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Time-series and cross-sectional momentum in anomaly returns

Feifei Wang[1] | **Xuemin (Sterling) Yan**[2] | **Lingling Zheng**[3]

[1]Farmer School of Business, Miami University, Oxford, Ohio, USA

[2]College of Business, Lehigh University, Bethlehem, Pennsylvania, USA

[3]School of Business, Renmin University of China, Beijing, China

Correspondence
Lingling Zheng, School of Business, Renmin University of China, Beijing 100872, China.
Email: Zhenglingling@rmbs.ruc.edu.cn

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 traditional asset-pricing models, and are more pronounced when arbitrage capital is scarcer or market liquidity is lower. Momentum in anomaly returns dissipates but does not reverse, in the long-run. Our findings are consistent with limits-to-arbitrage and slow-moving capital causing mispricing to persist. Supporting this explanation, we find that both the level and persistence of anomaly returns are positively related to idiosyncratic volatility.

KEYWORDS
anomalies, idiosyncratic volatility, limits to arbitrage, momentum

JEL CLASSIFICATION
G10; G11; G14

1 | INTRODUCTION

Finance researchers have documented hundreds of cross-sectional return anomalies (Harvey et al., 2016; Hou et al., 2020). An important debate in this literature is whether the abnormal long–short returns are compensation for systematic risk, evidence of market inefficiency, or the

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result of data mining. In this paper, we provide new evidence on this debate by examining the persistence of absolute and relative performance of a comprehensive sample of cross-sectional return anomalies. Intuitively, if anomalies result from data mining, that is, they are spurious, then any superior long-short performance would be due to random chance, and hence is unlikely to continue. In contrast, if the superior long–short returns represent compensation for risk, then they should persist indefinitely. However, such persistence should weaken when we remove the mean long–short return (an estimate of the expected return). Finally, if the anomaly returns are due to mispricing, and, to the extent that arbitrage capital is limited and slow-moving, we would expect the 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 begin by examining time-series momentum in our sample of 90 anomalies. We follow Moskowitz et al. (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 lag 1 to 52 weeks are positive, with eight of them statistically significant at the 5% level. We also follow Moskowitz et al. (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 formation periods and holding periods (both ranging from 1 to 52 weeks). For example, the CAPM α for the time-series momentum strategy with a formation period of 4 weeks and a holding period of 4 weeks is 0.19% per week (10% annualized) and is highly 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, that is, whether the relative performance of anomalies persists. The cross-sectional momentum is related to, but distinct from the time-series momentum, 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 α for the cross-sectional momentum strategy with a formation period of 4 weeks and a holding period of 4 weeks is 0.32% per week, 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, suggesting that the persistence of relative anomaly returns is also short-lived.

Momentum in anomaly returns is not merely a reflection of the stock momentum (Jegadeesh & 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. Our results are also robust to alternative asset pricing models including the Fama and French (2015) 5-factor model and the Hou et al. (2015) q-factor model. 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, and we use value weights. In addition, our results remain significant when we skip a week after portfolio formation, mitigating a concern that our results are driven by microstructure effects. 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 "significant" 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 differences in unconditional expected returns (Conrad & Kaul, 1998 and Jegadeesh & 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 exhibit higher returns 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. Second, if momentum in anomaly returns is due to 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. We find that both the time-series and cross-sectional momentum in anomaly returns are essentially unchanged. This finding is not only inconsistent with explanations based on constant expected returns but also casting 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.

Alternatively, momentum in anomaly returns may be driven by a time-varying risk premium. To explore this possibility, we estimate rolling CAPM, Fama and French 3-factor, and Carhart 4-factor models and remove the time-varying expected returns based on these models from each anomaly's long–short returns. We then test whether time-series and cross-sectional momentum exist in the residual anomaly returns. If the persistence in anomaly returns solely results 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 time-series or cross-sectional momentum. Our results are inconsistent with this prediction—both the time-series and cross-sectional momentum remain highly significant in residual anomaly returns.[1]

We argue that momentum in anomaly returns is more consistent with behavioral explanations in which limits to arbitrage and slow-moving arbitrage capital cause mispricing to persist. In the presence of costly arbitrage, mispricing will not be completely eliminated (Pontiff, 2006; Shleifer & Vishny, 1997). We show in a simple model that such incomplete arbitrage leads to persistence in anomaly returns in the short run. In the long run, the arrival of 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 results are consistent with these predictions.

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, that is, hedge fund total assets under management and aggregate short interest ratio. Consistent with the prediction of behavioral explanations, we find that the persistence in anomaly returns is negatively related to these proxies for arbitrage capital. Behavioral explanations also predict that momentum in anomaly returns should be more pronounced when the market is less liquid. Using the aggregate Amihud ratio, aggregate turnover, and a postdecimalization indicator as proxies for market liquidity, we find evidence consistent with this prediction.

Our model also makes two predictions related to idiosyncratic volatility (IVOL), an important limit to arbitrage. First, anomalies with greater IVOL exhibit higher anomaly returns.

[1]We acknowledge that, without knowing the true asset pricing model, we cannot completely rule out the possibility of time-varying risk premium.

Second, anomalies with greater IVOL have more persistent anomaly returns. We test the first prediction by sorting our sample anomalies into quintiles based on their IVOL. We find that anomalies in the highest IVOL quintile exhibit significantly higher 1-, 3-, and 4-factor αs than anomalies in the lowest IVOL quintile. We test the second prediction by first dividing our sample anomalies into high- and low-IVOL groups, and then evaluate the profitability of time-series and cross-sectional momentum strategies within each group of anomalies. We find that the abnormal returns to time-series and cross-sectional momentum strategies are significantly higher among high-IVOL anomalies than among low-IVOL anomalies. In short, we show that both the level and persistence of anomaly returns are significantly and positively related to idiosyncratic volatility. These findings provide strong support for the behavioral explanation.

Overall, we find significant evidence of time-series and cross-sectional momentum in anomaly returns.[2] Anomaly momentum is distinct from stock momentum in two important ways. First, anomaly momentum is more short-lived than stock momentum, concentrating in the first 2 months after portfolio formation. Second, momentum in anomaly returns dissipates but does not reverse, in the long run. We acknowledge that the short-term nature of the anomaly momentum strategy likely implies high trading costs. The primary objective of our study is to understand the dynamics of anomaly returns and thus shed new light on the underlying drivers of cross-sectional return anomalies. Nevertheless, our results should still be useful for fund 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 study adds to the growing literature on meta-analysis of market anomalies. Harvey et al. (2016) examine 315 published return predictors and conclude that most of them are likely to be false discoveries. Green et al. (2017) study which of the 94 firm characteristics provides independent information about the cross-section of stock returns. Yan and Zheng (2017) construct over 18,000 fundamental signals and study the impact of data mining on fundamental-based anomalies. Hou et al. (2020) find that most of the 452 anomalies cannot be replicated in their sample based on their methodologies. Our paper is particularly related to Chordia et al. (2014), who document that the performance of a number of well-documented anomalies declines over time as a result of increasing market liquidity and trading activity, and McLean and Pontiff (2016), who find an average decline of 58% of long–short returns after the original papers were published. A key difference between our paper and McLean and Pontiff (2016) and Chordia et al. (2014) is that the above two papers examine *deterministic* changes in anomaly returns, whereas we focus on *stochastic* changes in anomaly returns.

Our paper adds to the growing literature recognizing that anomaly returns vary considerably over time and such variation is linked to time-varying arbitrage capital. For example, Hanson and Sunderam (2014) infer the amount of arbitrage capital allocated to quantitative equity strategies from the cross-section of short interest. They provide evidence that an increase in arbitrage capital leads to a decline in strategy profits. Akbas et al. (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 is also related to an emerging literature that apply machine learning techniques to empirical asset pricing in general, and to the prediction of the cross-section of stock returns

[2] Subsequent to the first draft of our paper, Arnott et al. (2018) and Gupta and Kelly (2019) document evidence of cross-sectional momentum among 51 anomaly factors and time-series momentum among 65 factor portfolios, respectively. The findings of Arnott et al. (2018) and Gupta and Kelly (2019) confirm our findings; however, they do not investigate the sources of anomaly momentum or link it to arbitrage capital, market liquidity, or idiosyncratic volatility.

in particular. Gu et al. (2020) employ a comprehensive set of machine learning techniques to predict market and individual stock returns with hundreds of candidate predictors. Kozak et al. (2020) construct stochastic discount factors by using ridge and lasso estimators and conclude that a low-dimension model cannot adequately summarize the cross-section of expected returns. Freyberger et al. (2020) use the adaptive group LASSO to select characteristics and to estimate how selected characteristics affect expected returns nonparametrically. The results of our paper suggest that past anomaly returns are useful for predicting future anomaly returns and hence future stock returns.

Finally, our paper contributes to the extensive literature examining the role of idiosyncratic volatility in driving anomaly returns. Most prior studies (e.g., Ali et al., 2003; Mendenhall, 2004) in this literature focus on the IVOL of *individual stocks* and show that anomaly returns are higher among stocks with higher IVOL. In contrast, we examine the IVOL of *anomaly returns*. This focus is appropriate because arbitrageurs who wish to exploit stock return anomalies are likely to hold a diversified long-short portfolio instead of just a few stocks. As such, the IVOL of the long-short portfolio, rather than the IVOL of individual stocks, should be more relevant. Our paper also differs from prior studies in that we focus on a large sample of anomalies and demonstrate that both the level and persistence of long–short returns vary *across* anomalies based on their IVOL.

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 et al. (2015) and McLean and Pontiff (2016). We restrict our sample to anomaly variables that are continuous (rather than an indicator variable) and can be constructed using the CRSP, COMPUSTAT, and I/B/E/S data. Our final list includes 90 anomalies covering six major categories.[3] The detailed list and definitions of these 90 anomalies are contained in the Appendix. Our sample period is from July 1963 to December 2019.

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, and the short interest data from Compustat, and analyst forecast data from I/B/E/S. We obtain Fama and French (2015) three factors, five factors, and the momentum factor from Kenneth French's website.[4] We obtain Hou et al. (2015) q-factors from Lu Zhang. We obtain hedge fund assets under management from the Lipper TASS database. 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.

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

[3]Harvey et al. (2016) consider 315 return predictors, but many of them are macroeconomic variables or predictors of market returns. Hou et al. (2020) replicate 452 anomalies, many of which share the same underlying anomaly variable and differ only in the length of the holding period.

