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RESEARCH

The Many Facets of Stock Momentum: Distinguishing Factor and Stock Components

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This study aims to investigate the recent controversy surrounding the existence of stock-specific momentum. Stock momentum consists of both factor- and stock-specific components, but the risk associated with factor momentum might hinder the impact of stock-specific momentum. Using earnings announcement returns that occur during the formation months of the stock momentum strategy, the study captures a component largely unaffected by factor momentum, thereby mitigating the bad-model problem. This stock-specific momentum source predicts future returns, does not reverse in the long run, and is pervasive, as similar results are found in the US, Europe, and Japan over the last 30 years.

Keywords: earnings announcement returns; factor momentum; international equity markets; return predictability; stock-specific momentum

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Introduction

In this study, we challenge the view that stock momentum is merely factor momentum in disguise. To do so, we introduce a novel way of disentangling momentum in individual stocks from momentum in factor returns and present pervasive evidence of stock-specific momentum in three developed markets over the last 30 years.

Attempts to filter out the factor component of stock momentum are not new. For instance, a flurry of articles (see, e.g., Blitz, Huij, and Martens 2011; Grundy and Martin 2001) argue that strategies based on residual momentum—the component of stock momentum left after regressing past returns against sources of systematic risk—are a more robust source of return predictions than the standard strategy of Jegadeesh and Titman (1993), which can experience severe drawdowns. However, in what appears to be a sharp rebuke of these past findings, several prominent studies documenting the existence of factor momentum claim instead that stock momentum derives all its predictive power from its time-varying exposures to factors (see, e.g., Arnott, Kalesnik, and Linnainmaa 2023; Ehsani and Linnainmaa 2022). Accounts of residual momentum are dismissed as mere examples of the bad-model problem. Needless to say, this strand of the literature on the momentum effect has also faced criticism (see, e.g., Caciki et al. 2025; Falck, Rej, and Thesmar 2022; Fan et al. 2022), and the debate on the existence of stock momentum beyond factor momentum is still ongoing.

With this in mind, a convincing way to demonstrate that stock momentum is not simply timing factor returns is to uncover an authoritative source of stock-specific momentum and demonstrate that it is persistent and earns economically significant strategy returns. To this end, we depart from the established practice of equating residual momentum with stock-specific momentum and instead build our strategy using returns that fall around the release of firm-specific information. In particular, it is straightforward to show that one component of 12-month stock momentum is the sum of daily returns surrounding a firm's earnings announcements—both interim and annual—in the previous year. The component of stock momentum derived from returns around earnings announcements is likely to capture a disproportionately large amount of stock-specific news. Moreover, earnings announcement returns, being measured over just a few days, have an expected value close to zero and should be less prone to the bad-model problem.

Our strategy also differs in important ways from previous studies that only consider the latest announcement when examining the performance of calendar-time strategies based on earnings announcement surprises (see, e.g., Chan, Jegadeesh, and Lakonishok 1996). For instance, the portfolio turnover of our strategy, which considers all earnings announcements made over the previous year, is approximately half as high as that of its shorter-term counterpart, and we show that their performances display different patterns.

Our main findings are fourfold. First, the longer-term earnings-announcement strategy—our novel proxy for stock-specific momentum—performs strongly over the last 30 years and across three developed markets: the 1,000/400/200 largest stocks by market capitalization each month in the US, Europe, and Japan. This global evidence is robust to multiple testing adjustments and to controls for various sources of systematic risk, and it remains significant even after accounting for time-varying exposures to factor returns using the dynamic cross-sectional factor model of Fama and French (2020). By contrast, a strategy that focuses only on the latest earnings announcement surprise has shown no predictive power for future returns in recent years, consistent with accounts of the disappearance of the post–earnings announcement drift in the US (see, e.g., Chordia, Subrahmanyam, and Tong 2014; Johnson and Schwartz 2000; Martineau 2022; Richardson, Tuna, and Wysocki 2010).

Second, unlike the longer-term earnings-announcement strategy, the performance of the stock momentum strategy is dominated by factor risk and fares comparatively poorly in all markets during our study period. There is also scant global evidence that past stock returns predict future ones due to their timely exposure to factors. Instead, when the stock momentum strategy is implemented with a one-month gap between the end of its formation period and its rebalancing date, the component of its performance unexplained by common factor exposures performs significantly better than its factor counterpart.

Third, we find that a principal component (PC) time-series factor momentum strategy based on Ehsani and Linnainmaa (2022) performs strongly in the US and subsumes stock momentum. However, it fails to explain away the predictive power of our longer-term earnings-announcement strategy.

Fourth, although concentrated over a relatively short period immediately following the so-called tech-bubble burst, the underperformance of a strategy based on a stock's long-term performance provides some evidence of extreme overreaction in preceding years. This is not the case for the longer-term earnings-announcement strategy, which is not subject to short- or long-term reversal, even when the formation period is extended over multiple years.

Overall, the evidence in our study suggests that investors underreact to public information about stock-specific news—or at least to the firm-specific information released around earnings announcements in the previous 12 months—while tending to overreact to information on systematic factors. Therefore, recognizing the multifaceted nature of stock momentum is important not only for improving our understanding of the momentum effect but also for practitioners to build stronger, more resilient investment strategies.

Literature Review and Motivation

Factor Momentum or Stock Momentum?

Until recently, the momentum effect had been studied primarily at the asset level, but several recent studies report that factor returns also exhibit momentum (see, e.g., Arnott, Kalesnik, and Linnainmaa 2023; Avramov et al. 2017; Gupta and Kelly 2019; Leippold and Yang 2021). Since factors are portfolios of stocks, this raises the question of whether stock momentum mechanically creates factor momentum. The counterargument is that stock momentum is simply factor momentum in disguise, since stocks are exposed to factors. Ehsani and Linnainmaa (2022) argue in favor of the view that stock momentum is simply factor momentum in disguise, noting that factor momentum transmits into the cross-section of stocks and, as a result, explains stock momentum profits. Arnott, Kalesnik, and Linnainmaa (2023) add to this evidence by showing that factor momentum even captures the industry momentum effect documented by Moskowitz and Grinblatt (1999).

Both studies find factor momentum to be concentrated in high-eigenvalue PCs that explain most of the cross-section of factor returns. Profiting from the strategy therefore entails taking on significant systematic risk, which could explain why arbitrageurs fail to eliminate the premium (see, e.g., Haddad, Kozak, and Santosh 2020; Kozak, Nagel, and Santosh 2020). This line of reasoning precludes the existence of not only factor momentum in low-eigenvalue PCs but also stock-specific momentum, since such momentum would otherwise allow arbitrageurs to earn a profit while incurring minimal risk.

This conclusion contrasts sharply with prior efforts aimed at reducing the exposure of stock momentum to risk factors. For instance, several studies report that residual momentum—the component of stock momentum left after regressing past returns against sources of systematic risk—is a more robust source of return predictions than the standard strategy of Jegadeesh and Titman (1993), which can suffer severe drawdowns. In particular, Grundy and Martin (2001) and Blitz, Huij, and Martens (2011) demonstrate that stock momentum has large time-varying exposures to the systematic factors of Fama and French. Blitz, Huij, and Martens (2011) further propose ranking stocks on residual momentum to mitigate the strategy's exposure to these factors, showing that the resulting risk reduction is significant and comes with no detrimental effect on performance. Nevertheless, Ehsani and Linnainmaa (2022) challenge this earlier evidence, arguing that strategies based on residual momentum are likely to profit from omitted factors that happen to be more autocorrelated than those used to estimate residual returns.

The interpretation of the evidence for factor momentum has also been contested. For instance, Falck, Rej, and Thesmar (2022) show that "true" factor momentum is concentrated solely in the monthly return contiguous to the holding period. Contrary to individual stock returns, which revert in the short term, factor momentum—similar to industry momentum—is particularly strong at the one-month horizon. Moreover, Caciki et al. (2025) highlight how research designs critically shape conclusions about the nature of factor momentum. They confirm the existence of factor momentum in an international sample of firms but find no pervasive evidence supporting the claim that stock momentum is merely timing other factors. Likewise, while Fan et al. (2022) replicate the findings of Ehsani and Linnainmaa (2022) and Arnott, Kalesnik, and Linnainmaa (2023), they note that the factor momentum effect is not pervasive across all anomalies. Instead, persistence in factor returns is concentrated within a few factors, making the choice of factor set critical for implementing a successful factor momentum strategy.

Stock-Specific Momentum and the Post–Earnings Announcement Drift. Overall, the debate about the existence of stock momentum beyond factor momentum would benefit from uncovering an authoritative source of stock-specific momentum. A natural starting point is to focus on returns that occur around the release of firm-specific information.

In this study, we focus on earnings announcements and show that one component of 12-month stock momentum is the sum of the daily returns surrounding a firm's interim and annual earnings announcements in the previous year. Interim and annual earnings announcements are not the only sources of information about a firm's fundamentals, but it is reasonable to expect that returns around these events capture a disproportionately large amount of stock-specific news. This is important because one of the main criticisms of using residual returns as a proxy for investors' reaction to stock-specific information is the likely misspecification of the expected return model. However, this concern should be mitigated when returns are known to be driven by an unusually large amount of stock-specific news. Additionally, earnings announcement returns—being measured over just a few days—should have an expected value close to zero and therefore be less prone to the bad-model problem.

Although our proposed proxy for stock-specific momentum captures the previous 12 months of earnings announcement returns rather than the latest earnings announcement surprise, our analysis is closely related to the literature on the post–earnings announcement drift. Indeed, several attempts have been made to capture non-earnings news, since much of the market reaction around earnings announcements has been tied to non-earnings information (see, e.g., Deng, Lev, and Narin 1999; Gu 2005; Jegadeesh and Livnat 2006; Liu and Thomas 2000; Rajgopal, Shevlin, and Venkatachalam 2003). In particular, Chan, Jegadeesh, and Lakonishok (1996) use the cumulative excess return surrounding the latest earnings announcement date to capture a broader set of information.

There is also significant overlap between explanations for stock momentum and the post–earnings announcement drift, prompting several studies to examine the relationship between these momentum strategies. In their seminal study, Chan, Jegadeesh, and Lakonishok (1996) find that the post–earnings announcement drift and stock momentum strategy are complements rather than substitutes. Their results contrast with those of Chordia and Shivakumar (2006) and Novy-Marx (2015), who show that the predictive power of the latest earnings surprise dominates that of past stock returns. That said, recent evidence suggests that the post–earnings announcement drift is weakening and even disappearing among large and liquid US securities (see, e.g., Chordia, Subrahmanyam, and Tong 2014; Johnson and Schwartz 2000; Martineau 2022; Richardson, Tuna, and Wysocki 2010). Nonetheless, across firm sizes, the effect still appears to exist (see, e.g., Ali et al. 2020; Cox 2020). Our analysis, which uses a strategy based on a longer history of earnings announcement surprises and tests its predictive power across several developed markets, should therefore provide important novel insights into this phenomenon.

Sample Data and Methodology

Sample Data. The key variables in our analysis are the dates of interim and annual earnings announcements in the US, Europe, and Japan. These data are sourced from the I/B/E/S database for the period July 1992 to September 2024. However, due to data availability, our analysis of the Japanese market begins only in January 1998.

