)	0.03 (2.06)
	α3	0.24 (5.54)	0.22 (5.36)	0.18 (5.04)	0.16 (4.87)	0.12 (4.11)	0.08 (3.11)	0.07 (3.44)	0.06 (3.85)
	α4	0.33 (6.65)	0.28 (6.60)	0.24 (6.39)	0.21 (5.76)	0.16 (5.35)	0.11 (4.17)	0.08 (4.28)	0.07 (4.50)
3	α1	0.31 (6.00)	0.26 (6.14)	0.21 (5.96)	0.18 (5.25)	0.14 (4.64)	0.09 (3.42)	0.06 (3.34)	0.07 (4.11)
	α3	0.31 (6.49)	0.26 (5.73)	0.20 (5.20)	0.15 (4.15)	0.12 (3.45)	0.06 (2.36)	0.03 (1.59)	0.04 (2.12)
	α4	0.26 (5.85)	0.22 (5.06)	0.19 (4.81)	0.16 (4.36)	0.12 (3.48)	0.09 (2.92)	0.07 (3.01)	0.07 (3.71)
4	α1	0.36 (7.94)	0.30 (6.59)	0.26 (6.14)	0.23 (5.44)	0.18 (5.06)	0.12 (4.05)	0.09 (3.95)	0.08 (4.42)
	α3	0.32 (6.92)	0.27 (5.93)	0.23 (5.41)	0.20 (4.67)	0.16 (4.25)	0.10 (3.21)	0.07 (3.12)	0.07 (4.10)
	α4	0.30 (6.18)	0.24 (5.07)	0.19 (4.23)	0.15 (3.54)	0.12 (3.02)	0.06 (1.98)	0.03 (1.29)	0.04 (1.99)
8	α1	0.25 (5.46)	0.22 (5.19)	0.19 (4.62)	0.17 (4.24)	0.11 (3.05)	0.09 (2.69)	0.07 (2.73)	0.07 (3.40)
	α3	0.35 (7.24)	0.30 (6.07)	0.27 (5.68)	0.25 (5.33)	0.18 (4.61)	0.12 (3.74)	0.09 (3.73)	0.08 (4.16)
	α4	0.32 (6.22)	0.26 (5.30)	0.23 (4.88)	0.22 (4.56)	0.16 (3.87)	0.09 (2.88)	0.07 (2.97)	0.08 (3.86)
12	α1	0.26 (5.49)	0.21 (4.25)	0.18 (3.76)	0.16 (3.47)	0.11 (2.65)	0.05 (1.60)	0.03 (1.10)	0.03 (1.69)
	α3	0.23 (4.95)	0.20 (4.38)	0.17 (3.66)	0.14 (3.15)	0.10 (2.32)	0.09 (2.31)	0.08 (2.39)	0.08 (3.01)
	α4	0.33 (6.47)	0.30 (5.86)	0.27 (5.23)	0.23 (4.66)	0.16 (3.64)	0.12 (3.06)	0.10 (3.20)	0.09 (3.70)
26	α1	0.31 (5.83)	0.28 (5.13)	0.24 (4.55)	0.21 (4.03)	0.13 (2.97)	0.08 (2.22)	0.07 (2.54)	0.09 (3.56)
	α3	0.25 (4.82)	0.21 (3.97)	0.17 (3.30)	0.15 (2.79)	0.08 (1.72)	0.04 (0.92)	0.02 (0.63)	0.03 (1.33)
	α4	0.19 (4.14)	0.18 (3.83)	0.16 (3.42)	0.14 (3.09)	0.10 (2.33)	0.09 (2.10)	0.08 (2.35)	0.08 (2.99)
52	α1	0.28 (5.76)	0.26 (5.32)	0.23 (4.80)	0.21 (4.35)	0.15 (3.37)	0.12 (2.74)	0.10 (3.09)	0.10 (3.56)
	α3	0.25 (4.98)	0.23 (4.58)	0.20 (3.94)	0.18 (3.46)	0.11 (2.54)	0.08 (1.92)	0.08 (2.58)	0.09 (3.46)
	α4	0.19 (3.76)	0.16 (3.20)	0.12 (2.48)	0.10 (1.97)	0.05 (1.01)	0.01 (0.29)	0.02 (0.50)	0.03 (1.16)