[4]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

the portfolio formation date. We remove low-priced and microcap stocks to ensure that our results are not driven by small, illiquid stocks that comprise a tiny fraction of the market.

2.2 | Long–short anomaly 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 et al., 2008) have shown that low-asset growth firms earn significantly higher returns than high-asset growth firms. We construct both equal- and value-weighted returns but focus on value-weighted returns in most of our analyses to mitigate concerns about the impact of microcap stocks.

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 falls 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 1 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 α, Fama–French 3-factor α, and Carhart 4-factor α of long–short returns by running the following time-series regressions:

$$
\begin{aligned}
r_{i,t} &= \alpha_i + \beta_i \mathrm{MKT}_t + e_{i,t} \\
r_{i,t} &= \alpha_i + \beta_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + e_{i,t} \\
r_{i,t} &= \alpha_i + \beta_i \mathrm{MKT}_t + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + u_i \mathrm{UMD}_t + e_{i,t},
\end{aligned} \tag{1}
$$

where $r_{i,t}$ is the long–short return for anomaly i in week t, MKT, SMB, HML, and UMD are market, size, value, and momentum factors (Carhart, 1997; Fama & French, 1996), and $e_{i,t}$ is the regression residual.[5]

2.3 | Descriptive statistics

Table 1 reports the average long-short performance of our sample of anomalies. We follow Hou et al. (2015) and divide our sample of anomalies into six categories, Growth/Value, Intangibles,

[5]We also estimate Fama and French's (2015) 5-factor model and Hou et al.'s (2015) q-factor model and present the results in the Supporting Information Internet Appendix (discussed in Section 4.7).

TABLE 1 Anomaly returns

This table reports the summary statistics of anomaly returns. Our sample of 90 anomalies is compiled from Hou et al., (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 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 2019. 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 αs by regressing anomaly returns in the market, size, value, and momentum factors as defined in Fama and French (1996) and Carhart (1997). All results are reported in percentages per week. Numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

	Equal-weighted			**Value-weighted**		
Anomaly	**α1**	**α3**	**α4**	**α1**	**α3**	**α4**
(A) Growth/Value						
A/ME	0.15 (3.06)	0.10 (2.16)	0.15 (3.08)	0.09 (1.88)	0.01 (0.20)	0.07 (1.41)
B/M	0.19 (4.51)	0.14 (3.32)	0.16 (3.73)	0.10 (2.20)	0.02 (0.45)	0.06 (1.27)
B/P-E	0.11 (2.33)	0.07 (1.61)	0.12 (2.64)	0.05 (1.07)	−0.02 (−0.54)	0.02 (0.53)
B/P-Lev	0.06 (1.61)	0.05 (1.39)	−0.01 (−0.18)	0.04 (0.87)	0.04 (0.88)	0.00 (0.06)
CF/P	0.18 (4.64)	0.15 (3.77)	0.17 (3.96)	0.13 (3.00)	0.07 (1.63)	0.10 (2.22)
D/P	0.10 (2.25)	0.06 (1.26)	0.06 (1.25)	0.14 (2.48)	0.08 (1.29)	0.04 (0.64)
E/P	0.18 (4.67)	0.14 (3.64)	0.15 (3.86)	0.15 (3.43)	0.09 (2.01)	0.11 (2.43)
EF/P	0.25 (4.09)	0.30 (5.17)	0.32 (5.26)	0.32 (4.79)	0.38 (5.70)	0.32 (4.89)
Enter	0.11 (3.63)	0.05 (1.79)	0.08 (2.95)	0.08 (1.86)	−0.00 (−0.10)	0.04 (1.04)
LTG	0.28 (3.15)	0.34 (4.45)	0.30 (3.81)	0.24 (2.41)	0.30 (3.18)	0.21 (2.31)
NO/P	0.16 (4.20)	0.17 (4.23)	0.15 (3.66)	0.15 (3.49)	0.16 (3.56)	0.12 (2.79)
O/P	0.14 (3.83)	0.12 (3.36)	0.12 (3.14)	0.17 (3.34)	0.12 (2.15)	0.11 (2.06)
Rev	0.17 (4.84)	0.11 (3.13)	0.08 (2.16)	0.11 (2.40)	0.02 (0.48)	−0.03 (−0.57)
SG	0.08 (2.66)	0.08 (2.64)	0.08 (2.44)	0.07 (1.56)	0.06 (1.24)	0.06 (1.17)
STD_CF	0.20 (3.47)	0.25 (5.06)	0.23 (4.46)	0.17 (2.96)	0.23 (4.10)	0.17 (3.02)
(B) Intangibles						
AD/M	0.12 (2.23)	0.08 (1.68)	0.13 (2.61)	0.14 (2.02)	0.09 (1.27)	0.14 (1.97)
AccQ	−0.13 (−2.42)	−0.18 (−3.30)	−0.12 (−2.21)	−0.09 (−1.61)	−0.12 (−1.94)	−0.04 (−0.68)
Age	0.06 (1.27)	0.11 (2.04)	0.08 (1.53)	0.02 (0.38)	0.08 (1.48)	0.04 (0.83)
BC/A	0.04 (1.31)	0.04 (1.63)	0.05 (1.89)	0.04 (1.03)	0.06 (1.43)	0.08 (1.85)
H/N	0.13 (4.93)	0.12 (4.15)	0.11 (3.78)	0.08 (2.28)	0.07 (1.76)	0.04 (1.09)
OC/A	0.13 (3.46)	0.11 (2.91)	0.06 (1.60)	0.14 (2.75)	0.15 (2.96)	0.09 (1.81)
OL	0.08 (2.41)	0.06 (1.60)	0.04 (1.13)	0.08 (2.19)	0.08 (2.36)	0.04 (1.20)
RC/A	0.07 (0.89)	−0.01 (−0.10)	−0.04 (−0.65)	0.04 (0.53)	−0.05 (−0.76)	−0.05 (−0.74)
RD/M	0.13 (2.90)	0.06 (1.54)	0.06 (1.29)	0.03 (0.52)	−0.03 (−0.64)	0.00 (0.08)
RD/S	−0.08 (−1.02)	−0.15 (−2.50)	−0.17 (−2.79)	−0.12 (−1.47)	−0.21 (−2.78)	−0.18 (−2.30)

(Continues)

TABLE 1 (Continued)

Anomaly	Equal-weighted α1	α3	α4	Value-weighted α1	α3	α4
(C) Investment						
ACI	0.09 (5.41)	0.09 (5.18)	0.07 (4.10)	0.08 (2.86)	0.06 (2.15)	0.02 (0.89)
BeG	0.14 (5.56)	0.11 (4.27)	0.10 (3.84)	0.15 (4.04)	0.12 (3.03)	0.08 (2.06)
CEI	0.08 (3.71)	0.08 (3.83)	0.07 (3.43)	0.07 (2.57)	0.09 (3.28)	0.08 (2.91)
D_NCO	0.10 (4.19)	0.06 (2.54)	0.06 (2.69)	0.03 (1.58)	0.02 (0.87)	0.01 (0.68)
D_NWC	0.05 (3.13)	0.04 (2.68)	0.05 (3.27)	0.04 (2.41)	0.04 (2.26)	0.04 (2.01)
I-ADJ	0.08 (4.92)	0.07 (4.43)	0.06 (3.77)	0.09 (3.08)	0.06 (2.08)	0.05 (1.59)
I/A	0.18 (6.71)	0.15 (5.20)	0.13 (4.62)	0.15 (3.70)	0.13 (2.79)	0.09 (2.16)
IG	0.10 (5.23)	0.09 (4.50)	0.08 (4.03)	0.09 (3.03)	0.08 (2.41)	0.06 (1.80)
IvC	0.11 (5.40)	0.10 (4.80)	0.10 (4.57)	0.12 (3.92)	0.10 (3.04)	0.07 (2.08)
IvG	0.13 (6.23)	0.12 (5.50)	0.11 (4.89)	0.12 (3.28)	0.11 (2.74)	0.06 (1.56)
NOA	0.17 (4.95)	0.16 (4.53)	0.10 (2.82)	0.12 (3.22)	0.14 (3.82)	0.09 (2.68)
NoaG	0.16 (6.86)	0.14 (5.82)	0.11 (4.58)	0.13 (3.96)	0.12 (3.61)	0.08 (2.57)
NSI	0.18 (5.66)	0.20 (5.51)	0.15 (4.53)	0.10 (2.90)	0.13 (3.93)	0.12 (3.48)
NXF	0.23 (5.20)	0.25 (5.14)	0.18 (4.09)	0.18 (2.70)	0.23 (3.33)	0.12 (2.02)
OA	0.09 (4.34)	0.10 (4.77)	0.10 (4.64)	0.12 (3.62)	0.13 (4.06)	0.10 (3.19)
PI/A	0.18 (7.52)	0.16 (6.09)	0.11 (4.54)	0.13 (4.19)	0.12 (3.40)	0.07 (2.10)
POA	0.08 (3.97)	0.10 (4.67)	0.11 (4.94)	0.11 (3.64)	0.10 (3.60)	0.11 (3.56)
PTA	0.13 (7.11)	0.12 (6.57)	0.10 (5.66)	0.14 (4.99)	0.14 (4.65)	0.10 (3.66)
TA	0.13 (6.42)	0.12 (5.53)	0.10 (4.55)	0.10 (3.39)	0.09 (2.81)	0.07 (2.24)
(D) Momentum						
Abr-1	0.32 (13.78)	0.32 (13.97)	0.29 (13.12)	0.24 (6.54)	0.22 (6.15)	0.19 (5.30)
R11-1	0.37 (7.49)	0.40 (7.99)	0.23 (4.61)	0.36 (5.75)	0.39 (6.30)	0.15 (2.45)
R6-1	0.38 (7.95)	0.39 (7.91)	0.22 (4.68)	0.30 (5.22)	0.30 (5.10)	0.09 (1.62)
R6-Lag	0.24 (6.32)	0.27 (6.81)	0.19 (4.39)	0.30 (5.50)	0.33 (6.13)	0.20 (3.47)
RE-1	0.23 (6.86)	0.24 (7.31)	0.18 (5.41)	0.19 (3.62)	0.21 (4.16)	0.10 (2.06)
SUE	0.25 (7.62)	0.29 (9.66)	0.22 (7.79)	0.11 (2.80)	0.14 (3.63)	0.06 (1.62)
Season	0.05 (2.09)	0.05 (2.22)	0.05 (2.09)	0.15 (3.98)	0.17 (4.60)	0.16 (4.23)
W52	0.27 (4.13)	0.32 (4.81)	0.16 (2.32)	0.14 (2.33)	0.17 (2.74)	0.03 (0.42)
(E) Profitability						
ATO	0.03 (1.06)	0.02 (0.73)	0.00 (0.14)	0.03 (0.71)	0.05 (1.49)	0.03 (0.68)
CTO	0.05 (1.46)	0.05 (1.38)	0.04 (1.20)	0.05 (1.25)	0.06 (1.76)	0.03 (0.89)
D_ATO	−0.00 (−0.26)	0.01 (0.33)	0.01 (0.81)	−0.01 (−0.39)	−0.01 (−0.43)	−0.02 (−0.71)
D_PM	0.03 (1.28)	0.04 (1.93)	0.01 (0.52)	0.03 (0.92)	0.04 (1.33)	−0.00 (−0.12)
F	0.14 (5.05)	0.17 (6.01)	0.12 (4.90)	0.09 (2.99)	0.10 (3.18)	0.09 (2.88)
FP	0.29 (5.06)	0.34 (6.07)	0.18 (3.86)	0.31 (3.87)	0.39 (5.03)	0.17 (2.79)
GP/A	0.12 (3.65)	0.14 (4.30)	0.11 (3.30)	0.07 (2.16)	0.10 (2.95)	0.06 (1.76)
O	0.10 (3.12)	0.15 (4.59)	0.09 (3.25)	0.07 (1.57)	0.16 (3.41)	0.09 (2.20)
PM	0.08 (1.67)	0.16 (3.25)	0.11 (2.45)	0.07 (1.09)	0.15 (2.43)	0.08 (1.41)
RNA	0.06 (1.61)	0.11 (3.32)	0.05 (1.79)	0.05 (0.93)	0.15 (2.84)	0.06 (1.24)
ROA	0.27 (5.47)	0.33 (6.77)	0.26 (5.72)	0.22 (4.01)	0.31 (5.38)	0.20 (4.00)
ROE	0.31 (6.17)	0.38 (7.69)	0.30 (6.63)	0.23 (4.26)	0.30 (5.45)	0.19 (3.92)
RS	0.20 (5.13)	0.23 (7.22)	0.17 (5.92)	0.13 (2.76)	0.14 (3.47)	0.06 (1.81)