As detailed in the following section, our proxy for stock-specific momentum—the longer-term earnings-announcement strategy—considers all annual and interim earnings announcements occurring in the year prior to the portfolio rebalancing date. In Europe, this means that up until September 2003, only one earnings announcement per year is available for most stocks in our universe. This number jumps abruptly in October 2003 to an average of two earnings announcements per year, then continues to increase until it reaches approximately 3.5 earnings announcements per year in early 2007. A similar discontinuity is observed in our Japanese sample, where the average number of earnings announcements increases from two to well above three per year in late 2003.

To mitigate investability concerns, we focus our analysis on the largest names in each universe: the 1,000 largest stocks by market capitalization each month in the US, the largest 400 stocks each month in Europe, and the largest 200 stocks in Japan. These sample sizes were selected to match the coverage of well-known large-cap indices such as the Russell 1000, the Nikkei 225, and the FTSE Developed Europe. We obtained all financial statement data from the Worldscope database and stock market data from the Datastream database. All returns are expressed in US dollars.

Decomposing the Stock Momentum Strategy. Our standard metrics of stock momentum are the returns of each security in the universe over the past 12 months, calculated both including and excluding the latest month. One specificity is that we use log returns when computing past performance, allowing for the seamless decomposition of its components. At the end of each month, t, we estimate the stock momentum of stock i as:

$$\mathrm{r\_12M}_{i,t} = \sum_{m=0}^{11} \log\left(1 + r_{i,t-m}\right) \tag{1}$$

and, to control for the one-month reversal effect of Jegadeesh (1990),

$$\mathrm{r\_12m1M}_{i,t} = \sum_{m=1}^{11} \log\left(1 + r_{i,t-m}\right) \tag{2}$$

where $r_{i,t-m}$ is the monthly return of stock i, m months prior to the portfolio rebalancing date.

We then create 100% long and 100% short strategy portfolios, with holdings linear in the performance metrics. For stock i at time t, the stock momentum holding based on the performance estimate in equation (1) is given by:

$$\mathrm{Momentum\_12M}_{i,t} = \left(\mathrm{r\_12M}_{i,t} - \overline{\mathrm{r\_12M}_t}\right) \Big/ \left(\frac{1}{2} \cdot \sum_{i=1}^{N} \left|\mathrm{r\_12M}_{i,t} - \overline{\mathrm{r\_12M}_t}\right|\right) \tag{3}$$

where $\overline{\mathrm{r\_12M}_t}$ is the average performance metric of all N securities in the universe at time t.

To compute our longer-term earnings-announcement strategy, we consider only daily returns falling within ±2 days of all earnings announcements in the past 12 months. Specifically, for stock i at time t, the measure is:

$$\text{r\_12M\_EAR}_{i,t} = \sum_{d=0}^{D} 1_{i,t-d} \cdot \left\{ \log\left(1 + \mathrm{r}_{\mathrm{i,t-d}}\right) - bm_{\mathrm{i,t-d}} \right\} \quad (4)$$

Here, $r_{i,t-d}$ is the daily return of stock i at time $t-d$, and $bm_{i,t-d}$ is its benchmark return. While there are D days in the 12-month estimation window, we only include days within ±2 of an earnings announcement occurring no later than time t. These dates are assigned a value of one (instead of zero) by the indicator variable $1_{i,t-d}$.

We construct a measure of stock momentum excluding earnings announcement returns (exEAR) such that when the benchmark return is the equally weighted average of the daily log returns of all securities in the universe,

$$\text{r\_12M}_{i,t} = \text{r\_12M\_EAR}_{i,t} + \text{r\_12M\_exEAR}_{i,t} + \overline{\text{r\_12M}}_t \quad (5)$$

Each performance metric is standardized to form 100% long and 100% short portfolios as in equation (3), so that:

$$\text{Momentum\_12M}_{i,t} = w_{1,t} \cdot \text{Momentum\_12M\_EAR}_{\mathrm{i,t}} + w_{2,t} \cdot \text{Momentum\_12M\_exEAR}_{\mathrm{i,t}} \quad (6)$$

where

$$w_{1,t} = \sum_{i=1}^{N} \left| \text{r\_12M\_EAR}_{i,t} - \overline{\text{r\_12M\_EAR}}_t \right| \Big/ \sum_{i=1}^{N} \left| \text{r\_12M}_{i,t} - \overline{\text{r\_12M}}_t \right|,$$

$$w_{2,t} = \sum_{i=1}^{N} \left| \text{r\_12M\_exEAR}_{i,t} - \overline{\text{r\_12M\_exEAR}}_t \right| \Big/ \sum_{i=1}^{N} \left| \text{r\_12M}_{i,t} - \overline{\text{r\_12M}}_t \right|$$

In addition to using an equally weighted average benchmark of daily log returns for all securities, we also adjust daily stock returns by equally weighted industry returns. This limits the amount of industry momentum embedded in past performance via industry exposure. The industry-adjusted stock momentum strategy also allows for the same seamless decomposition as in Equation (6).

Capturing Time-Varying Systematic Exposures.

Focusing on returns around earnings announcements and controlling for industry performance significantly reduces the longer-term earnings-announcement strategy's exposure to common factors. Nevertheless, we also explicitly control for these exposures following the approach of Fama and French (2020) in their dynamic asset pricing model. This cross-sectional model of stock returns better describes average returns partly because it allows for changing exposures to common factors over time.

The model's logic is similar to traditional holdings-based attribution used by investment practitioners, where portfolio sensitivities to factor returns are estimated using changing exposures to each factor. An alternative, time-series regression-based model (Fama and French 1993) could also capture changing factor exposures via a rolling estimation window or conditioning variables. However, due to estimation challenges, return-based models typically assume constant exposures.

Each month, we run a cross-sectional regression of one-month forward returns against a set of common factors in each market. These factors include Global Industry Classification Standards (GICS Level 3) dummy variables, market betas, size (market capitalization), value, profitability, and the year-on-year change in total assets (Cooper, Gulen, and Schill 2008). Value is measured as book-to-market ratio (Fama and French 1992), and profitability is based on cash-based operating profitability, replaced by operating income for financial firms (Ball et al. 2016). Except for indicator variables, all factor scores are normalized to have a mean of zero and a standard deviation of one.

We then perform holdings-based attribution to decompose a strategy's performance into factor and residual components.[1] If stock momentum derives its predictive power from timely exposures to factor returns, we would anticipate only the factor component to be significant. By contrast, if stock-specific momentum exists, we would expect the residual component of the longer-term earnings-announcement strategy to be significant, with the factor component weak or insignificant.

Univariate Analysis of Stock-Specific Momentum

A Novel Proxy of Stock-Specific Momentum.
Before starting our comparison of the performance of stock momentum and that of the longer-term earnings-announcement strategy, it is important to demonstrate how the performance of our novel proxy of stock-specific momentum differs from that of calendar-time strategies based on the latest earnings announcement surprise (see, e.g., Chan, Jegadeesh, and Lakonishok 1996). This is particularly relevant in the US, where firms release their earnings on a quarterly basis.

Table 1 reports the performance in the US of our longer-term earnings-announcement strategy and that of a trading strategy that ranks stocks based on their latest earnings surprise. Earnings announcements are market-adjusted, but industry-adjusting them does not change our main findings. Each strategy is rebalanced monthly with holdings linear in the scores of their respective metric, demeaned and scaled such that they are 100% long and 100% short. Unsurprisingly, the portfolio turnover of our longer-term earnings-announcement strategy is half that of its shorter-term counterpart. It experiences an annualized one-way turnover of 430% over the full sample period (Period I) and 429% over the most recent 15 years (Period II). By contrast, the annualized turnover of a strategy that only considers the latest market-adjusted earnings announcement return is a staggering 976% over the full sample period (Period I) and 996% in recent years (Period II).

Their performance also displays different patterns. In line with recent accounts of the disappearance of the post–earnings announcement drift in the US, we find that a strategy relying only on the latest earnings announcement surprise has no predictive power for future returns in Period II. By contrast, the 12-month earnings-announcement strategy shows no sign of performance decay. On the contrary, while it earns an annualized average return of 3.51% over the full period (Period I), performance increases to 4.90% over the latest 15 years (Period II), as if investors failed to fully incorporate information from surprises occurring prior to the latest earnings announcement (see, e.g., Ball and Bartov 1996; Bernard and Thomas 1990; Chan, Jegadeesh, and Lakonishok 1996; Livnat and Mendenhall 2006).

Global Evidence of Stock-Specific Momentum.
In Table 2, we proceed with our comparative analysis of the performance of a traditional stock momentum strategy and that of the longer-term earnings-announcement strategy in the large-capitalization segments of three developed markets: the US, Europe, and Japan.[2] We follow a monthly rebalancing frequency, which should help mitigate concerns that our findings for the longer-term earnings-announcement strategy are subject to implementation issues and/or contaminated by potential market microstructure biases. Indeed, under this specification, even when an earnings announcement occurs within the rebalancing month, several days should still separate the announcement date from the start of the holding period.

Table 1. Short- and Medium-Term Earnings Surprises in the US

	Ann. Return	Ann. Risk	*t* Statistic	Ann. Turnover (One-way)
Period I: July 1992 to September 2024				
Latest_EAR	3.05%	8.10%	2.13*	976%
Momentum_12M_EAR	3.51%	7.91%	2.51*	430%
Period II: January 2010 to September 2024				
Latest_EAR	1.15%	6.54%	0.67	996%
Momentum_12M_EAR	4.90%	6.39%	2.94**	429%

We compute earnings surprises as the sum of adjusted daily log returns within a ±2-day window surrounding an earnings announcement. We then either consider only the latest earnings surprise prior to the rebalancing date (Latest_EAR) or compute the sum of all earnings surprises from the previous 12 months (Momentum_12M_EAR). Earnings surprises are market-adjusted, and each strategy is rebalanced monthly using the largest 1,000 US securities that month. Portfolio holdings are linear in the scores of their respective strategy, demeaned and scaled to be 100% long and 100% short. Ann.Return is a strategy's annualized average monthly return, and Ann.Risk is the annualized standard deviation of monthly strategy returns. Ann.Turnover is the strategy portfolio's annualized monthly turnover (one-way).
** and *indicate statistical significance of a two-tailed test at the 1% and 5% levels, respectively.