Panel B: Value-weighted returns

Past Returns		Holding period (weeks) 1	2	3	4	8	12	26	52
1	α1	0.13 (2.85)	0.15 (4.24)	0.13 (4.54)	0.12 (4.51)	0.08 (3.99)	0.05 (2.79)	0.04 (3.37)	0.04 (3.86)
	α3	0.23 (4.79)	0.24 (5.88)	0.20 (6.65)	0.17 (6.20)	0.12 (5.31)	0.08 (4.20)	0.06 (4.27)	0.04 (4.13)
	α4	0.24 (4.72)	0.24 (5.50)	0.18 (6.34)	0.17 (5.79)	0.12 (4.49)	0.07 (3.40)	0.05 (3.42)	0.04 (3.86)
2	α1	0.23 (4.71)	0.22 (5.83)	0.17 (5.41)	0.14 (5.13)	0.08 (3.46)	0.04 (1.94)	0.02 (1.49)	0.02 (1.71)
	α3	0.22 (4.49)	0.20 (4.74)	0.18 (5.04)	0.16 (4.99)	0.10 (3.94)	0.06 (2.77)	0.05 (3.44)	0.05 (3.93)
	α4	0.34 (6.49)	0.28 (6.53)	0.25 (6.72)	0.21 (6.05)	0.15 (5.29)	0.10 (4.13)	0.07 (4.03)	0.05 (4.06)
3	α1	0.33 (6.10)	0.26 (6.03)	0.23 (6.37)	0.20 (5.74)	0.14 (4.56)	0.09 (3.40)	0.06 (3.10)	0.05 (3.72)
	α3	0.33 (6.63)	0.26 (5.83)	0.22 (5.73)	0.17 (4.72)	0.10 (3.39)	0.05 (2.16)	0.02 (1.30)	0.02 (1.64)
	α4	0.25 (5.20)	0.22 (5.00)	0.20 (5.15)	0.16 (4.63)	0.10 (3.22)	0.07 (2.71)	0.05 (2.89)	0.05 (3.62)
4	α1	0.35 (7.37)	0.31 (6.74)	0.27 (6.25)	0.23 (5.36)	0.16 (4.54)	0.11 (3.82)	0.07 (3.51)	0.06 (3.65)
	α3	0.32 (6.67)	0.28 (6.22)	0.24 (5.73)	0.21 (4.94)	0.15 (3.87)	0.09 (3.03)	0.06 (2.72)	0.06 (3.44)
	α4	0.31 (6.10)	0.25 (5.47)	0.20 (4.59)	0.16 (3.83)	0.10 (2.69)	0.05 (1.73)	0.02 (0.82)	0.02 (1.29)
8	α1	0.25 (5.11)	0.23 (5.18)	0.19 (4.58)	0.15 (4.01)	0.08 (2.36)	0.06 (2.10)	0.05 (2.34)	0.05 (3.29)
	α3	0.36 (7.12)	0.31 (6.12)	0.26 (5.52)	0.23 (4.88)	0.15 (3.83)	0.10 (3.22)	0.06 (3.01)	0.06 (3.40)
	α4	0.34 (6.50)	0.28 (5.62)	0.24 (5.10)	0.22 (4.55)	0.14 (3.32)	0.08 (2.53)	0.06 (2.36)	0.06 (3.20)
12	α1	0.29 (5.90)	0.23 (4.65)	0.19 (3.93)	0.16 (3.43)	0.08 (2.06)	0.03 (1.05)	0.01 (0.38)	0.02 (0.94)
	α3	0.20 (4.12)	0.17 (3.60)	0.14 (2.96)	0.11 (2.32)	0.06 (1.45)	0.05 (1.40)	0.05 (1.89)	0.06 (3.00)
	α4	0.32 (5.91)	0.28 (5.25)	0.24 (4.67)	0.20 (3.98)	0.13 (2.84)	0.09 (2.27)	0.06 (2.24)	0.07 (3.05)
26	α1	0.31 (5.56)	0.26 (4.72)	0.23 (4.11)	0.19 (3.50)	0.11 (2.31)	0.07 (1.59)	0.05 (1.74)	0.07 (3.01)
	α3	0.24 (4.37)	0.18 (3.38)	0.14 (2.67)	0.11 (2.12)	0.04 (0.82)	-0.00 (-0.06)	-0.01 (-0.29)	0.01 (0.54)
	α4	0.15 (2.89)	0.14 (2.77)	0.12 (2.51)	0.11 (2.23)	0.06 (1.42)	0.05 (1.27)	0.06 (1.98)	0.07 (3.12)
52	α1	0.25 (4.73)	0.23 (4.46)	0.21 (3.93)	0.18 (3.47)	0.12 (2.43)	0.08 (1.86)	0.07 (2.19)	0.08 (3.05)
	α3	0.23 (4.18)	0.22 (3.95)	0.19 (3.31)	0.16 (2.79)	0.09 (1.75)	0.06 (1.26)	0.06 (1.82)	0.08 (2.97)
	α4	0.15 (2.78)	0.13 (2.47)	0.09 (1.77)	0.06 (1.23)	0.00 (0.04)	-0.03 (-0.61)	-0.01 (-0.35)	0.01 (0.41)

Table 11
Alphas of time series and cross-sectional momentum strategies – Long vs. Short

Table 11 reports the alphas of time-series and cross-sectional momentum strategies separately for long and short legs. We calculate each anomaly's prior returns during formation period ranging from one week to 52 weeks. The time-series strategies are constructed by going long the anomalies with positive past returns and short those with negative returns. Portfolios are kept for a holding period of one week to 52 weeks. All results are reported in percentage per week. Numbers in parentheses are the *t*-statistics, adjusted for heteroscedasticity and autocorrelations. The time-series momentum strategies are described in Section 4.1. The cross-sectional momentum strategies are described in Section 4.2. The results below are based on strategies with a look-back period of 4 weeks and a holding-period of 4 weeks.

Panel A: Time-series Momentum

	Long		Short		Long-Short	
EW						
α1	0.16	(6.90)	-0.12	(-7.74)	0.29	(10.16)
α3	0.14	(6.38)	-0.11	(-7.35)	0.26	(9.34)
α4	0.13	(5.46)	-0.11	(-7.10)	0.24	(8.38)
VW						
α1	0.10	(6.97)	-0.11	(-8.40)	0.21	(8.76)
α3	0.10	(6.84)	-0.10	(-7.75)	0.20	(8.16)
α4	0.09	(5.90)	-0.09	(-7.41)	0.18	(7.35)

Panel B: Cross-sectional Momentum

	Long		Short		Long-Short	
EW						
α1	0.17	(6.85)	-0.15	(-7.40)	0.33	(7.06)
α3	0.15	(5.91)	-0.14	(-6.51)	0.29	(6.05)
α4	0.12	(4.86)	-0.12	(-5.45)	0.23	(5.01)
VW						
α1	0.15	(6.67)	-0.16	(-6.45)	0.30	(6.54)
α3	0.14	(6.31)	-0.14	(-5.52)	0.28	(5.93)
α4	0.11	(5.02)	-0.12	(-4.69)	0.23	(4.82)