TABLE 1 (Continued)

Anomaly	Equal-weighted α1	α3	α4	Value-weighted α1	α3	α4
S/IV	0.06 (3.70)	0.07 (4.04)	0.06 (3.55)	0.06 (2.20)	0.07 (2.52)	0.05 (1.64)
S/P	0.16 (3.21)	0.12 (2.50)	0.15 (3.11)	0.13 (2.45)	0.04 (0.88)	0.08 (1.72)
S/SGA	−0.00 (−0.18)	0.01 (0.31)	0.02 (0.84)	−0.01 (−0.21)	0.00 (0.12)	0.01 (0.31)
TES	0.06 (2.17)	0.07 (2.66)	0.05 (1.88)	0.02 (0.47)	0.04 (0.92)	−0.00 (−0.06)
TI/BI	0.06 (2.45)	0.08 (3.18)	0.06 (2.41)	0.06 (1.82)	0.08 (2.73)	0.03 (1.16)
Z	0.04 (1.11)	0.03 (0.81)	0.05 (1.42)	0.06 (1.40)	0.01 (0.22)	0.03 (0.53)
(F) Trading						
1/P	−0.08 (−1.60)	−0.19 (−3.95)	−0.07 (−1.45)	−0.11 (−1.77)	−0.25 (−4.21)	−0.08 (−1.52)
B-A	−0.15 (−2.33)	−0.25 (−4.02)	−0.15 (−2.41)	−0.15 (−1.98)	−0.25 (−3.44)	−0.13 (−1.85)
BETA_D	0.24 (3.70)	0.25 (3.84)	0.15 (2.16)	0.19 (2.71)	0.19 (2.59)	0.09 (1.18)
BETA_FP	0.32 (3.56)	0.38 (4.11)	0.24 (2.61)	0.28 (3.00)	0.29 (3.04)	0.16 (1.70)
BETA_M	0.26 (3.20)	0.32 (3.88)	0.20 (2.43)	0.23 (2.39)	0.27 (2.80)	0.15 (1.62)
Disp	0.24 (5.73)	0.30 (7.30)	0.22 (5.56)	0.23 (4.11)	0.30 (5.43)	0.19 (3.46)
Dvol	0.17 (4.86)	0.08 (2.04)	0.09 (2.40)	0.13 (3.76)	0.01 (0.35)	0.06 (1.93)
Illiq	0.13 (3.84)	0.01 (0.34)	0.06 (1.86)	0.13 (3.46)	−0.00 (−0.13)	0.05 (1.68)
Ivol	0.30 (4.30)	0.37 (5.07)	0.27 (3.90)	0.28 (3.73)	0.36 (4.66)	0.25 (3.51)
MDR	0.29 (4.61)	0.35 (5.40)	0.27 (4.23)	0.21 (2.91)	0.27 (3.55)	0.17 (2.34)
ME	0.08 (1.95)	−0.05 (−1.36)	−0.01 (−0.21)	0.08 (1.84)	−0.07 (−1.70)	−0.02 (−0.48)
S-Rev	0.07 (1.51)	0.07 (1.45)	0.13 (2.67)	−0.05 (−0.86)	−0.04 (−0.67)	0.04 (0.68)
STD_DVOL	0.22 (5.53)	0.14 (3.33)	0.13 (3.06)	0.16 (5.04)	0.05 (1.58)	0.09 (2.73)
Short	0.26 (5.68)	0.29 (6.12)	0.24 (5.10)	0.15 (2.95)	0.18 (3.51)	0.12 (2.41)
Skew	0.06 (2.28)	0.04 (1.52)	0.05 (1.88)	0.03 (0.84)	0.01 (0.27)	0.02 (0.59)
Svol	0.08 (2.16)	0.10 (2.58)	0.07 (1.86)	0.17 (2.73)	0.21 (3.29)	0.11 (1.90)
Turn	0.27 (4.05)	0.28 (4.07)	0.24 (3.31)	0.14 (1.98)	0.16 (2.04)	0.12 (1.54)
Tvol	0.34 (4.29)	0.41 (5.00)	0.29 (3.60)	0.30 (3.55)	0.36 (3.99)	0.22 (2.57)
Vol-T	0.24 (6.31)	0.22 (5.39)	0.19 (4.56)	0.22 (4.92)	0.19 (3.70)	0.14 (2.92)

Investment, Momentum, Profitability, and Trading, and report the results in six panels. In each panel, we present 1-, 3-, and 4-factor αs for both equal- and value-weighted long–short returns. We find that the majority of the anomalies in our sample exhibit significant 1-factor αs. Specifically, 72 of the 90 anomalies have an equal-weighted 1-factor α that is positive and statistically significant at the 5% level. For value-weighted returns, the number is 62. Not surprisingly, the number of significant 3- or 4-factor αs is lower. Specifically, 67 (56) of the 90 anomalies exhibit significant 3-factor αs for equal- (value-) weighted returns. The corresponding numbers for 4-factor αs are 66 and 39. We do not exclude anomalies that have insignificant αs 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:

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

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

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

where

$$\mathrm{var}(e_i) = \sigma_i^2 \equiv \sigma^2 \ \forall \ i,$$

$$\mathrm{cov}(e_i, e_m) = 0 \ \forall \ i,$$

$$\mathrm{cov}(e_i, e_j) = 0 \ \forall \ i \neq j,$$

that is, we assume all anomalies have the same idiosyncratic volatility. We also assume that anomaly returns are uncorrelated with each other and uncorrelated with 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 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:

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

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

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

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

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

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

The optimal weight on the risk-free asset is 1 minus the weight in 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:

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

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. Without loss of generality, we assume that each arbitrageur has an initial wealth of $1. For each $1 employed by the arbitrageurs to trade against an anomaly, the α 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 α as follows:

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

From (9), 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 in α are then as follows:

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

and the expected α at $t = 1$ is as follows:

$$E(\alpha_{i,1}) = \alpha_{i,0}\left(1 - \frac{\gamma Np}{\lambda\sigma^2}\right). \tag{13}$$

We further assume that:

$$\gamma < \frac{\lambda\sigma^2}{Np}. \tag{14}$$

The inequality in Equation (14) implies that the initial mispricing will not completely go away when the expected number of arbitrageurs show up and trade against the anomaly.

Equation (13), combined with the assumption in Equation (14), indicates 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 (13), we can show that

$$E(\alpha_{i,1}) - E(\alpha_{j,1}) = (\alpha_{i,0} - \alpha_{j,0})\left(1 - \frac{\gamma Np}{\lambda\sigma^2}\right). \tag{15}$$

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

$$E(\alpha_{i,1}) - E(\alpha_{j,1}) < (\alpha_{i,0} - \alpha_{j,0}), \tag{16}$$

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

Finally, our model offers two predictions related to idiosyncratic volatility. First, everything else equal, the α of an anomaly increases in IVOL, as can be seen in Equation (13). Second, the expected reduction in α decreases in idiosyncratic volatility, as shown in Equation (12). That is, our model predicts that anomalies with higher IVOL will exhibit higher and more persistent αs. We will test these two predictions in Section 4.6.

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 et al. (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.

$$\frac{r_{i,t}}{\sigma_{i,t-1}} = \alpha + \beta\frac{r_{i,t-m}}{\sigma_{i,t-m-1}} + e_{i,t}, \tag{17}$$

We follow Moskowitz et al. (2012) and stack all anomalies and dates and run a pooled panel regression and compute t-statistics that account for clustering by time. We estimate the regression using lags of $m = 1, 2, ..., 104$ weeks.

The top panel of Figure 1 plots the coefficient estimates as well as t statistics of β from the regression (17) for equal-weighted anomaly returns. We find strong evidence of persistence during the first 52 lags. Forty-seven of the 52 autoregression coefficients are positive, and 13 of them are statistically significant at the 5% level. In contrast, only five 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.