Table 2. Momentum Strategies

Panel A: Largest 1,000 US Stocks from July 1992 to September 2024

	Ann. Return	Ann. Risk	*t* Statistic	Ann. Turnover (One-way)	Rho
Market-adjusted returns over formation months					
Momentum_12m1M	6.52%	21.79%	1.70	605%	0.54
Momentum_12m1M_exEAR	5.82%	21.37%	1.55	611%	
Momentum_12M_EAR	3.51%	7.91%	2.51*,[aa]	430%	0.92
Momentum_12m1M_EAR	2.44%	7.74%	1.79[a]	522%	
Industry-adjusted returns over formation months					
Momentum_12m1M	3.63%	13.49%	1.53	621%	0.79
Momentum_12m1M_exEAR	3.06%	12.57%	1.38	627%	
Momentum_12M_EAR	2.83%	7.01%	2.29*,[aa]	443%	0.94
Momentum_12m1M_EAR	1.84%	6.95%	1.50	530%	

Panel B: Largest 400 European Stocks from July 1992 to September 2024

	Ann. Return	Ann. Risk	*t* Statistic	Ann. Turnover (One-way)	Rho
Market-adjusted returns over formation months					
Momentum_12m1M	5.82%	17.77%	1.86[a]	598%	0.69
Momentum_12m1M_exEAR	5.23%	17.41%	1.71	602%	
Momentum_12M_EAR	3.06%	6.77%	2.57*,[aa]	384%	0.95
Momentum_12m1M_EAR	2.55%	6.60%	2.19*,[aa]	463%	
Industry-adjusted returns over formation months					
Momentum_12m1M	2.47%	11.81%	1.19	628%	0.85
Momentum_12m1M_exEAR	1.90%	11.41%	0.94	632%	
Momentum_12M_EAR	2.24%	6.12%	2.09*,[a]	403%	0.95
Momentum_12m1M_EAR	1.76%	5.96%	1.68	478%	

Panel C: Largest 200 Japanese Stocks from January 1998 to September 2024

	Ann. Return	Ann. Risk	*t* Statistic	Ann. Turnover (One-way)	Rho
Market-adjusted returns over formation months					
Momentum_12m1M	0.09%	17.39%	0.03	616%	0.57
Momentum_12m1M_exEAR	−1.26%	17.14%	−0.38	621%	
Momentum_12M_EAR	4.00%	8.30%	2.49*,[aa]	422%	0.89
Momentum_12m1M_EAR	3.82%	8.30%	2.37*,[aa]	508%	
Industry-adjusted returns over formation months					
Momentum_12m1M	−1.34%	10.59%	−0.65	648%	0.81
Momentum_12m1M_exEAR	−2.33%	10.17%	−1.18	654%	
Momentum_12M_EAR	2.89%	7.09%	2.11*,[a]	448%	0.92
Momentum_12m1M_EAR	2.45%	7.04%	1.80	530%	

Our standard stock momentum strategy is the sum of adjusted daily log returns over the last 12 months, with the most recent month skipped (12m1M). The strategy with the suffix exEAR excludes the adjusted daily log returns that fall within a ±2-day window around all the earnings announcements during the formation months. By contrast, the strategy with the suffix EAR is based only on the earnings announcement returns of the previous 12 months, either including (12M) or excluding (12m1M) the most recent month. Daily log returns are either market- or industry-adjusted. Each strategy is rebalanced monthly using the largest securities in our universe that month. Portfolio holdings are linear in the scores of their respective strategy, demeaned and scaled to be 100% long and 100% short. Ann.Return is a strategy's annualized average monthly return, and Ann.Risk is the annualized standard deviation of monthly strategy returns. Ann.Turnover is the strategy portfolio's annualized monthly turnover (one-way). Rho is the correlation between the performance of the long and short sides of a strategy portfolio.
** and *indicate statistical significance in a two-tailed test at the 1% and 5% levels, respectively.
[aaa], [aa], and [a] indicate that the estimated probability of observing a *t* statistic as high or higher under multiple testing, when the global null hypothesis is true, is less than 1%, 5%, and 10%, respectively.

Nevertheless, we also show results where we impose a one-month lag between the portfolio formation date and the implementation date. This serves as a test of the robustness of our findings for the longer-term earnings-announcement strategy. By contrast, it is well known that the performance of a standard stock momentum strategy is negatively impacted by the short-term reversal effect of Jegadeesh (1990). For this reason, we only report in Table 2—and in the remaining tables of our paper—the performance of stock momentum strategies where a month is skipped between the formation and holding periods. We apply the same approach to the stock momentum strategy that excludes returns around earnings announcements. While this strategy should, by construction, have higher exposure to factor momentum—and despite the fact that factor momentum has been shown to be more powerful just following its formation period—we invariably find that it performs more strongly after skipping a month between the formation end date and the rebalancing date.[3]

As expected, preliminary findings suggest that the longer-term earnings-announcement strategy has little undiversifiable systematic risk. The annualized risk of the longer-term earnings-announcement strategy is on average 59% lower than that of stock momentum and 43% lower when the strategies are industry-adjusted.[4] Moreover, the correlation between the returns of the long and short sides of this portfolio is, on average, 0.92 over the last 30 years and across the three developed markets in our study. When we adjust the strategy by industry returns, the average correlation increases marginally to 0.94. These significant correlations imply that much of the systematic risk of the long side of the portfolio is hedged by that of the short side. By contrast, a standard stock momentum strategy displays an average correlation of 0.60, increasing to 0.82 after adjusting for industry returns—hinting that the two sides of the strategy load asymmetrically on certain sources of systematic risk. Overall, these results largely corroborate our initial hypothesis that focusing on returns surrounding the previous year's earnings announcements helps capture a disproportionate amount of stock-specific information, while systematic information is more salient when aggregating a stock's remaining daily returns.

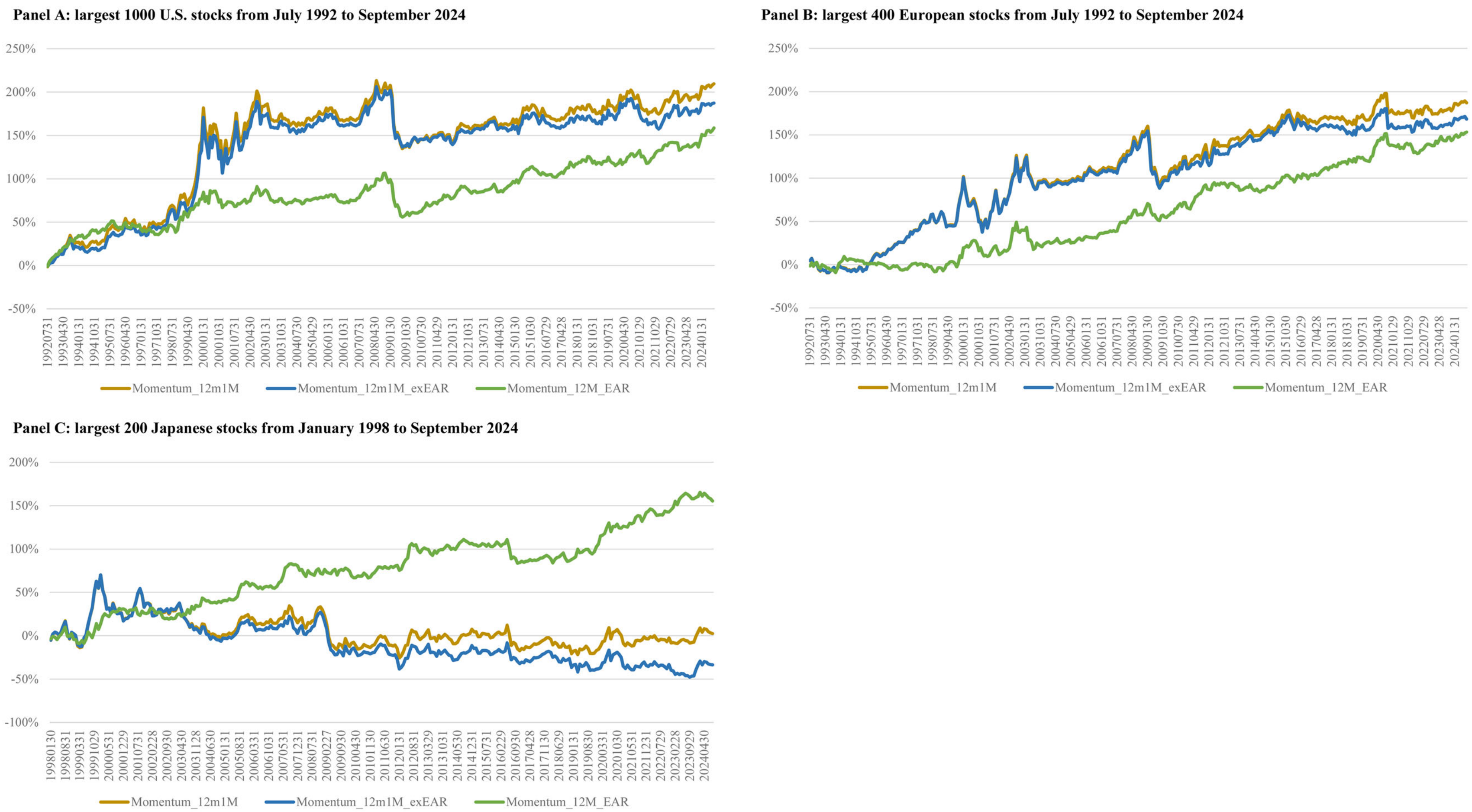
We also report consistent evidence of performance continuation for the longer-term earnings-announcement component of stock momentum over the last 30 years. Table 2, Panel A, shows the performance of all US momentum strategies over our study period. As already documented in Table 1, the market-adjusted longer-term earnings-announcement strategy earns an annualized return of 3.51%, with an annualized risk of only 7.91%, which remains statistically significant even after accounting for multiple testing. Controlling for industry returns has little impact on performance. The annualized return of the strategy decreases by 0.67% and its risk by 0.9%, so statistical significance barely changes. Skipping the month immediately following the formation period has a somewhat larger effect—annualized performance decreases by approximately 1% irrespective of whether the strategy is market- or industry-adjusted—and statistical significance becomes weak.

The annualized performance of the traditional stock momentum strategy (with one month skipped) and that of a similarly constructed strategy excluding returns around earnings announcements are 6.52% and 5.82% respectively. These returns are markedly larger than those of the longer-term earnings-announcement strategy. However, the turnover of the longer-term earnings-announcement strategy is approximately 30% lower, so when the return of its market-adjusted (industry-adjusted) specification is levered proportionally, it reaches a comparable level to that of the competing momentum strategies: almost 5% (4%).[5] Moreover, the risk levels of the traditional stock momentum strategy and the strategy excluding earnings announcement returns are 21.79% and 21.37%, respectively. Their statistical significance is weak at best and does not survive multiple testing adjustment.

In contrast to the evidence for the longer-term earnings-announcement strategy, controlling for industry returns has a dramatic impact on performance for standard stock momentum. The annualized return of the standard stock momentum strategy drops to 3.63% and then to 3.06% when excluding announcement returns from the formation period. Consequently, despite a concomitant 40% reduction in risk, statistical significance deteriorates further. Differences in the strategies' risk–return tradeoffs—where the performance of the longer-term earnings-announcement strategy is levered to achieve the same turnover as standard stock momentum—are immediately obvious in Figure 1, Panel A, where we plot their cumulative returns.

In Table 2, Panel B, we perform the same analysis in the European market. Our results echo those in

Figure 1. Momentum Strategies' Cumulated Monthly Returns



Our standard stock momentum strategy is the sum of adjusted daily log returns over the last 12 months, with the most recent month skipped (12m1M). The strategy with the suffix exEAR excludes the adjusted daily log returns that fall within a ±2-day window around all the earnings announcements during the formation months. In contrast, the strategy with the suffix EAR is based only on the earnings announcement returns of the previous 12 months, including the most recent month (12 M). Daily log returns are market-adjusted, and each strategy is rebalanced monthly using the largest securities in our universe for that month. Portfolio holdings are linear in the scores of their respective strategy, demeaned and scaled to be 100% long and 100% short. A fixed amount of leverage is applied to Momentum_12M_EAR so that it achieves the same average turnover as Momentum_12m1M.

the US market. The longer-term earnings-announcement strategy, where announcement returns are market-adjusted, earns an annualized return of 3.06% and experiences an annualized risk of only 6.77%. In turn, the evidence is statistically significant even after accounting for multiple testing. Skipping a month between the formation and holding periods reduces the annualized return by −0.51%, but the impact on statistical significance is negligible. This time, we find the industry adjustment to have a slightly larger impact on performance. The annualized return drops to 2.24%, but so does the risk of the strategy, which is now equal to 6.12%. All in all, statistical significance holds and survives our multiple testing adjustment. However, skipping a month reduces performance by −0.48%, so that while the strategy is marginally significant on an individual basis, this is no longer the case after controlling for multiple testing.

The annualized performance of the market-adjusted stock momentum strategy and that of its counterpart where earnings announcement returns are excluded are equal to 5.82% and 5.23%, respectively. Again, it is worth pointing out that the turnover of the longer-term earnings-announcement strategy is 36% lower than that of traditional stock momentum. Consequently, leveraging the performance of the longer-term market-adjusted earnings-announcement strategy so that it achieves the same turnover as standard stock momentum would increase its annualized return to almost 5%, bringing it in line with the returns of the competing stock momentum strategies. In addition, the risk of these stock momentum strategies is large, at approximately 17.6%, such that they barely achieve statistical significance. Worse still, while industry-adjusting the computation of the contending stock momentum strategies leads to a meaningful reduction in risk of approximately 6%, performance drops by more than 3% to 2.47% and 1.90% when we exclude earnings-announcement returns. In comparison, the longer-term earnings-announcement strategy would earn a larger annualized return of 3.5% with a risk of only 9.54% if it was levered to achieve a comparable turnover. In turn, when returns are industry-adjusted over the formation months, the statistical significance of these stock momentum strategies vanishes entirely. These findings, along with our earlier ones in the US, suggest that industry momentum is an important driver behind the performance of standard stock momentum, even though exposure to this factor is associated with a significant increase in risk. In Figure 1, Panel B, we show the cumulated returns of the momentum strategies in Europe. These plots help illustrate how differently the risk of the various strategies is being compensated. Additionally, it is important to note that prior to 2003, most firms in our European sample were only making one earnings announcement per year. Therefore, the data used to construct the earnings-announcement strategy are rather stale over the period, which might help explain their subdued performance in the early years. That said, as coverage improves, so does the strength of the strategy.

Next, in Table 2, Panel C, we summarize the evidence for the Japanese market starting in January 1998 due to limitations in the availability of earnings-announcement dates. Stock momentum is one of the seminal quant factors that has been found to work in most regions, with the notable exception of Japan. Our study period is no exception, as neither the traditional stock momentum strategy nor its alternative version that excludes earnings-announcement returns are found to earn a statistically significant positive return. Risk, however, is on par with that in other markets. These market-adjusted stock momentum strategies experience an annualized risk of approximately 17%, while their industry-adjusted versions see their risk dropping to approximately 10%. In striking contrast, our longer-term earnings-announcement strategy continues to deliver a significant positive performance. When earnings-announcement returns are market-adjusted, the strategy earns an annualized return of 4%, with a risk of only 8.30%, and statistical significance survives our control for multiple testing. Skipping a month makes little difference, as the strategy's annualized return only drops to 3.82%. The industry adjustment has a larger impact, resulting in an annualized return of 2.89%, but risk decreases as well to 7.09%, so statistical significance holds. However, skipping a month between the formation and holding periods further decreases the annualized return of the industry-adjusted strategy to 2.45%, with no meaningful change in risk. Consequently, the strategy's statistical significance becomes marginal and no longer survives the multiple testing adjustment. To keep in line with our analyses in the US and Europe, we also compute the performance of the longer-term earnings-announcement strategy levered so that its turnover matches that of standard stock momentum. When doing so, the annualized return of the market-adjusted longer-term earnings-announcement strategy approaches 6%, and its industry-adjusted counterpart approaches 4%. Last, Figure 1, Panel C displays the significant differences in the cumulated monthly returns of these various momentum strategies in Japan.

Finally, a word of caution is in order when reflecting on the results of our analysis. Despite being lower than the turnover of traditional stock momentum as well as that of a strategy based solely on the latest earnings-announcement return, the turnover of the longer-term earnings-announcement strategy is nonetheless relatively high. Such a strategy would benefit from techniques that aim at reducing "unnecessary" turnover (see, e.g., Novy-Marx and Velikov 2016, 2019), and it would make sense to consider including it in a multifactor model where diversification opportunities across factors would help bring portfolio turnover down. Having said that, even with the crude stand-alone construction of Table 2, we find that a one-way transaction cost of 0.15% and a borrowing cost of 0.40% would only halve the premium of the market-adjusted longer-term earnings-announcement strategy over our study period.[6] For large, liquid, and easy-to-borrow securities, these values would typically provide a realistic estimate of total implementation costs. However, this is before factoring in taxes on financial transactions, which can be rather steep in some European countries. A case in point is the UK, which imposes a stamp duty of 0.50% on purchases. Consequently, in our European sample, it is debatable whether harvesting the longer-term earnings-announcement premium with a stand-alone strategy makes much economic sense.

Underreaction or Delayed Overreaction?

Our investigation of the performance of momentum strategies would not be complete without examining the persistence of their predictive power in the long run. There are arguably many ways to do this. However, since the likelihood of observing some reversal typically increases with stocks whose performance has drifted upward or downward over an extended period, we expand the formation window of our momentum strategies to 24 months and implement a 12-month lag between the end of the formation period and the beginning of the holding period. We construct our strategy portfolios as described earlier, using a monthly rebalancing frequency as well as portfolio holdings that are linear in the scores of these longer-term momentum metrics, demeaned and scaled to be 100% long and 100% short. Our findings are reported in Panels A, B, and C of Table 3 and Figure 2 for the US, Europe, and Japan, respectively.

The first important result of this analysis is that the longer-term earnings-announcement strategy is not associated with any performance reversal in the long term. This evidence is consistent across markets and holds irrespective of whether we adjust the strategy for industry returns. Second, in line with the findings of Gutierrez and Prinsky (2007), we show that the performance of the competing stock momentum strategies reverts over the longer term, particularly when excluding from the formation period the few days surrounding earnings announcements. For instance, a market-adjusted stock momentum strategy that excludes earnings announcement returns from the formation period earns an annualized return of −6.11% in the US and −4.66% in Japan. As with its medium-term variant, the impact of the industry adjustment is rather large: The annualized return increases to −4.63% in the US and −3.62% in Japan, while risk drops significantly—from 14.84% to 7.39% in the US and from 14.30% to 7.94% in Japan. In turn, statistical significance improves once we control for industry returns. The evidence in Europe is weaker and never achieves statistical significance. Nevertheless, the same performance pattern is observed across all markets. Figure 2 indicates that this performance reversal is concentrated over just a few years encompassing the period from the so-called tech-bubble burst to the end of the ensuing recession in early 2004. These are also periods when cheap value stocks performed notably well, so it is perhaps not surprising that the reverse phenomenon is observed for our measures of past long-term performance.

To conclude, the univariate results of this section suggest that our proxy for stock-specific momentum and its systematic counterpart capture different behavioral anomalies. While the persistence of longer-term earnings-announcement returns supports the view that investors underreact to stock-specific news—or at least to the firm-specific information released around earnings announcements—the evidence that only stock momentum reverses in the long run suggests that investors may overreact to the impact of systematic information on firms' values.

Controlling Factor Exposures

Constant Factor Loadings. Having investigated the univariate performance of the different momentum strategies, we now examine the extent to

Table 3. Long-Term Momentum Strategies

Panel A: Largest 1,000 US Stocks from July 1992 to September 2024

	Ann. Return	Ann. Risk	*t* statistic	Ann. Turnover (One-way)
Market-adjusted returns over formation months				
Momentum_12Mago24M	−4.96%	15.10%	−1.87[a]	444%
Momentum_12Mago24M_EAR	1.19%	6.61%	1.02	335%
Momentum_12Mago24M_exEAR	−6.11%	14.84%	−2.34*,[aa]	452%
Industry-adjusted returns over formation months				
Momentum_12Mago24M	−3.52%	8.04%	−2.48*,[aa]	461%
Momentum_12Mago24M_EAR	1.42%	5.46%	1.48	347%
Momentum_12Mago24M_exEAR	−4.63%	7.39%	−3.55**,[aaa]	469%

Panel B: Largest 400 European Stocks from July 1992 to September 2024

	Ann. Return	Ann. Risk	*t* Statistic	Ann. Turnover (One-way)
Market-adjusted returns over formation months				
Momentum_12Mago24M	−2.08%	13.07%	−0.90	433%
Momentum_12Mago24M_EAR	0.01%	5.67%	0.01	307%
Momentum_12Mago24M_exEAR	−2.32%	12.94%	−1.01	438%
Industry-adjusted returns over formation months				
Momentum_12Mago24M	−0.48%	7.78%	−0.35	460%
Momentum_12Mago24M_EAR	0.33%	4.91%	0.38	327%
Momentum_12Mago24M_exEAR	−0.62%	7.66%	−0.46	463%

Panel C: Largest 200 Japanese Stocks from January 1998 to September 2024

	Ann. Return	Ann. Risk	*t* Statistic	Ann. Turnover (One-way)
Market-adjusted returns over formation months				
Momentum_12Mago24M	−4.20%	14.66%	−1.48	461%
Momentum_12Mago24M_EAR	0.07%	7.12%	0.05	331%
Momentum_12Mago24M_exEAR	−4.66%	14.30%	−1.69*	466%
Industry-adjusted returns over formation months				
Momentum_12Mago24M	−3.27%	8.34%	−2.03**,[a]	501%
Momentum_12Mago24M_EAR	−0.13%	6.17%	−0.11	360%
Momentum_12Mago24M_exEAR	−3.62%	7.94%	−2.36**,[aa]	505%

To compute the long-term momentum strategies, we expand the formation window to 24 months and introduce a 12-month lag between the end of the formation period and the start of the holding period. Our standard long-term stock momentum strategy is the sum of adjusted daily log returns over the formation months. The strategy with the suffix exEAR excludes the adjusted daily log returns within a ±2-day window around all the earnings announcements during the formation months. By contrast, the strategy with the suffix EAR is based solely on the earnings announcement returns of the formation period. Daily log returns are either market- or industry-adjusted. Each strategy is rebalanced monthly using the largest securities in our universe that month. Portfolio holdings are linear in the scores of their respective strategy, demeaned and scaled to be 100% long and 100% short. Ann.Return is a strategy's annualized average monthly return, and Ann.Risk is the annualized standard deviation of monthly strategy returns. Ann.Turnover is the strategy portfolio's annualized monthly turnover (one-way).