The bottom panel presents the results for value-weighted anomaly returns. The results are qualitatively similar to those in the top panel. We find strong evidence of persistence during the

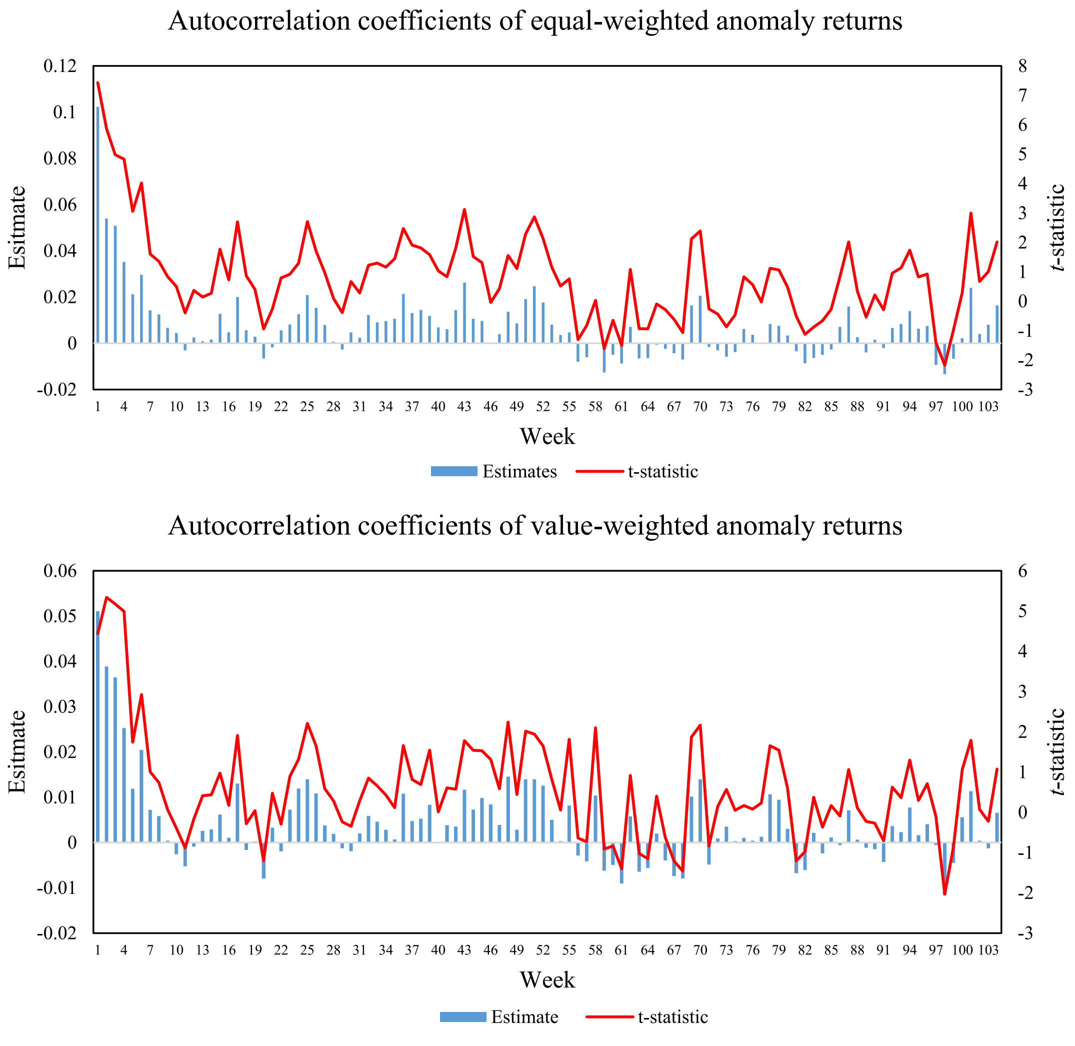

FIGURE 1 **Autocorrelation coefficients of anomaly returns.** This figure plots the t statistics of autocorrelation coefficients (β) in the regression equation (17). Our sample of 90 anomalies is compiled from Hou et al. (2015) and McLean and Pontiff (2016). The detailed list and definitions of these 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. 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 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 2019

first 52 weeks. Forty-four of the 52 autoregression coefficients are positive, with eight being statistically significant at the 5% level. In contrast, only eight coefficients are negative and none of them are statistically significant. The results for weeks 52 through 104 are largely insignificant.

Next, we follow Moskowitz et al. (2012) and construct 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 long the anomaly if positive and "short" the anomaly if negative.[6] 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 et al. (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 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 1963–2019.

Table 2 presents the 1-, 3-, and 4-factor αs for the above time-series momentum strategies.[7] The results for equal-weighted anomaly returns are much stronger than those for value-weighted returns. But to conserve space and to minimize any concern about the influence of microcap stocks, we report only the results for value-weighted returns in the main paper and present the equal-weighted results in the Supporting Information Internet Appendix. 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 α for the time-series momentum trading strategy with a look-back period of 4 weeks and a holding period of 4 weeks is 0.19% per week (10% annualized), and highly statistically significant. The 3- and 4-factor αs are similar at 0.19% and 0.17% per week, respectively, and continue to be statistically significant. Moreover, the significant 4-factor αs indicate that momentum in anomaly returns is not mechanically driven by the momentum in stock returns.

Looking at the results across different look-back and holding periods, we find that the results are most pronounced at shorter horizons, that is, 1 to 8 weeks. Extending the look-back period beyond 8 weeks reduces the αs slightly, whereas extending the holding period beyond 4–8 weeks lead to significantly lower αs, 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 1-factor α from 0.19% to 0.12% per week. A simple calculation indicates that the average 1-factor α for Week 5 through Week 8 is only 0.05% per week.

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, that is, whether the relative performance of anomalies is persistent. We develop our cross-sectional momentum strategies similar to the traditional stock momentum strategies (Jegadeesh & 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) includes the 18 anomalies that performed the worst during the past k weeks. We then long the past winners and "short" the past losers.[8] We hold the portfolios for h weeks. We vary

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

[7]Although we report results for CAPM 1-factor, Fama and French 3-factor, and Carhart 4-factor αs, we note that the CAPM 1-factor α 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 significant persistence in anomaly returns. Consistent with this expectation, we find that our results are strongest when we use 1-factor αs.

[8]Again, "shorting" here means we take the opposite positions to the original long-short portfolio, that is, long the original short portfolio and short the original long portfolio.

TABLE 2 Alphas of time-series momentum strategies

This table reports the αs of time-series momentum strategies. Our sample of 90 anamolies is complied from Hou et al., (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. Our sample period is from July 1963 to December 2019. We calculate each anomaly's prior returns during formation period ranging from 1 to 52 weeks. The time-series momentum strategies— long, the anomalies with positive past returns and short, those with negative returns. Portfolios are kept for a holding period of 1 to 52 weeks. The time-series momentum strategies are described in Section 4.1. All results are reported in percentages per week. Numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

		Holding period (weeks)							
Past return		**1**	**2**	**3**	**4**	**8**	**12**	**26**	**52**
1	$\alpha1$	0.21 (8.38)	0.18 (9.36)	0.16 (9.99)	0.14 (9.52)	0.10 (8.88)	0.07 (6.90)	0.04 (6.07)	0.03 (5.50)
	$\alpha3$	0.19 (7.78)	0.17 (9.00)	0.16 (9.43)	0.13 (9.10)	0.09 (8.69)	0.06 (6.53)	0.04 (5.65)	0.03 (5.24)
	$\alpha4$	0.18 (7.23)	0.16 (8.55)	0.15 (9.01)	0.13 (8.44)	0.08 (7.50)	0.05 (5.42)	0.03 (4.29)	0.02 (3.78)
2	$\alpha1$	0.25 (9.87)	0.22 (9.82)	0.20 (9.60)	0.17 (9.30)	0.12 (8.34)	0.08 (6.44)	0.05 (5.60)	0.04 (5.12)
	$\alpha3$	0.24 (9.49)	0.22 (9.50)	0.19 (9.32)	0.17 (9.13)	0.12 (8.32)	0.08 (6.17)	0.05 (5.21)	0.04 (4.93)
	$\alpha4$	0.23 (9.10)	0.21 (9.21)	0.18 (8.83)	0.16 (8.46)	0.10 (7.16)	0.07 (5.16)	0.04 (3.94)	0.03 (3.50)
3	$\alpha1$	0.28 (10.73)	0.25 (10.03)	0.22 (9.48)	0.19 (8.92)	0.13 (7.59)	0.09 (5.87)	0.05 (5.03)	0.04 (4.74)
	$\alpha3$	0.27 (10.21)	0.24 (9.67)	0.21 (9.12)	0.19 (8.68)	0.13 (7.50)	0.09 (5.62)	0.05 (4.78)	0.04 (4.68)
	$\alpha4$	0.26 (9.76)	0.23 (9.14)	0.20 (8.47)	0.17 (7.81)	0.11 (6.31)	0.07 (4.50)	0.04 (3.38)	0.03 (3.12)
4	$\alpha1$	0.27 (10.35)	0.24 (9.68)	0.22 (8.92)	0.19 (8.49)	0.12 (6.71)	0.09 (5.18)	0.05 (4.54)	0.04 (4.40)
	$\alpha3$	0.27 (9.95)	0.24 (9.39)	0.21 (8.63)	0.19 (8.33)	0.12 (6.61)	0.08 (4.93)	0.05 (4.31)	0.04 (4.29)
	$\alpha4$	0.25 (9.22)	0.22 (8.65)	0.20 (7.77)	0.17 (7.31)	0.10 (5.39)	0.06 (3.81)	0.03 (2.90)	0.03 (2.67)
8	$\alpha1$	0.25 (9.54)	0.23 (9.06)	0.20 (8.22)	0.17 (7.28)	0.11 (4.83)	0.08 (3.69)	0.05 (3.26)	0.04 (3.88)
	$\alpha3$	0.25 (9.47)	0.23 (9.03)	0.20 (8.08)	0.17 (7.17)	0.11 (4.69)	0.07 (3.45)	0.05 (3.12)	0.05 (3.87)
	$\alpha4$	0.22 (8.25)	0.20 (7.75)	0.17 (6.73)	0.14 (5.79)	0.08 (3.40)	0.05 (2.16)	0.02 (1.58)	0.02 (2.07)

(Continues)

TABLE 2 (Continued)

Past return		Holding period (weeks) 1	2	3	4	8	12	26	52
12	$\alpha 1$	0.21 (8.02)	0.19 (7.24)	0.16 (6.35)	0.14 (5.57)	0.09 (3.69)	0.06 (2.63)	0.04 (2.60)	0.05 (3.53)
	$\alpha 3$	0.20 (7.88)	0.18 (7.09)	0.16 (6.25)	0.14 (5.47)	0.09 (3.54)	0.06 (2.49)	0.05 (2.63)	0.05 (3.63)
	$\alpha 4$	0.18 (6.64)	0.15 (5.83)	0.13 (4.93)	0.11 (4.11)	0.05 (2.17)	0.03 (1.14)	0.02 (1.05)	0.02 (1.81)
26	$\alpha 1$	0.16 (6.36)	0.15 (5.78)	0.14 (5.36)	0.13 (4.87)	0.09 (3.62)	0.08 (2.96)	0.06 (2.82)	0.06 (3.10)
	$\alpha 3$	0.16 (6.11)	0.15 (5.61)	0.14 (5.23)	0.12 (4.77)	0.09 (3.63)	0.08 (3.01)	0.07 (2.95)	0.06 (3.29)
	$\alpha 4$	0.11 (4.27)	0.10 (3.80)	0.09 (3.40)	0.08 (2.96)	0.05 (1.89)	0.03 (1.37)	0.03 (1.18)	0.03 (1.41)
52	$\alpha 1$	0.16 (6.06)	0.15 (5.63)	0.14 (5.24)	0.14 (4.92)	0.12 (4.12)	0.11 (3.63)	0.08 (2.95)	0.06 (2.71)
	$\alpha 3$	0.16 (6.20)	0.15 (5.81)	0.14 (5.40)	0.14 (5.08)	0.12 (4.32)	0.11 (3.82)	0.09 (3.18)	0.07 (3.17)
	$\alpha 4$	0.10 (3.80)	0.09 (3.51)	0.09 (3.15)	0.08 (2.89)	0.06 (2.27)	0.05 (1.90)	0.04 (1.47)	0.04 (1.69)

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.

Table 3 presents the detailed results for value-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 α for the momentum strategy with a formation period of 4 weeks and a holding period of 4 weeks is 0.32% per week (17% annualized), and highly statistically significant. The 3- and 4-factor αs are slightly lower at 0.31% and 0.24% per week, respectively, and continue to be economically and statistically significant. The significant 4-factor α again indicates that the cross-sectional momentum in 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, that is, 1–8 weeks. In particular, extending the holding period beyond 4–8 weeks leads to significantly lower αs, 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 3- to 12-month horizons.

The long–short return to each anomaly is composed of a long leg and a short leg. The persistence in the long–short return, therefore, could be driven by the long leg, the short leg, or both. If the persistence in long–short returns is attributable to the short leg, then it may not be implementable. In Table 4 we estimate the 1-, 3-, and 4-factor αs for the long leg and short leg separately. We then form time-series or cross-sectional momentum strategies based on either the long leg or the short leg rather than the long–short return. The results in Table 4 indicate strong evidence of persistence in both the long-leg αs and short-leg αs, indicating that the profits to our time-series and cross-sectional momentum strategies are attributable to both long and short legs.

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 data mining is unlikely to explain our results, 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. Sections 4.5 and 4.6 provide evidence on behavioral explanations.

4.3 | Constant expected returns

Momentum in anomaly returns could be due to differences in unconditional expected returns. We test this possibility in two ways by following the previous literature on stock momentum.[9] 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

[9]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, whereas Jegadeesh and Titman (2001) find evidence inconsistent with the hypothesis.

TABLE 3 Alphas of cross-sectional momentum strategies

This table reports the αs of cross-sectional momentum strategies. Our sample of 90 anamolies is complied from Hou et al. (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. Our sample period is from July 1963 to December 2019. We sort 90 anomalies into quintile portfolios based on prior returns during the formation period ranging from 1 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 1 to 52 weeks. The cross-sectional momentum strategies are described in detail in Section 4.2. All results are reported in percentages per week. Numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

		Holding period (weeks)							
Past returns		**1**	**2**	**3**	**4**	**8**	**12**	**26**	**52**
1	$\alpha 1$	0.35 (6.02)	0.29 (6.34)	0.28 (6.74)	0.23 (7.07)	0.16 (6.07)	0.11 (5.26)	0.07 (4.86)	0.05 (4.13)
	$\alpha 3$	0.31 (5.28)	0.29 (6.08)	0.27 (6.25)	0.22 (6.71)	0.16 (5.54)	0.10 (4.33)	0.06 (3.73)	0.04 (3.46)
	$\alpha 4$	0.26 (4.47)	0.25 (5.68)	0.24 (6.05)	0.19 (5.51)	0.11 (3.97)	0.07 (2.82)	0.03 (1.55)	0.01 (0.98)
2	$\alpha 1$	0.41 (7.18)	0.37 (7.11)	0.32 (7.41)	0.28 (7.39)	0.20 (6.17)	0.14 (5.18)	0.09 (4.64)	0.06 (4.09)
	$\alpha 3$	0.41 (7.16)	0.37 (7.00)	0.32 (7.27)	0.27 (7.37)	0.20 (5.85)	0.12 (4.39)	0.08 (3.63)	0.06 (3.63)
	$\alpha 4$	0.37 (6.75)	0.35 (6.99)	0.30 (6.46)	0.25 (6.27)	0.15 (4.29)	0.09 (2.98)	0.03 (1.58)	0.02 (1.17)
3	$\alpha 1$	0.47 (7.87)	0.41 (7.63)	0.36 (7.28)	0.32 (6.90)	0.22 (5.44)	0.15 (4.63)	0.09 (4.21)	0.07 (3.87)
	$\alpha 3$	0.46 (7.45)	0.40 (7.37)	0.35 (7.02)	0.30 (6.66)	0.21 (5.05)	0.13 (3.87)	0.08 (3.30)	0.06 (3.49)
	$\alpha 4$	0.41 (6.86)	0.36 (6.42)	0.31 (5.93)	0.25 (5.32)	0.15 (3.48)	0.08 (2.40)	0.03 (1.13)	0.02 (0.98)
4	$\alpha 1$	0.46 (7.76)	0.40 (7.20)	0.36 (6.62)	0.32 (6.15)	0.22 (4.96)	0.15 (4.28)	0.09 (3.74)	0.07 (3.57)
	$\alpha 3$	0.45 (7.38)	0.40 (6.99)	0.35 (6.30)	0.31 (5.90)	0.21 (4.55)	0.13 (3.51)	0.08 (2.95)	0.06 (3.23)
	$\alpha 4$	0.39 (6.29)	0.34 (5.95)	0.28 (5.08)	0.24 (4.49)	0.14 (2.98)	0.07 (1.95)	0.02 (0.68)	0.01 (0.56)
8	$\alpha 1$	0.43 (7.10)	0.39 (6.50)	0.34 (5.93)	0.30 (5.35)	0.20 (4.03)	0.15 (3.40)	0.09 (2.83)	0.07 (3.10)
	$\alpha 3$	0.43 (6.94)	0.39 (6.32)	0.34 (5.57)	0.30 (4.96)	0.19 (3.46)	0.12 (2.64)	0.07 (2.14)	0.07 (2.87)
	$\alpha 4$	0.34 (5.34)	0.30 (4.78)	0.25 (3.98)	0.21 (3.33)	0.10 (1.84)	0.04 (0.94)	−0.00 (−0.10)	0.00 (0.06)

TABLE 3 (Continued)

Past returns		Holding period (weeks) 1	2	3	4	8	12	26	52
12	α1	0.34 (5.76)	0.30 (5.20)	0.28 (4.88)	0.26 (4.50)	0.18 (3.50)	0.12 (2.60)	0.08 (2.46)	0.08 (2.98)
	α3	0.33 (5.49)	0.29 (4.86)	0.27 (4.45)	0.24 (3.95)	0.15 (2.77)	0.09 (1.93)	0.07 (1.90)	0.08 (2.68)
	α4	0.25 (4.01)	0.21 (3.32)	0.18 (2.83)	0.14 (2.28)	0.06 (1.04)	−0.00 (−0.06)	−0.02 (−0.46)	−0.00 (−0.15)
26	α1	0.30 (5.24)	0.27 (4.82)	0.25 (4.43)	0.23 (4.02)	0.17 (3.20)	0.14 (2.78)	0.12 (2.72)	0.10 (2.63)
	α3	0.27 (4.69)	0.25 (4.34)	0.23 (4.00)	0.21 (3.64)	0.16 (2.84)	0.13 (2.43)	0.12 (2.49)	0.10 (2.59)
	α4	0.13 (2.28)	0.11 (1.92)	0.09 (1.54)	0.07 (1.13)	0.02 (0.29)	−0.00 (−0.09)	−0.00 (−0.10)	−0.01 (−0.22)
52	α1	0.29 (4.89)	0.27 (4.55)	0.25 (4.24)	0.24 (3.98)	0.20 (3.33)	0.17 (2.86)	0.14 (2.28)	0.10 (1.75)
	α3	0.29 (5.02)	0.27 (4.67)	0.25 (4.34)	0.24 (4.06)	0.20 (3.40)	0.17 (2.97)	0.14 (2.51)	0.11 (2.28)
	α4	0.10 (1.70)	0.08 (1.43)	0.07 (1.16)	0.05 (0.91)	0.02 (0.38)	0.00 (0.01)	−0.01 (−0.21)	−0.01 (−0.17)

TABLE 4 Alphas of time-series and cross-sectional momentum strategies—long versus short leg
This table reports the αs of time-series and cross-sectional momentum strategies separately for long and short legs for the anomalies. The results are based on the following two momentum strategies: Value-weighted time-series momentum strategies and value-weighted cross-sectional momentum strategies, both with a look-back period and a holding period of 4 weeks. 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. All results are reported in percentages per week. The numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

	Long	Short	Long–Short
(A) Time-series momentum			
$\alpha 1$	0.10 (7.50)	−0.09 (−7.69)	0.19 (8.49)
$\alpha 3$	0.10 (7.54)	−0.09 (−7.41)	0.19 (8.33)
$\alpha 4$	0.09 (6.46)	−0.08 (−6.70)	0.17 (7.31)
(B) Cross-sectional momentum			
$\alpha 1$	0.15 (6.17)	−0.17 (−5.76)	0.32 (6.15)
$\alpha 3$	0.15 (6.08)	−0.16 (−5.36)	0.31 (5.90)
$\alpha 4$	0.12 (4.53)	−0.12 (−4.17)	0.24 (4.49)

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 (the formation period is 4 weeks). 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. 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.

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 examine demeaned long–short returns. Table 5 presents the results. For brevity, we present the results for the following four look-back and holding periods: 2, 4, 8, and 12 weeks. 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 returns. For example, the CAPM α for the time-series momentum strategy with a look-back period of 4 weeks and a holding period of 4 weeks is 0.18% per week. Similarly, the cross-sectional momentum strategies with a 4-week formation period and a 4-week holding period exhibit a 1-factor α of 0.31% per week.