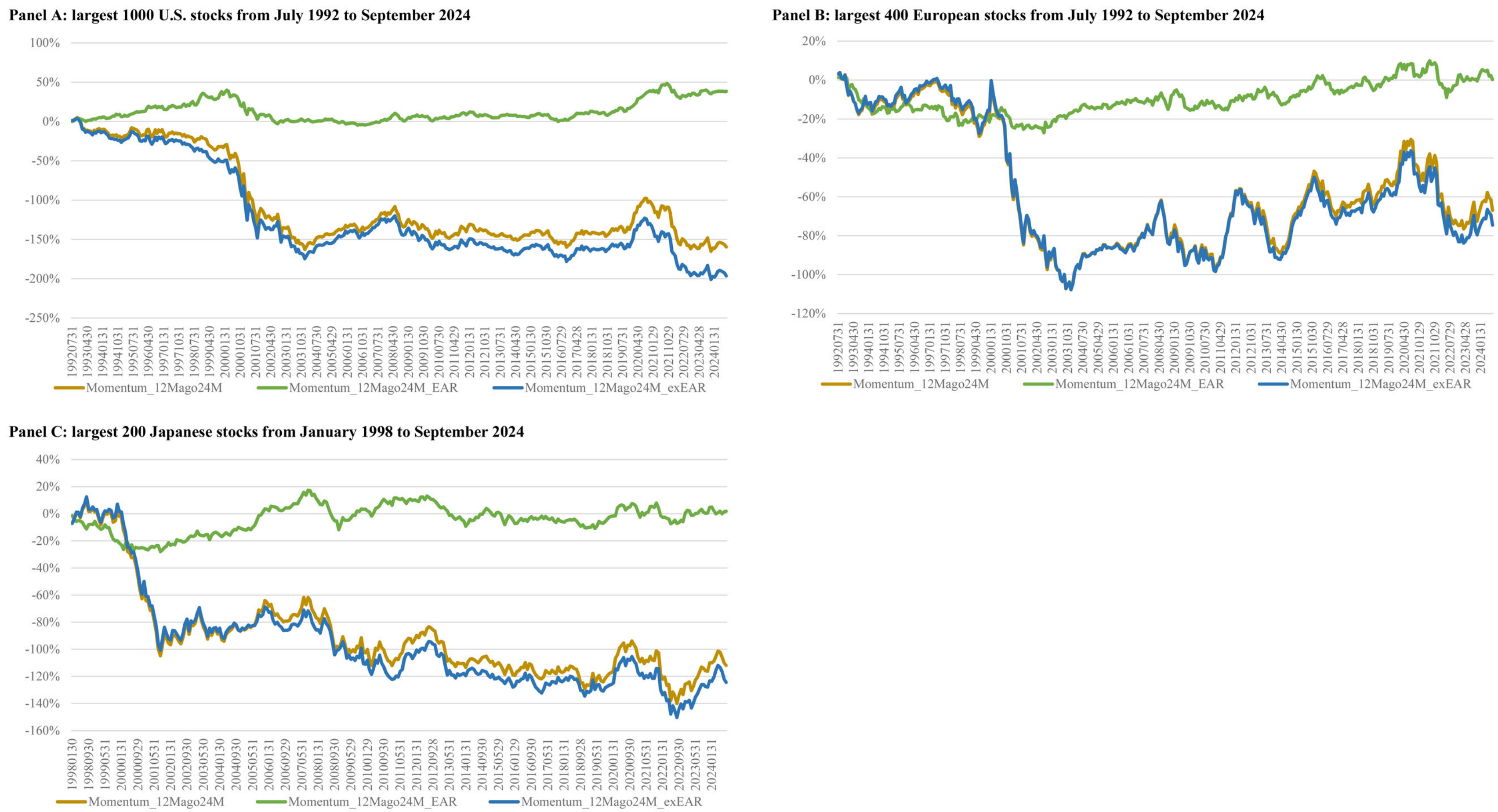
** and *indicate statistical significance in a two-tailed test at the 1% and 5% levels, respectively.

[aaa, aa and, a]indicate that the estimated probability of observing a *t* statistic as high or higher under multiple testing, when the global null hypothesis is true, is less than 1%, 5%, and 10%, respectively.

which their performance can be explained by their static loadings on the systematic factors in the Fama and French five-factor model (Fama and French 2015). For conciseness, we do not present results based on industry-adjusted returns, as these do not alter the central message of our analysis.

In Table 4, Panel A, we report our findings for the US market. When we control for the Fama and French five-factor model, the annualized abnormal returns of all momentum strategies increase along with their statistical significance. Moreover, in line with previous findings in the literature, the

Figure 2. Long-Term Momentum Strategies' Cumulated Monthly Returns



To compute the long-term momentum strategies, we expand the formation window to 24 months and implement a 12-month lag between the end of the formation period and the beginning of the holding period. Our standard long-term stock momentum strategy is the sum of adjusted daily log returns over the formation months. The strategy with the suffix exEAR excludes the adjusted daily log returns that fall within a ±2-day window around all the earnings announcements during the formation months. In contrast, the strategy with the suffix EAR is based only on the earnings announcement returns of the formation period. Daily log returns are market-adjusted, and each strategy is rebalanced monthly using the largest securities in our universe for that month. Portfolio holdings are linear in the scores of their respective strategy, demeaned and scaled to be 100% long and 100% short.

Table 4. Momentum Strategies and Their Loadings on Common Factors

Panel A: Largest 1,000 US Stocks from July 1992 to September 2024

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic
Ann. Alpha	9.40%	2.53*	8.70%	2.39*	4.72%	3.48**	3.38%	2.51*
MKT-RF	−0.32	−4.26**	−0.32	−4.31**	−0.10	−3.57**	−0.07	−2.37*
SMB	0.32	2.97**	0.31	2.88**	0.09	2.16*	0.07	1.71
HML	−0.75	−5.97**	−0.73	−5.95**	−0.23	−4.92**	−0.19	−4.09**
RMW	−0.06	−0.41	−0.10	−0.74	0.03	0.53	0.04	0.83
CMA	0.45	2.42*	0.52	2.86**	−0.08	−1.12	−0.13	−1.95
R-squared	0.17		0.17		0.16		0.13	

Panel B: Largest 400 European Stocks from July 1992 to September 2024

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic
Ann. Alpha	4.64%	1.59	3.97%	1.39	2.82%	2.41*	2.31%	2.02*
MKT-RF	−0.21	−3.91**	−0.21	−3.85**	−0.06	−2.67**	−0.06	−2.63**
SMB	0.19	1.72	0.20	1.87	0.00	−0.03	0.01	0.14
HML	−0.26	−1.89*	−0.24	−1.78	−0.08	−1.44	−0.07	−1.24
RMW	0.96	5.40**	0.94	5.34**	0.30	4.22**	0.28	4.03**
CMA	0.14	0.80	0.17	0.94	−0.04	−0.61	−0.05	−0.75
R-squared	0.25		0.24		0.17		0.15	

Panel C: Largest 200 Japanese Stocks from January 1998 to September 2024

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic
Ann. Alpha	1.21%	0.36	−0.30%	−0.09	4.50%	2.76**	4.38%	2.71**
MKT-RF	−0.09	−1.54	−0.09	−1.51	−0.03	−1.02	−0.03	−0.99
SMB	0.14	1.27	0.13	1.22	0.02	0.46	0.03	0.59
HML	−0.31	−2.57*	−0.27	−2.23*	−0.14	−2.42**	−0.16	−2.72**
RMW	0.27	1.31	0.26	1.29	0.12	1.19	0.12	1.24
CMA	0.06	0.33	0.03	0.15	0.10	1.21	0.09	1.01
R-squared	0.08		0.07		0.05		0.06	

Our standard stock momentum strategy is the sum of adjusted daily log returns over the last 12 months, with the most recent month skipped (12m1M). The strategy with the suffix exEAR excludes the adjusted daily log returns within a ±2-day window around all the earnings announcements during the formation months. By contrast, the strategy with the suffix EAR is based only on earnings announcement returns from the previous 12 months, either including (12M) or excluding (12m1M) the most recent month. Daily log returns are market-adjusted, and each strategy is rebalanced monthly using the largest securities in our universe that month. Portfolio holdings are linear in the scores of their respective strategy, demeaned and scaled to be 100% long and 100% short. We regress each strategy's monthly returns on the factors of the Fama–French five-factor model. The factor data are sourced from Kenneth French's website at Dartmouth. Ann.Alpha is the annualized value of the constant term estimated from this time-series regression.
** and *indicate statistical significance in a two-tailed test at the 1% and 5% levels, respectively.

strategies show significant negative loadings on the returns of the HML factor, in addition to their significant negative loading on the excess market return.

More importantly, Table 5, Panel A shows that the abnormal performance of the longer-term earnings-announcement strategy remains statistically significant when we add the returns of rival stock momentum strategies as additional control variables in the Fama and French five-factor model. For instance, the abnormal return of the longer-term earnings-announcement strategy decreases from 4.72% to 2.72% when we add as a control variable the performance of the stock momentum strategy that excludes earnings announcement returns from the formation period, yet its *t* statistic remains above 2. The same is not true for the competing stock momentum strategies, which lose both statistical and economic significance once the longer-term earnings-announcement strategy is included as a control. For instance, the stock momentum strategy that excludes earnings announcement returns experiences a drop in abnormal return of almost 8%.

Table 4, Panel B reports results from regressing the returns of the European momentum strategies against those of the Fama and French five-factor

Table 5. Spanning Tests

Panel A: Largest 1,000 US Stocks from July 1992 to September 2024

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12M_EAR	
	Coeff.	*t* statistic	Coeff.	*t* statistic	Coeff.	*t* statistic	Coeff.	*t* statistic
Ann. Alpha	0.44%	0.16	0.88%	0.30	2.34%	2.37*	2.72%	2.52*
MKT-RF	−0.14	−2.43*	−0.16	−2.63**	−0.02	−0.83	−0.03	−1.12
SMB	0.16	2.04*	0.17	1.96	0.00	0.13	0.01	0.47
HML	−0.32	−3.44**	−0.36	−3.59**	−0.04	−1.03	−0.06	−1.51
RMW	−0.11	−1.08	−0.15	−1.36	0.04	1.13	0.05	1.26
CMA	0.60	4.42**	0.65	4.50**	−0.19	−3.85**	−0.20	−3.63**
Momentum_12M_EAR	1.90	18.75**	1.66	15.31**				
Momentum_12m1M					0.25	18.75**		
Momentum_12m1M_exEAR							0.23	15.31**
R-squared	0.57		0.49		0.56		0.48	

Panel B: Largest 400 European Stocks from July 1992 to September 2024

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12M_EAR	
	Coeff.	*t* statistic	Coeff.	*t* statistic	Coeff.	*t* statistic	Coeff.	*t* statistic
Ann. Alpha	0.42%	0.18	0.26%	0.11	1.69%	1.81	1.95%	1.97*
MKT-RF	−0.13	−2.86**	−0.13	−2.83**	−0.01	−0.38	−0.01	−0.70
SMB	0.19	2.17*	0.20	2.23*	−0.05	−1.32	−0.05	−1.21
HML	−0.14	−1.26	−0.13	−1.18	−0.02	−0.38	−0.03	−0.58
RMW	0.51	3.5**	0.54	3.57**	0.07	1.16	0.10	1.53
CMA	0.21	1.45	0.22	1.50	−0.08	−1.36	−0.08	−1.32
Momentum_12M_EAR	1.50	14.69**	1.32	12.41**				
Momentum_12m1M					0.24	14.69**		
Momentum_12m1M_exEAR							0.22	12.41**
R-squared	0.52		0.46		0.47		0.41	