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

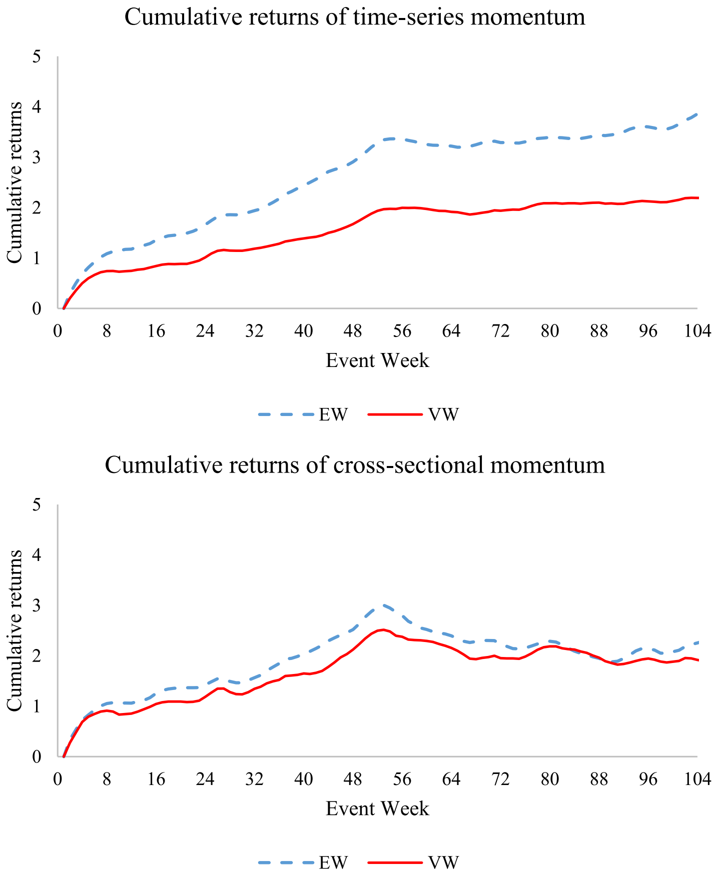

FIGURE 2 **Cumulative returns of time-series and cross-sectional momentum strategies.** This figure plots the cumulative returns of time-series and cross-sectional momentum strategies of anomalies by event week. Our sample of 90 anomalies is compiled from Hou et al. (2015) and McLean and Pontiff (2016). 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 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 2019. 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

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

TABLE 5 Alphas of time-series and cross-sectional momentum strategies—Using demeaned returns

This table reports the αs of momentum strategies based on demeaned anomaly returns. For each anomaly, we compute the demeaned anomaly returns by subtracting the full-sample 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 2 to 12 weeks. The time-series strategies—long, the anomalies with positive past returns and short, those with negative past returns. 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 2 to 12 weeks. All results are reported in percentages per week. Numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

		Holding period (weeks)							
		Time-series momentum strategies				Cross-sectional momentum strategies			
Past return		2	4	8	12	2	4	8	12
2	$\alpha 1$	0.21 (9.47)	0.16 (8.90)	0.11 (8.00)	0.07 (6.10)	0.36 (6.98)	0.27 (7.14)	0.19 (5.89)	0.13 (4.89)
	$\alpha 3$	0.21 (9.16)	0.16 (8.74)	0.11 (7.97)	0.07 (5.81)	0.36 (6.85)	0.26 (7.08)	0.19 (5.54)	0.12 (4.07)
	$\alpha 4$	0.20 (8.90)	0.15 (8.12)	0.10 (6.85)	0.06 (4.84)	0.34 (6.85)	0.24 (6.03)	0.15 (4.03)	0.08 (2.70)
4	$\alpha 1$	0.23 (9.32)	0.18 (8.11)	0.11 (6.37)	0.08 (4.82)	0.39 (7.04)	0.31 (5.93)	0.21 (4.76)	0.14 (4.06)
	$\alpha 3$	0.23 (9.00)	0.18 (7.89)	0.11 (6.22)	0.07 (4.53)	0.39 (6.79)	0.30 (5.66)	0.20 (4.30)	0.12 (3.25)
	$\alpha 4$	0.22 (8.34)	0.16 (6.95)	0.10 (5.06)	0.06 (3.43)	0.33 (5.83)	0.23 (4.31)	0.14 (2.80)	0.06 (1.74)
8	$\alpha 1$	0.22 (8.72)	0.16 (6.98)	0.10 (4.43)	0.07 (3.24)	0.37 (6.30)	0.29 (5.10)	0.18 (3.74)	0.13 (3.08)
	$\alpha 3$	0.22 (8.65)	0.16 (6.84)	0.09 (4.27)	0.06 (2.97)	0.37 (6.02)	0.28 (4.65)	0.17 (3.13)	0.10 (2.26)
	$\alpha 4$	0.19 (7.47)	0.14 (5.54)	0.07 (3.05)	0.04 (1.75)	0.29 (4.53)	0.19 (3.09)	0.09 (1.59)	0.03 (0.61)
12	$\alpha 1$	0.17 (6.76)	0.13 (5.21)	0.08 (3.23)	0.05 (2.12)	0.29 (5.12)	0.24 (4.31)	0.17 (3.25)	0.11 (2.36)
	$\alpha 3$	0.17 (6.58)	0.13 (5.07)	0.07 (3.05)	0.05 (1.95)	0.28 (4.65)	0.22 (3.68)	0.14 (2.46)	0.08 (1.62)
	$\alpha 4$	0.14 (5.40)	0.10 (3.79)	0.04 (1.76)	0.02 (0.68)	0.20 (3.17)	0.13 (2.07)	0.04 (0.76)	−0.02 (−0.34)

are driven by the time-varying risk premium. In this section, we test this 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 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 primarily 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. Overall, we continue to find significant returns to our momentum strategies. For example, the profits for the time-series momentum strategy (after removing time-varying 1-factor returns) with a look-back period of 4 weeks and a holding period of 4 weeks is 0.22% per week. 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 0.34% per week. These results are similar to those in Tables 2 and 3, suggesting that momentum in anomaly returns is not driven by 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 presented several pieces of evidence that constitute 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, is risky, and incurs transaction cost and holding cost (Pontiff, 2006; Shleifer and Vishny, 1997). 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, that is,

TABLE 6 Alphas of time-series and cross-sectional momentum strategies—Removing time-varying expected returns

This table reports the αs of momentum strategies after removing time-varying expected returns as described in Section 4.4. We calculate each anomaly's prior returns during the formation period ranging from 2 to 12 weeks. The time-series strategies—long, the anomalies with positive past residual returns and short, those with negative past residual returns. 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 2 to 12 weeks. All results are reported in percentages per week. Numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

		Holding period (weeks)							
		Time-series momentum strategies				Cross-sectional momentum strategies			
Past return		2	4	8	12	2	4	8	12
2	α1	0.23 (9.59)	0.18 (9.05)	0.13 (7.78)	0.10 (6.64)	0.36 (6.66)	0.28 (5.88)	0.21 (5.33)	0.16 (5.03)
	α3	0.14 (6.30)	0.12 (6.60)	0.09 (6.39)	0.08 (6.07)	0.17 (3.34)	0.14 (3.29)	0.12 (3.27)	0.12 (3.53)
	α4	0.13 (5.97)	0.10 (6.18)	0.07 (5.82)	0.07 (5.85)	0.18 (4.33)	0.13 (3.83)	0.09 (3.53)	0.09 (3.87)
4	α1	0.26 (10.02)	0.22 (8.81)	0.14 (6.92)	0.11 (6.22)	0.41 (6.76)	0.34 (5.84)	0.25 (5.07)	0.20 (4.77)
	α3	0.17 (7.17)	0.15 (6.60)	0.11 (5.85)	0.10 (5.71)	0.18 (3.00)	0.17 (2.94)	0.14 (2.82)	0.14 (3.14)
	α4	0.15 (6.98)	0.13 (6.23)	0.09 (5.75)	0.09 (5.72)	0.16 (3.51)	0.12 (2.68)	0.10 (2.77)	0.10 (3.11)
8	α1	0.25 (8.98)	0.20 (7.54)	0.14 (5.91)	0.11 (5.02)	0.41 (6.59)	0.34 (5.68)	0.26 (4.76)	0.21 (4.17)
	α3	0.18 (7.31)	0.15 (6.53)	0.13 (5.44)	0.12 (5.28)	0.20 (3.07)	0.18 (2.99)	0.18 (3.03)	0.18 (3.12)
	α4	0.15 (6.91)	0.13 (6.33)	0.10 (5.11)	0.10 (5.11)	0.16 (3.47)	0.14 (3.11)	0.12 (3.08)	0.13 (3.24)
12	α1	0.23 (8.04)	0.19 (6.81)	0.13 (5.01)	0.10 (4.21)	0.38 (6.30)	0.32 (5.38)	0.25 (4.23)	0.19 (3.51)
	α3	0.16 (6.14)	0.15 (5.93)	0.14 (5.21)	0.13 (4.65)	0.21 (3.44)	0.22 (3.47)	0.21 (3.28)	0.20 (3.05)
	α4	0.15 (6.91)	0.13 (6.16)	0.12 (5.44)	0.10 (4.84)	0.17 (3.94)	0.16 (3.73)	0.15 (3.49)	0.14 (3.07)

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 these proxies for arbitrage capital. The behavioral explanation also predicts that momentum in anomaly returns is more significant when market is less liquid (i.e., when arbitrage is more limited). To proxy for market liquidity, we use the aggregate Amihud's illiquidity measure, aggregate turnover, and an indicator variable for the postdecimalization period.

Table 7 reports the regression results. There are two panels in this table, corresponding to time-series and cross-sectional momentum strategies, respectively. In each panel, we estimate five regressions, one for each of the proxies for arbitrage capital and market liquidity. Looking

TABLE 7 Arbitrage capital, market liquidity, and the performance of the time-series and cross-sectional momentum strategies

This table reports the estimates of b in the regression: $R_{i,t} = a + bX_t + e_t$. X_t includes HFAUM, SI, Aggilliq, AggTurn, and a decimalization dummy. $R_{i,t}$ is the return to the following two momentum strategies: Value-weighted time-series momentum strategies and value-weighted cross-sectional momentum strategies, where both the formation and holding periods are 4 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 the total market capitalization of all NYSE/AMEX stocks. Aggilliq is the aggregate Amihud's illiquidity measure. AggTurn is the aggregate turnover rate. Decimal is an indicator variable that takes a value of 1 after April 2001. Our sample period is from July 1963 to December 2019. 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.

	Intercept	HFAUM	SI	Aggilliq	AggTurn	Decimal
(A) Time-series momentum						
(1)	0.17	−4.12				
	(5.21)	(−2.67)				
(2)	0.24		−8.82			
	(4.66)		(−2.94)			
(3)	0.05			0.48		
	(1.69)			(2.88)		
(4)	0.23				−0.02	
	(4.68)				(−2.89)	
(5)	0.17					−0.12
	(5.17)					(−2.72)
(B) Cross-sectional momentum						
(1)	0.28	−6.76				
	(3.61)	(−1.56)				
(2)	0.38		−14.11			
	(3.76)		(−2.22)			
(3)	0.11			0.57		
	(1.28)			(1.64)		
(4)	0.38				−0.04	
	(3.51)				(−1.90)	
(5)	0.30					−0.25
	(3.79)					(−2.11)

TABLE 8 Idiosyncratic volatility (IVOL) and anomaly returns

This table reports the αs of anomalies sorted by the anomalies' idiosyncratic volatility. Our sample of 90 anomalies is compiled from Hou et al. (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. Our sample period is from July 1963 to December 2019. We report the difference in αs between anomalies in the highest and lowest IVOL quintiles. All results are reported in percentages per week. Numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

	IVOL					
	Low	**2**	**3**	**4**	**High**	**High − Low**
α1	0.09	0.08	0.09	0.13	0.17	0.08
	(6.93)	(5.27)	(5.50)	(4.08)	(6.48)	(3.04)
α3	0.06	0.08	0.06	0.16	0.18	0.12
	(4.36)	(4.91)	(3.51)	(4.60)	(6.25)	(4.66)
α4	0.06	0.06	0.06	0.10	0.11	0.05
	(4.14)	(3.68)	(3.40)	(3.18)	(4.19)	(2.20)

at Panel A, we find significant evidence that time-series momentum profits are decreasing in hedge fund assets under management and aggregate short interest. The momentum strategy profits are also increasing in aggregate market illiquidity, decreasing in aggregate turnover, and significantly lower after decimalization. These results are consistent with the prediction of the behavioral explanation, that is, the persistence in anomaly returns is weaker when arbitrage capital is more abundant and when the market is more liquid.

Panel B reports the results for cross-sectional momentum. Here, we find qualitatively similar results to those presented in Panel A. That is, we find that cross-sectional momentum profits are decreasing in hedge fund assets under management, aggregate short interest, aggregate turnover, and a postdecimalization indicator, and increasing in aggregate Amihud's illiquidity measure. However, the level of statistical significance is lower. Overall, the results reported in Table 7 provide additional support for behavioral explanations.[10]

4.6 | Idiosyncratic volatility

The simple behavioral model presented in Section 3 offers two predictions related to idiosyncratic volatility (IVOL). First, anomalies with greater IVOL exhibit higher average anomaly returns. Second, anomalies with greater IVOL have more persistent anomaly returns. We test the first prediction in Table 8. Specifically, we sort our sample of anomalies based on their IVOL into quintile portfolios.[11] We then estimate 1-, 3-, and 4-factor αs of each IVOL quintile by equal weighting all anomalies in

[10]The impact of aggregate short interest on the returns to the time-series and cross-sectional momentum strategies should be stronger among anomalies whose short leg is more important. Our results reported in Table IA.6 of the Supporting Information Internet Appendix are consistent with this prediction.

[11]We estimate each anomaly's IVOL by running Fama and French 3-factor model regressions with daily anomaly returns over the entire sample period. We define IVOL as the standard deviation of the residuals from this regression.

that quintile portfolio. We also compute the difference in αs between the highest and lowest IVOL quintiles. Our results indicate that anomalies in the highest IVOL quintile exhibit significantly higher αs than anomalies in the lowest IVOL quintile. For example, anomalies in the lowest IVOL quintile exhibit a 3-factor α of 6 basis points per week, whereas anomalies in the highest IVOL quintile have a 3-factor α of 18 basis points per week. The difference of 12 basis points is economically large (>6% per year) and statistically significant (t-stat = 4.66). The differences are smaller for 1- and 4-factor αs (8 basis points and 5 basis points), but they remain highly statistically significant. Overall, we find a positive relation between anomaly returns and idiosyncratic volatility.

We note that the above analysis differs from much of the previous literature examining the impact of IVOL on anomaly returns. Most prior studies in this literature focus on the IVOL of *individual stocks* and show that anomaly returns are higher among stocks with higher IVOL. In contrast, we examine the IVOL of *anomaly returns*. This focus is motivated by the idea that arbitrageurs who wish to exploit anomalies are likely to hold a diversified long-short portfolio instead of just a few stocks. As such, the arbitrageurs should be more concerned about the IVOL of the long-short portfolio than the IVOL of individual stocks. Our paper also differs from prior studies in that that we focus on a large sample of anomalies and examine whether long–short returns vary *across* anomalies with IVOL.

We test the second prediction of our model regarding IVOL by first dividing all sample anomalies into two groups based on their IVOL. We then evaluate the profitability of time-series and cross-sectional momentum strategies within each group of anomalies, that is, high-IVOL anomalies and low-IVOL anomalies. We report the abnormal returns to momentum strategies for each group and also compute the difference between the two groups. Table 9 presents the results for time-series momentum strategies, whereas Table 10 presents the results for cross-sectional momentum strategies.

The results in Table 9 indicate that anomalies in the high-IVOL group exhibit significantly higher time-series momentum than anomalies in the low-IVOL group. For example, the 3-factor α to the time-series momentum strategy with a 4-week look-back period and a 4-week formation period is 21 basis points per week for high-IVOL anomalies and only 17 basis points per week for low-IVOL anomalies. The difference of 4 basis points per week is statistically significant (t-stat = 2.41). This result is robust across different asset pricing models and returns-weighting schemes. Indeed, Panel B shows that 46 of the 48 differences in αs between high- and low-IVOL anomalies are statistically significant at the 10% level, with 38 significant at the 5% level.

The results in Table 10 on cross-sectional momentum are similar. We find that high-IVOL anomalies exhibit significantly higher cross-sectional momentum than low-IVOL anomalies. For example, the 3-factor α to the cross-sectional momentum strategy with a 4-week look-back period and a 4-week formation period is 39 basis points per week for high-IVOL anomalies and only 22 basis points per week for low-IVOL anomalies. The difference of 17 basis points per week is highly significant, both economically and statistically (t-stat = 3.81). Overall, our results in Tables 8 through 10 indicate that both the level and persistence of anomaly returns are significantly and positively related to idiosyncratic volatility. These findings provide strong support for the behavioral explanations for momentum in anomaly returns.

4.7 | 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

TABLE 9 Idiosyncratic volatility (IVOL) and time-series momentum in anomaly returns

This table reports the αs of time-series momentum strategies conditioning on anomalies' IVOL. We sort all anomalies into high- and low-IVOL groups and examine the time-series momentum in each group. We calculate each anomaly's prior returns during formation period ranging from 2 to 12 weeks. The time-series strategies—long, the anomalies with positive past returns and short, those with negative past returns. Portfolios are kept for a holding period of 2 to 12 weeks. All results are reported in percentages per week. Numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

(A) High IVOL and low IVOL anomalies

		Holding period (weeks)							
		High IVOL				**Low IVOL**			
Past return		**2**	**4**	**8**	**12**	**2**	**4**	**8**	**12**
2	$\alpha1$	0.25 (9.06)	0.19 (8.34)	0.13 (7.29)	0.09 (6.00)	0.19 (9.08)	0.15 (8.80)	0.10 (7.82)	0.06 (5.49)
	$\alpha3$	0.25 (8.92)	0.18 (8.31)	0.13 (7.46)	0.09 (5.81)	0.19 (8.61)	0.15 (8.50)	0.10 (7.64)	0.06 (5.27)
	$\alpha4$	0.24 (8.58)	0.17 (7.59)	0.11 (6.29)	0.07 (4.80)	0.18 (8.34)	0.14 (8.05)	0.09 (6.79)	0.05 (4.46)
4	$\alpha1$	0.27 (9.02)	0.21 (7.65)	0.14 (6.14)	0.10 (5.04)	0.21 (9.01)	0.17 (8.06)	0.10 (5.92)	0.06 (4.20)
	$\alpha3$	0.27 (8.78)	0.21 (7.56)	0.14 (6.16)	0.10 (4.80)	0.21 (8.70)	0.16 (7.86)	0.10 (5.77)	0.06 (4.06)
	$\alpha4$	0.25 (7.91)	0.18 (6.44)	0.12 (4.91)	0.08 (3.65)	0.20 (8.29)	0.16 (7.18)	0.08 (4.89)	0.05 (3.17)
8	$\alpha1$	0.26 (8.50)	0.19 (6.62)	0.13 (4.67)	0.10 (3.81)	0.19 (8.01)	0.14 (6.43)	0.08 (3.84)	0.05 (2.70)
	$\alpha3$	0.26 (8.56)	0.19 (6.59)	0.12 (4.53)	0.09 (3.50)	0.19 (7.89)	0.14 (6.28)	0.08 (3.75)	0.05 (2.58)
	$\alpha4$	0.23 (7.24)	0.15 (5.19)	0.09 (3.24)	0.06 (2.26)	0.17 (6.90)	0.12 (5.21)	0.06 (2.66)	0.03 (1.42)
12	$\alpha1$	0.21 (6.80)	0.16 (5.27)	0.12 (3.87)	0.08 (3.00)	0.15 (6.26)	0.12 (4.71)	0.07 (2.70)	0.04 (1.63)
	$\alpha3$	0.21 (6.70)	0.16 (5.17)	0.11 (3.67)	0.08 (2.74)	0.15 (6.10)	0.11 (4.63)	0.06 (2.66)	0.04 (1.70)
	$\alpha4$	0.17 (5.44)	0.12 (3.84)	0.07 (2.36)	0.04 (1.47)	0.13 (5.07)	0.08 (3.45)	0.03 (1.39)	0.01 (0.40)