Stock momentum is defined as the sum of adjusted daily log returns over the past 12 months, excluding the most recent month (12m1M). The strategy with the suffix exEAR excludes the adjusted daily log returns within a ±2-day window around all the earnings announcements during the formation months. By contrast, the strategy with the suffix EAR is based only on earnings announcement returns from the previous 12 months, including the most recent month (12M). Daily log returns are market-adjusted, and each strategy is rebalanced monthly. Portfolio holdings are linear in the scores of their respective strategy, demeaned and scaled to be 100% long and 100% short. Each strategy's monthly returns are regressed on the Fama–French five-factor model, extended with the returns of a competing momentum strategy. Factor data are sourced from Kenneth French's website at Dartmouth. Ann.Alpha is the annualized value of the constant term.
** and *indicate statistical significance in a two-tailed test at the 1% and 5%, levels respectively.

model for this region. Contrary to the case for the US, the economic and statistical significance of the abnormal returns of the stock momentum strategies diminishes when controlling for these common factors. The standard stock momentum strategy is left with an insignificant annualized abnormal return of 4.64%. A similar pattern emerges when excluding earnings announcement returns from the formation period, as the strategy's annualized abnormal return is statistically insignificant at 3.97%. Looking at the factor loadings from the European version of the Fama and French five-factor model, we again find a negative sensitivity to HML returns. However, statistical significance is stronger for the negative loading on the excess market return and the positive loading on RMW. Common factors explain much less of the performance of the longer-term earnings-announcement strategy, leaving its abnormal return statistically significant. One similarity across strategies is that the longer-term earnings-announcement strategy also has a significant positive exposure to RMW in Europe.

Given this, it is not surprising that Table 5, Panel B shows that the longer-term earnings-announcement strategy explains away the abnormal returns of the other stock momentum strategies while continuing to earn significant abnormal returns when each competing strategy is added to the control set. For instance, the annualized abnormal return of the stock momentum strategy that excludes earnings announcement returns drops to 0.26% after controlling for the longer-term earnings-announcement strategy. Conversely, when this competing strategy is included as a control, the abnormal return of the longer-term earnings-announcement strategy remains significant at the 5% level (two-tailed), decreasing only from 2.82% to 1.95%.

In Table 4, Panel C, we find that the standard stock momentum strategy and its counterpart excluding earnings announcement returns do not earn a significant abnormal return over the study period in Japan. As in the US, their performance loads negatively on the returns of the HML factor as well as the excess market return. Also in line with US evidence, the longer-term earnings-announcement strategy earns a larger annualized abnormal return than in the univariate analysis. However, we do not find that it loads significantly on the market excess return. Its only significant factor loading is its negative covariance with HML returns. Finally, since standard stock momentum is weak in both univariate and multivariate analyses in Japan, we omit the spanning test results of Table 5 for this market.

Robustness Tests and Control for PC Time-Series Factor Momentum.

In this section, we address possible concerns regarding the presence of outlying signal values in the least liquid securities of our universes, as well as the robustness of our findings to the PC time-series factor momentum strategy described in Ehsani and Linnainmaa (2022).

As explained in the methodology section, the motivation for using portfolio holdings linear in their respective metrics is to demonstrate how the returns of the stock momentum strategy can be decomposed seamlessly into those of two subportfolios that capture stock-specific and systematic sources of past returns, respectively. That said, we are cognizant of the fact that our methodological choice can result, for the longer-term earnings-announcement strategy, in extreme positions in securities with very large announcement returns that are relatively illiquid and volatile. For this reason, we present in Table 6 abnormal returns estimated with the Fama and French five-factor model (Fama and French 2015) for monthly longer-term earnings-announcement portfolio holdings that are linear in the intersection of capped score exposures and capped value weights. Specifically, using the same universes of larger stocks in each market as in the previous sections, we winsorize each month the scores of the longer-term earnings-announcement strategy at the top and bottom 2.5th percentile. These are then demeaned and multiplied by a stock's market capitalization at the rebalancing date before being scaled such that the final portfolio is 100% long and 100% short. We cap market capitalizations as in Jensen, Kelly, and Pedersen (2023), who winsorize market values at the NYSE 80th percentile to avoid a few mega-cap stocks dominating their portfolios.

This ensures comparability between our strategy returns and those of PC time-series factor momentum strategies based on Ehsani and Linnainmaa (2022), since we use Jensen, Kelly and Pedersen's database[7] as a source of global factor returns. The focus of our strategy is on larger companies, where liquidity issues are less severe, and the authors' database provides monthly and daily returns for capped value-weighted factors globally. We used the list of factors in Ehsani and Linnainmaa (2022) as a guide in selecting factors from this database. Ehsani and Linnainmaa (2022) already exclude momentum-like characteristics when comparing their strategy to stock momentum. We also exclude the Seasonality and PEAD (SUE) factors from their list because of the similarities in the construction of these factors and the longer-term earnings-announcement strategy. We ultimately selected 37 factors[8] from Jensen, Kelly and Pedersen's database that closely match the description of the remaining 45 factors in the study of Ehsani and Linnainmaa (2022). Following their methodology, we used a moving window of 10 years of daily factor returns to estimate the correlation matrix and extract eigenvectors and eigenvalues. We then computed monthly PC returns, demeaned them using their latest 10-year history of monthly returns, and scaled them so that the volatility of each PC matches that of the average factor over the formation years. Finally, the PC time-series factor momentum strategy is based on the last 12 monthly returns of the PCs associated with the 10 largest eigenvalues. We encountered no difficulty constructing the US signal but could not compute a European version comparable to the longer-term earnings-announcement strategy because factor returns are available only at the country level. We were able to create a signal for the Japanese market but had to exclude several

Table 6. Robustness Tests

Panel A: Largest 1,000 US Stocks from July 1992 to September 2024

	Robust_ Momentum_ 12m1M		Robust_ Momentum_ 12m1M		Robust_ Momentum_ 12m1M		Robust_ Momentum_ 12M_EAR		Robust_ Momentum_ 12M_EAR		Robust_ Momentum_ 12M_EAR	
	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic
Ann. Alpha	7.57%	2.27*	0.57%	0.21	1.89%	0.66	4.72%	3.43**	2.81%	2.56*	3.34%	2.52*
MKT-RF	−0.24	−3.45**	−0.17	−3.16**	−0.07	−1.10	−0.04	−1.54	0.02	0.71	0.00	−0.07
SMB	0.25	2.51*	0.20	2.58*	0.07	0.83	0.03	0.75	−0.03	−0.97	−0.01	−0.31
HML	−0.70	−6.21**	−0.43	−4.79**	−0.47	−4.82**	−0.18	−3.84**	0.00	−0.05	−0.12	−2.73**
RMW	−0.07	−0.58	−0.06	−0.60	−0.01	−0.08	−0.01	−0.17	0.01	0.23	0.01	0.13
CMA	0.38	2.23*	0.71	5.29**	0.28	1.93	−0.23	−3.30**	−0.32	−5.85**	−0.25	−3.82**
Robust_Momentum_12M_EAR			1.48	15.06**								
Robust_Momentum_12m1M									0.25	15.06**		
PC Time-Series Factor Momentum					1.69	12.04**					0.41	6.30**
Momentum_12M_EAR												
R-squared	0.16		0.48		0.39		0.18		0.49		0.26	

Panel A: Continued

	Momentum_ 12M_EAR		PC Time-Series Factor Momentum		PC Time-Series Factor Momentum		PC Time-Series Factor Momentum		PC Time-Series Factor Momentum	
	Coeff.	*t*-statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic
Ann. Alpha	2.85%	2.29*	3.36%	3.24**	2.12%	2.38*	1.36%	1.42	1.83%	1.90
MKT-RF	−0.04	−1.67*	−0.10	−4.73**	−0.06	−3.37**	−0.07	−3.53**	−0.07	−3.48**
SMB	0.03	0.78	0.10	3.39**	0.06	2.41*	0.06	2.32*	0.08	2.71**
HML	−0.15	−3.55**	−0.14	−3.85**	−0.02	−0.65	−0.10	−3.04**	−0.06	−1.89
RMW	0.05	1.04	−0.04	−0.96	−0.03	−0.78	0.03	0.95	−0.05	−1.31
CMA	−0.11	−1.75	0.06	1.10	0.00	−0.08	0.09	1.79	0.08	1.74

continued

	Coeff.	t Statistic	Coeff.	t Statistic	Coeff.	t Statistic	Coeff.	t Statistic	Coeff.	t Statistic
Robust_Momentum_12M_EAR							0.71	20.30**		
Robust_Momentum_12m1M					0.16	12.04**				
PC Time-Series Factor Momentum	0.56	9.15**								
Momentum_12M_EAR									0.33	9.15**
R-squared	0.31		0.14		0.37		0.60		0.29	

Panel B: Largest 400 European Stocks from October 2003 to September 2024

	Robust_ Momentum_ 12m1M		Robust_ Momentum_ 12m1M		Robust_ Momentum_ 12M_EAR		Robust_ Momentum_ 12M_EAR	
	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic
Ann. Alpha	7.02%	2.41*	1.70%	0.68	4.57%	3.35**	2.79%	2.41*
MKT-RF	–0.18	–3.25**	–0.10	–2.26*	–0.06	–2.43*	–0.02	–0.77
SMB	0.10	0.72	0.15	1.36	–0.05	–0.79	–0.07	–1.40
HML	–0.99	–6.19**	–0.63	–4.48**	–0.32	–4.21**	–0.06	–0.93
RMW	–0.09	–0.40	0.08	0.40	–0.15	–1.36	–0.13	–1.36
CMA	0.82	3.80**	0.75	4.15**	0.06	0.56	–0.15	–1.74
Robust_Momentum_12M_EAR			1.16	10.15**				
Robust_Momentum_12m1M							0.25	10.15**
R-squared	0.36		0.55		0.19		0.43	

Panel C: Largest 200 Japanese Stocks from January 1998 to September 2024

	Robust_Momentum_12m1M		Robust_Momentum_12m1M		Robust_Momentum_12M_EAR		Robust_Momentum_12M_EAR	
	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic	Coeff.	*t* Statistic
Ann. Alpha	1.28%	0.39	–2.66%	–0.88	4.71%	2.78**	4.43%	2.9**
MKT-RF	–0.11	–1.84*	–0.09	–1.58	–0.03	–0.96	–0.01	–0.19
SMB	0.12	1.10	0.10	1.09	0.01	0.27	–0.01	–0.22
HML	–0.36	–3.03**	–0.22	–2.04*	–0.17	–2.71**	–0.09	–1.52
RMW	0.21	1.06	0.20	1.09	0.02	0.16	–0.03	–0.33
CMA	0.12	0.70	0.06	0.42	0.07	0.75	0.04	0.50
Robust_Momentum_12M_EAR			0.84	8.43**				
Robust_Momentum_12m1M							0.22	8.43**
R-squared	0.08		0.25		0.04		0.21	

We compute robust versions of Momentum_12m1M and Momentum_12M_EAR based on capped score values intersected with capped market-value weights, as well as a PC Time-Series Factor Momentum strategy based on Ehsani and Linnainmaa (2022). The latter uses the past 12-month returns of the 10 PCs associated with the largest eigenvalues, extracted from the 10-year correlation matrix of daily returns for 37 US factors,[7] sourced from the database of Jensen, Kelly, and Pedersen (2023), available at https://jkpfactors.com/. Each strategy's monthly returns are regressed on the Fama–French five-factor model, extended (or not) with the returns of a competing momentum strategy. Factor data are sourced from Kenneth French's website at Dartmouth. Ann.Alpha is the annualized value of the constant term.
** and *indicate statistical significance in a two-tailed test at the 1% and 5% levels, respectively.

factors in the early years due to missing daily and monthly returns. However, we found no evidence of PC time-series factor momentum in this market. These results are possibly in line with previous findings showing how different research designs impact the effectiveness of factor momentum strategies (see, e.g., Caciki et al. 2025; Falck, Rej, and Thesmar 2022; Fan et al. 2022).

Finally, we took the opportunity offered by the robustness section to report results for our European sample over the period starting in October 2003. As mentioned in the data section, the average number of earnings announcements per year in Europe increases in October 2003 from 1 to 2, before reaching approximately 3.5 announcements per year in early 2007. Because of this higher frequency of updates to the key variable of our study from October 2003 onward, our European results may be more convincing over this period despite its shorter length. However, while our results appear stronger in the more recent years, the different samples lead to qualitatively similar conclusions, so we revert to using the full period in the ensuing section.

Overall, controlling for possible outlying signal values and size, we continue to find that the "robust" longer-term earnings-announcement strategy earns significant abnormal returns in each market, irrespective of whether we control for a similarly constructed "robust" stock momentum strategy. Moreover, this "robust" version of longer-term earnings-announcement strategy still dominates the "robust" stock momentum strategy. In Table 6, Panel A, we show that the "robust" version of stock momentum in the US earns a significant annualized abnormal return of 7.57%. However, this abnormal return almost entirely disappears once we control for the "robust" longer-term earnings-announcement strategy. By contrast, the "robust" longer-term earnings-announcement strategy experiences a much smaller reduction in abnormal return once we control for "robust" stock momentum, from 4.72% to 2.81%, while statistical significance remains high. The same is true in Panel B for the European market, where the "robust" stock momentum strategy earns an annualized abnormal return of 7.02% that falls to an insignificant 1.70% after controlling for the "robust" longer-term earnings-announcement strategy. Controlling for "robust" stock momentum also reduces the annualized abnormal return of the "robust" longer-term earnings-announcement strategy in Europe, but only from 4.57% to 2.79%, and its *t* statistic remains well above two. As in previous sections, we find no evidence in Panel C that a "robust" stock momentum strategy earns a significant abnormal return over the study period in Japan. However, controlling for possible outliers and size has little impact on our findings for the performance of the "robust" longer-term earnings-announcement strategy in this market, which earns a highly significant annualized abnormal return of 4.71%.

Turning to the US results on PC time-series factor momentum in Table 6, Panel A, we report strong statistical evidence that this effect exists after controlling for the Fama and French five-factor model, with or without including a stock momentum strategy. This factor momentum strategy also dominates the performance of stock momentum in our US sample. However, it does not subsume the longer-term earnings-announcement strategy in larger-cap stocks (the largest 1,000 US securities each month), irrespective of whether it is computed based on scores or capped score values intersected with capped market-value weights. Conversely, while the longer-term earnings-announcement strategy based only on scores does not fully subsume PC time-series factor momentum either, we find that its "robust" version, with controls for possible outliers and size, explains away the abnormal return of the PC time-series factor momentum strategy. Overall, the evidence from our robustness tests corroborates the view that at least some form of stock-specific momentum exists over and above factor momentum.

Time-Varying Factor Exposures. The most glaring limitation of the previous analysis is its assumption that momentum strategies have constant loadings on common sources of systematic risk. To address this issue, we now adopt the latest asset pricing model of Fama and French (2020). The authors propose decomposing stock returns using a cross-sectional factor model and estimating a portfolio's sensitivities to factor returns from its changing exposures to the scores of each factor in the model. This approach is akin to a traditional holdings-based attribution, which is widely used by investment practitioners. In line with the rebalancing frequency of our strategy portfolios, we estimate the cross-sectional factor model and attribute performance to systematic and residual components monthly. In turn, this monthly decomposition allows us to compute, for each momentum strategy, the risk contribution of its systematic and residual components.[9]

Looking at Table 7, we find that the factor component of the market-adjusted longer-term earnings-announcement strategy explains on average 55% of its risk. By contrast, the stock momentum strategy, excluding earnings-announcement returns, has 78% of its risk explained by systematic components when returns over the formation period are market-adjusted. This, along with our earlier observation that the risk of the longer-term earnings-announcement strategy is on average 59% lower than that of stock momentum, largely corroborates our hypothesis that focusing on the returns surrounding earnings-announcement dates should capture a disproportionate amount of stock-specific information, while systematic information is likely to be more salient when aggregating the remaining daily returns of the year.

Despite systematic factors being the main contributors to the risk of the market-adjusted stock momentum strategy and its counterpart that excludes earnings-announcement returns, their impact on performance is almost never significant. This result is robust to not skipping the month that follows the strategies' formation period, where most of the predictive power of factor momentum has been shown to reside. Moreover, the impact of systematic factors turns negative when industry-adjusting these stock momentum strategies, as it appears that industry momentum is an important component of the performance of traditional stock momentum over the period of our analysis. This adds to the existing evidence that factor returns display different levels of autocorrelation, such that the selection of the set of factors is key to obtaining a successful factor momentum strategy. For instance, while the systematic component of the market-adjusted stock momentum strategy, excluding earnings-announcement returns, is equal to 2.44% in the US and 2.51% in Europe, it drops to −0.99% and −1.43%, respectively, after industry-adjusting the returns of the formation period. In Japan, performance deteriorates further, falling from −1.26% when market-adjusting the strategy to −2.29% after industry-adjusting returns. However, being exposed to industry momentum requires bearing a large amount of systematic risk. Indeed, when neutralizing the impact of industry momentum, we observe a significant reduction in the risk contribution of the systematic component of all the contending stock momentum strategies. For instance, the strategy that excludes earnings-announcement returns from the formation period sees the risk contribution of its factor component drop to 46% after industry-adjusting the returns of its formation period.

Finally, it is ironic to find in Table 7 that the residual component of the performance of stock momentum is consistently larger than the factor component. The market-adjusted (industry-adjusted) stock momentum strategy that excludes earnings announcement returns has a residual component that is equal to 3.39% (4.05%) in the US and 2.72% (3.33%) in Europe and is flat in Japan. Given their low risk, these components also achieve statistical significance in the US and in Europe. However, these results need to be interpreted with caution for two reasons. First, our factor model might suffer from misspecification bias. Second, in the US and in Europe, we find in unreported results that the impact of the residual components of these stock momentum strategies on performance is no longer larger than that of their factor components when we neither industry-adjust our strategies nor skip the month that immediately follows their formation period. Interestingly, this is not only because the impact of factor momentum is stronger in that month. The performance of the residual component is also weaker, as it is subject to the short-term reversal effect.

Turning to the evidence for the longer-term earnings-announcement strategy, which should arguably be less sensitive to the specification of the factor model, we find that the results in the previous sections are robust to controlling for the strategy's dynamic exposures to common factors. This is especially striking when industry-adjusting the strategy. First, doing so reduces the risk contribution of the factor component to merely 35% on average. Second, under this specification, only the residual component of the performance of the earnings-announcement strategy is statistically significant. It equals 2.61% in the US, 2.13% in Europe, and 2.18% in Japan, with *t* statistics greater than 2 in all markets.

All in all, the results in this section and the previous ones strongly suggest that at least some form of stock-specific momentum exists. We concede, however, that stock momentum is dominated by systematic risk. As a result, while we show that stock momentum is not just timing factor returns, unraveling the presence of stock-specific momentum is challenging.

Conclusion

Stock momentum is exposed to both factor and stock-specific components, but the systematic risk of factor momentum is such that it might hinder the impact of stock-specific momentum on

Table 7. Momentum Strategies and Their Time-Varying Exposures to Common Factors

Panel A: Largest 1,000 US Stocks from July 1992 to September 2024

Market-adjusted returns over formation months

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Factors	Residual	Factors	Residual	Factors	Residual	Factors	Residual
Ann. Return Contribution	2.77%	3.74%	2.44%	3.39%	1.12%	2.39%	0.77%	1.67%
Ann. Risk	16.99%	6.54%	17.00%	5.94%	4.95%	4.62%	4.87%	4.51%
t Statistic	0.93	3.24**	0.81	3.24**	1.28	2.94**	0.90	2.10*
Ann. Risk Contribution	76%	24%	78%	22%	53%	47%	53%	47%

Industry-adjusted returns over formation months

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Factors	Residual	Factors	Residual	Factors	Residual	Factors	Residual
Ann. Return Contribution	–0.88%	4.51%	–0.99%	4.05%	0.22%	2.61%	–0.05%	1.89%
Ann. Risk	6.78%	7.96%	6.40%	7.39%	3.46%	4.94%	3.46%	4.85%
t Statistic	–0.74	3.22**	–0.87	3.11**	0.36	3.01**	–0.09	2.22*
Ann. Risk Contribution	45%	55%	46%	54%	37%	63%	38%	62%

Panel B: Largest 400 European Stocks from July 1992 to September 2024

Market-adjusted returns over formation months

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Factors	Residual	Factors	Residual	Factors	Residual	Factors	Residual
Ann. Return Contribution	2.81%	3.01%	2.51%	2.72%	1.38%	1.69%	1.02%	1.53%
Ann. Risk	13.35%	5.85%	13.26%	5.55%	3.86%	4.28%	3.85%	4.21%
t Statistic	1.19	2.92**	1.07	2.78**	2.02*	2.24*	1.50	2.07*
Ann. Risk Contribution	73%	27%	74%	26%	46%	54%	47%	53%

Industry-adjusted returns over formation months

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Factors	Residual	Factors	Residual	Factors	Residual	Factors	Residual
Ann. Return Contribution	–1.25%	3.72%	–1.43%	3.33%	0.12%	2.13%	–0.13%	1.89%
Ann. Risk	5.77%	7.36%	5.69%	7.03%	2.72%	4.70%	2.73%	4.64%
t Statistic	–1.23	2.87**	–1.42	2.69**	0.24	2.57*	–0.26	2.32*
Ann. Risk Contribution	43%	57%	43%	57%	30%	70%	30%	70%