(B) High IVOL–Low IVOL

		Holding period (weeks)			
Past return		**2**	**4**	**8**	**12**
2	$\alpha1$	0.06 (2.91)	0.03 (2.17)	0.03 (2.23)	0.03 (2.84)
	$\alpha3$	0.06 (3.33)	0.04 (2.46)	0.03 (2.52)	0.03 (2.85)
	$\alpha4$	0.06 (3.10)	0.03 (1.94)	0.02 (1.82)	0.02 (2.16)
4	$\alpha1$	0.06 (2.95)	0.05 (2.41)	0.04 (2.70)	0.04 (2.76)
	$\alpha3$	0.06 (3.03)	0.05 (2.42)	0.04 (2.82)	0.04 (2.60)
	$\alpha4$	0.04 (2.23)	0.03 (1.56)	0.03 (1.97)	0.03 (1.84)
8	$\alpha1$	0.06 (2.99)	0.05 (2.24)	0.05 (2.40)	0.04 (2.49)
	$\alpha3$	0.07 (3.21)	0.05 (2.37)	0.04 (2.31)	0.04 (2.18)
	$\alpha4$	0.05 (2.54)	0.03 (1.61)	0.03 (1.71)	0.03 (1.67)
12	$\alpha1$	0.06 (2.75)	0.05 (2.29)	0.05 (2.57)	0.05 (2.50)
	$\alpha3$	0.06 (2.77)	0.05 (2.23)	0.05 (2.28)	0.04 (2.08)
	$\alpha4$	0.05 (2.18)	0.04 (1.66)	0.04 (1.84)	0.03 (1.67)

price less than $5 or with market capitalization ranked in the lowest NYSE decile, and we use value weights. To further examine whether our results are due to possible market microstructure effects, we present three robustness tests. In the first test, we skip a week after portfolio formation (i.e., before we compute holding period returns). To conserve space, we

TABLE 10 Idiosyncratic volatility (IVOL) and cross-sectional momentum in anomaly returns
This table reports the αs of cross-sectional momentum strategies conditioning on anomalies' IVOL. We sort all anomalies into high- and low-IVOL groups and examine the cross-sectional momentum in each group. We calculate each anomaly's prior returns during the formation period ranging from 2 to 12 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 2 to 12 weeks. All results are reported in percentages per week. Numbers in parentheses are the t statistics, adjusted for heteroscedasticity and autocorrelations.

(A) High IVOL and low IVOL Anomalies

		Holding period (weeks)							
		High IVOL				Low IVOL			
Past return		2	4	8	12	2	4	8	12
2	$\alpha1$	0.44 (6.65)	0.33 (6.71)	0.23 (5.60)	0.17 (4.74)	0.27 (8.31)	0.21 (8.26)	0.14 (7.02)	0.09 (5.43)
	$\alpha3$	0.44 (6.75)	0.32 (6.84)	0.23 (5.49)	0.15 (4.13)	0.26 (7.90)	0.20 (8.01)	0.14 (6.49)	0.09 (4.72)
	$\alpha4$	0.42 (6.58)	0.29 (5.77)	0.18 (3.92)	0.11 (2.77)	0.25 (7.86)	0.19 (7.35)	0.11 (5.27)	0.06 (3.57)
4	$\alpha1$	0.49 (7.04)	0.39 (5.89)	0.27 (4.65)	0.19 (4.11)	0.29 (8.12)	0.22 (6.74)	0.14 (5.23)	0.09 (4.15)
	$\alpha3$	0.48 (6.84)	0.37 (5.68)	0.26 (4.35)	0.16 (3.40)	0.28 (7.74)	0.22 (6.51)	0.14 (4.75)	0.09 (3.60)
	$\alpha4$	0.41 (5.67)	0.29 (4.25)	0.18 (2.83)	0.09 (1.94)	0.25 (6.92)	0.18 (5.33)	0.10 (3.39)	0.05 (2.11)
8	$\alpha1$	0.45 (6.08)	0.35 (4.98)	0.25 (3.90)	0.19 (3.37)	0.27 (7.04)	0.21 (5.67)	0.12 (3.72)	0.08 (2.70)
	$\alpha3$	0.44 (5.83)	0.34 (4.66)	0.23 (3.35)	0.15 (2.57)	0.27 (6.79)	0.20 (5.34)	0.12 (3.39)	0.07 (2.32)
	$\alpha4$	0.35 (4.36)	0.24 (3.06)	0.13 (1.79)	0.05 (0.95)	0.22 (5.47)	0.15 (3.86)	0.06 (1.77)	0.01 (0.52)
12	$\alpha1$	0.38 (5.19)	0.32 (4.46)	0.23 (3.51)	0.17 (2.75)	0.21 (5.37)	0.16 (4.24)	0.10 (2.73)	0.05 (1.70)
	$\alpha3$	0.36 (4.78)	0.29 (3.87)	0.19 (2.75)	0.13 (1.97)	0.20 (5.18)	0.16 (3.97)	0.09 (2.39)	0.05 (1.47)
	$\alpha4$	0.26 (3.27)	0.18 (2.24)	0.07 (1.07)	0.00 (0.05)	0.14 (3.57)	0.09 (2.26)	0.02 (0.48)	−0.02 (−0.58)

(B) High IVOL–Low IVOL

		Holding period (weeks)			
Past return		2	4	8	12
2	$\alpha1$	0.17 (3.60)	0.12 (3.47)	0.09 (3.18)	0.08 (2.81)
	$\alpha3$	0.18 (4.06)	0.12 (3.81)	0.09 (3.37)	0.06 (2.57)
	$\alpha4$	0.18 (3.87)	0.10 (3.01)	0.07 (2.14)	0.04 (1.52)
4	$\alpha1$	0.20 (4.36)	0.17 (3.81)	0.13 (3.20)	0.10 (2.92)
	$\alpha3$	0.20 (4.42)	0.15 (3.67)	0.12 (3.15)	0.08 (2.44)
	$\alpha4$	0.16 (3.29)	0.11 (2.44)	0.08 (1.92)	0.04 (1.34)
8	$\alpha1$	0.18 (3.63)	0.15 (3.08)	0.12 (2.80)	0.11 (2.75)
	$\alpha3$	0.17 (3.57)	0.14 (2.96)	0.11 (2.43)	0.08 (2.02)
	$\alpha4$	0.13 (2.46)	0.09 (1.79)	0.07 (1.37)	0.04 (0.98)
12	$\alpha1$	0.17 (3.52)	0.16 (3.31)	0.14 (2.98)	0.11 (2.68)
	$\alpha3$	0.16 (3.18)	0.14 (2.77)	0.11 (2.26)	0.08 (1.78)
	$\alpha4$	0.12 (2.24)	0.09 (1.68)	0.06 (1.18)	0.02 (0.49)

present the results in the Supporting Information Internet Appendix. 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 are in line with our finding that momentum in anomaly returns is relatively short-lived. We also examine whether our results are robust to alternative asset pricing models. Specifically, we repeat our main analyses by using the Fama and French (2015) 5-factor model and the Hou et al. (2015) *q*-factor model to evaluate the performance of momentum strategies. Overall, we find our results to be qualitatively unchanged under these alternative asset pricing models. The final robustness test we perform is to repeat our analysis after removing three stock momentum anomalies from our sample. We find our results are nearly unchanged, mitigating a concern that our results may be mechanically driven by the inclusion of these momentum anomalies.

5 | CONCLUSIONS

We find strong evidence of time-series and cross-sectional momentum in the long–short returns of a comprehensive sample of 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). The anomaly momentum is distinct from stock momentum in that anomaly momentum is more short-lived and it dissipates but does not reverse in the long run. 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 and is robust to alternative asset pricing models. 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. Moreover, we find that the level and persistence of anomaly returns are both positively related to idiosyncratic volatility.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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APPENDIX A: LIST OF ANOMALIES

We compile a comprehensive list of anomalies by merging the samples of Hou et al. (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
(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	DeBondt and Thaler (1985)	HXZ
SG	Sales growth	Lakonishok et al. (1994)	HXZ
σ(CF)	Cash flow variance	Haugen and Baker (1996)	MP
(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, Lin, and Vitorino, (2014)	HXZ
H/N	Hiring rate	Belo, Lin, and Bazdresch, (2014)	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
(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	Investment-to-assets	Cooper et al. (2008)	HXZ
I-ADJ	Industry-adjusted growth in investment	Abarbanell and Bushee (1998)	MP

(Continues)

Abbreviation	Anomaly	Authors	Source
IG	Investment growth	Xing (2008)	HXZ
IvC	Inventory changes	Thomas and Zhang (2002)	HXZ
IvG	Inventory growth	Belo and Lin (2012)	HXZ
ΔNCO	Changes in net noncurrent operating assets	Richardson et al. (2005)	MP
NOA	Net operating assets	Hirshleifer et al. (2004)	HXZ
NoaG	Growth in net operating assets minus accruals	Fairfield et al. (2003)	MP
NSI	Net stock issues	Pontiff and Woodgate (2008)	HXZ
ΔNWC	Changes in net noncash 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 accruals	Hafzalla et al. (2011)	HXZ
PTA	Percent total accruals	Hafzalla et al. (2011)	HXZ
TA	Total accruals	Richardson et al. (2005)	HXZ
ΔPI/A	Changes in PP&E plus changes in inventory	Lyandres et al. (2008)	HXZ
(D) Momentum			
Abr-1	Cumulative abnormal stock returns around earnings announcements	Chan et al. (1996)	HXZ
R11-1	Price momentum (11-month prior returns)	Fama and French (1996)	HXZ
R6-1	Price 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
(E) Profitability			
ATO	Asset turnover	Soliman (2008)	HXZ
CTO	Capital turnover	Haugen and Baker (1996)	HXZ
F	F-score	Piotroski (2000)	HXZ
FP	Failure probability	Campbell et al. (2008)	HXZ
GP/A	Gross profitability-to-assets	Novy-Marx (2013)	HXZ
O	O-score	Dichev (1998)	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	Changes in sales minus changes in inventory	Abarbanell and Bushee (1998)	MP

(Continues)

Abbreviation	Anomaly	Authors	Source
S/P	Sales-to-price	Barbee et al. (1996)	MP
S/SG&A	Changes in sales minus changes in SG&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. (2017)	HXZ
Z	Z-score	Dichev (1998)	MP
ΔATO	Changes in asset turnover	Soliman (2008)	MP
ΔPM	Changes in profit margin	Soliman (2008)	MP
(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 as absolute return-to-volume	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	Fama and MacBeth's β (monthly data)	Fama and MacBeth (1973)	MP
β-D	Dimson's beta (daily data)	Dimson (1979)	HXZ
β-FP	Frazzini and Pedersen's β	Frazzini and Pedersen (2014)	HXZ
σ(Dvol)	Dollar volume volatility	Chordia et al. (2001)	MP