Panel C: Largest 200 Japanese Stocks from January 1998 to September 2024

Market-adjusted returns over formation months

	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Factors	Residual	Factors	Residual	Factors	Residual	Factors	Residual
Ann. Return Contribution	–0.39%	0.48%	–1.26%	0.00%	2.32%	1.68%	2.32%	1.50%
Ann. Risk	14.74%	4.67%	14.65%	4.45%	6.42%	4.54%	6.40%	4.55%

continued

t Statistic	−0.14	0.54	−0.44	0.00	1.87	1.92	1.88	1.71
Ann. Risk Contribution	82%	18%	83%	17%	65%	35%	65%	35%
	Industry-adjusted returns over formation months							
	Momentum_12m1M		Momentum_12m1M_exEAR		Momentum_12M_EAR		Momentum_12m1M_EAR	
	Factors	Residual	Factors	Residual	Factors	Residual	Factors	Residual
Ann. Return Contribution	−1.89%	0.56%	−2.29%	−0.04%	0.71%	2.18%	0.52%	1.93%
Ann. Risk	6.20%	6.40%	5.96%	6.19%	3.90%	5.29%	4.02%	5.24%
t Statistic	−1.58	0.45	−1.99*	−0.03	0.94	2.13*	0.67	1.91
Ann. Risk Contribution	49%	51%	49%	51%	37%	63%	39%	61%

Each month, we run a cross-sectional regression of one-month-ahead returns on a set of common factors. These include dummy variables based on Global Industry Classification Standards (GICS Level 3); market betas of the stocks in our universe; size (measured using market capitalization); value (book-to-market ratio); profitability (cash-based operating profitability, or operating income for financials); and the year-on-year change in total assets. With the exception of indicator variables, all factor scores are normalized to have a mean of zero and a standard deviation of one. We then perform a holdings-based attribution to decompose the performance of each strategy into a factor component and a residual component.[1] Ann.Return Contribution is the annualized average monthly return of a strategy's factor or residual component. Ann.Risk is the annualized standard deviation of the monthly contribution of the factor or residual component. Finally, Ann.Risk Contribution is the contribution of the factor or residual component to the overall risk of the strategy; for clarity, this metric is reported in relative terms.[9]
** and *indicate statistical significance in a two-tailed test at the 1% and 5% levels, respectively.

performance. To try to defuse the controversy around the existence of stock momentum above and beyond factor momentum, we isolate the component of stock momentum that comes from returns around earnings announcements and use it as our novel proxy for stock-specific momentum.

This longer-term earnings-announcement strategy differs from strategies used in studies of the post–earnings announcement drift that only consider the latest earnings surprise to avoid stale data. As a result, it is subject to much lower portfolio turnover than its shorter-term counterpart. Yet, contrary to some recent findings suggesting that the post–earnings announcement drift might be disappearing, we present ubiquitous evidence that our longer-term earnings-announcement strategy is predictive of future returns for the largest securities in several developed markets. Moreover, this performance is not subject to reversal in the long run. This seems to rule out the possibility that stock-specific momentum, or at the very least the dimension associated with the release of firm-specific information around earnings announcements, is the result of delayed overreaction. Instead, the evidence in our study is consistent with theories of underreaction to firm-specific news.

Finally, we show that the performance of the longer-term earnings-announcement strategy is largely unaffected by factor momentum and cannot be explained by the PC time-series factor momentum strategy of Ehsani and Linnainmaa (2022). By contrast, the performance of stock momentum is dominated by factor risk and subsumed in the US by PC time-series factor momentum. We also find particularly strong evidence of performance reversal for a long-term stock momentum strategy that excludes earnings-announcement returns from the formation period, indicating that investors may overreact to the information in common factors.

Our findings and those in prior studies suggest that much of the difficulty in explaining the momentum effect, despite the colossal efforts dedicated to its research, likely stems from its multifaceted nature. In turn, studies such as ours that shed light on the complex nature of stock momentum should help practitioners build more effective investment strategies. For instance, while earnings announcements capture one important aspect of firm-specific announcements, numerous other events could be considered in future research, such as news headlines about individual companies or analysts' upgrades/downgrades.

Editor's Note

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Notes

1. Each month, we estimate our cross-sectional model of stock returns in each of our universes of larger-cap stocks separately:

$$r_{t+1} = X_t \cdot \beta_{t+1} + \varepsilon_{t+1}$$

where r_{t+1} is a $N \times 1$ column vector of stock returns at time $t+1$, with N the number of stocks in the universe. X_t is the $N \times K$ matrix of factor scores at the previous month-end, and K the number of factors in our model. β_{t+1} is a $K \times 1$ column vector of estimated factor returns, and ε_{t+1} a $N \times 1$ column vector of residual returns.

This model is then used to decompose the performance of a strategy portfolio, $h_{p,t}$, into a factor and a stock-specific component:

$$r_{p,t+1} = h'_{p,t} \cdot r_{t+1}$$
$$r_{p,t+1} = h'_{p,t} \cdot X_t \cdot \beta_{t+1} + h'_{p,t} \cdot \varepsilon_{t+1}$$
$$r_{p,t+1} = x_{p,t} \cdot \beta_{t+1} + \varepsilon_{p,t+1}$$

where $x_{p,t} \cdot \beta_{t+1}$ is the factor contribution to the portfolio return and $\varepsilon_{p,t+1}$ its residual component.

2. Since we test multiple definitions of the momentum strategy, we need to account for multiple testing when interpreting the statistical significance of our findings. We control the family-wise error rate (FWER) of our group of tests under the global null hypothesis that all our momentum strategies have an expected return of zero. In line with common practice (see, e.g., Fama and French 2010), we address the dependence across experiments with a bootstrapping methodology. The bootstrap adjustment works as follows: We draw with replacement vectors of monthly strategy returns, across all the momentum strategies tested, to preserve their cross-sectional dependence under the global null hypothesis that the mean return of each strategy is zero. We then compute, for each resampled time series of strategy returns, a t statistic. The same process is repeated 5,000 times, and we compute the probability of observing in a resample at least one t statistic with a value as high or higher than those for each t statistic estimated from the original sample of momentum strategies.

   To test the specification of the bootstrapping adjustment, we used simulations and investigated Type I and Type II error rates. Assuming the global null is true, our test is well specified if we reject the null hypothesis for at least one strategy at the chosen significance level. This was estimated by repeating the bootstrap experiment 1,000 times and computing the probability of finding at least one strategy positive and significant at each iteration, across a range of significance levels. To run these simulations, we assumed that all strategy returns have an expected value of zero and that the data are either multivariate normal or log-normal (so we ran two analyses) with the covariance matrix of strategy returns equal to its estimated value using the original data. To assess the power of the test, that is, 1 – Type II error rate, we ran a similar simulation exercise where the expected strategy returns were those estimated from the original data (we took the mean of all positive estimates when a strategy average return was negative over the period of our analysis). Then, we computed the probability of finding at least one strategy significant under different significance levels.

   In short, we found that the realized Type I error rates across the range of significance levels considered fell closely in line with their theoretical values. Moreover, it appeared that using a significance threshold of 10% allows us to achieve a desirable balance between Type I and Type II error rates. While we rejected the null at least once across all strategies only 10% of the time when the global null hypothesis was true, we found at least one strategy significant more than 80% of the time when all strategies had a positive expected return estimated from the data. In comparison, not adjusting our tests for multiple testing led us to reject the null hypothesis at least once, when the global null was true, more than 20% of the time: more than twice the theoretical rate when the significance threshold is set to 10%. Evidently, when the global null was false, the rejection rate was also higher than when using our correction, but not dramatically so, as it reached 90%.

3. However, since we ran analyses with no month skipped for the standard stock momentum strategy and its counterpart that excludes returns around earnings announcement dates, we accounted for them when adjusting our tests for multiple testing.

4. It should be clear that the longer-term earnings-announcement strategy explains only a small proportion of the risk of the standard stock momentum strategy. We ran a time-series regression to decompose the monthly returns of the traditional stock momentum strategy and used this decomposition to compute the contribution to its risk of each one of its components. In the US, the market-adjusted (industry-adjusted) longer-term earnings-announcement strategy explains 9% (17%) of the risk of the corresponding stock momentum strategy. In Europe and Japan, the longer-term earnings-announcement component explains 7% (8%) and 8% (13%) of the risk of stock momentum, respectively.

5. To simulate the impact on performance from applying some leverage to the longer-term earnings-announcement strategy so that it achieves the same average turnover as stock momentum, we simply multiply performance by a constant

term equal to the value needed to bring the average turnover of the longer-term earnings-announcement strategy on par with that of stock momentum.

6. Implementation cost = 2 × one-way turnover × one-way transaction cost + borrowing cost.

7. The factor data are publicly available at https://jkpfactors.com/.

8. Factor definition (mnemonic): age (age), asset growth (at_gr1), total assets scaled by market equity (at_me), asset turnover (at_turnover), book equity scaled by market equity (be_me), CAPM beta (beta_60m), abnormal investment (capx_abn), investment growth (capx_gr1), change in shares - 12 month (chcsho_12m), net debt issuance scaled by asset (dbnetis_at), dividend yield (div12m_me), return on operating asset (ebit_bev), profit margin (ebit_sale), equity duration (eq_dur), equity net issuance scaled by asset (eqnetis_at), equity net payout (eqnpo_12m), Piotroski's *F* score (f_score), gross profitability (gp_at), inventory change one-year (inv_gr1a), Fama and French idiosyncratic vol. (ivol_ff3_21d), change in LT NOA scaled by average assets (lnoa_gr1a), market equity (market_equity), net issuance scaled by asset (netis_at), ROE (ni_be), net income scaled by ME (ni_me), quarterly income scaled by AT (niq_at), quarterly income scaled by BE (niq_be), net operating assets to total assets (noa_at), accruals (oaccruals_at), operating cash flow to market (ocf_me), change in PPE and inventory one-year (ppeinv_gr1a), R&D to sales (rd_sale), short-term reversal (ret_1_0), long-term reversal (ret_60_12), sales growth (sale_gr1), sales scaled by ME (sale_me), and share turnover (turnover_126d).

9. The attribution of the risk of each strategy into factor and idiosyncratic components is based on the return decomposition of note (1). The realized volatility of each strategy can be expressed as: $\sigma_p = \sqrt{1' \cdot \Phi \cdot 1}$, where $\Phi = \begin{pmatrix} \sigma_f^2 & \sigma_{f,\varepsilon} \\ \sigma_{f,\varepsilon} & \sigma_\varepsilon^2 \end{pmatrix}$ is the covariance matrix for the factor and specific components of strategy return, with σ_f^2 the realized variance of the return contribution of the *K* factors, σ_ε^2 the idiosyncratic risk, and $\sigma_{f,\varepsilon}$ the covariance between the contributions of the factor and the specific components of performance.

   The decomposition of strategy risk then broadly follows the methodology presented by Grinold and Kahn (2000). One can estimate the marginal contribution of each component by computing partial derivatives of $\sqrt{\omega' \cdot \Phi \cdot \omega}$ with respect to a variable vector, ω, and evaluate these at $\omega = 1$ to obtain their respective contribution to the risk of the strategy: contribution to strategy risk $= \frac{\partial \sqrt{\omega' \cdot \Phi \cdot \omega}}{\partial \omega}(1) = \frac{\Phi \cdot 1}{\sigma_p}$.

   In this article, we divide these contributions by σ_p so that they are expressed as a proportion of total strategy risk.

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