Asset Growth, Style Investing, and Momentum*

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Abstract

We establish a significant and robust connection between asset growth (AG) and style investing by showing that past style returns constructed based on AG and size jointly predict future stock returns significantly. Motivated by this notion, we propose a style momentum strategy based on AG and size and find that it dominates price momentum and size-BM style momentum in generating momentum profits. We examine two explanations for this predictability, including risk exposure to common risk factors and the limited-attention theory. Empirical evidence shows that the AG-size style momentum profit is induced because investors neglect the AG-size style performance, consistent with the limited-attention explanation, but not risk exposure to the investment factor. Further, we show that the profit of the AG-size style momentum is robust to different time periods partitioned by several time-series predictors.

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1. Introduction

In real investments, a style refers to a particular set of risky assets categorized by investors that share some common characteristics. The process by which investors allocate funds based on the relative performance of investment styles is known as "style investing." Barberis and Shleifer (2003) establish the linkage between investment styles and return predictability and present a model to show that style investing generates excess comovement of assets within styles and induces both style and asset-level momentum in the intermediate term and reversals in the long term. Confirming Barberis and Shleifer's (2003) prediction, Wahal and Yavuz (2013) find that past style returns formed on size and book-to-market (BM) ratio positively predict future stock returns and that a firm's comovement with its style plays an important role in generating momentum profits.

To test Barberis and Shleifer's (2003) predictions implied by style investing, it is important to have a concrete way to identify styles. In a broad sense, as a style refers to a group of stocks with similar characteristics that tend to perform analogously, market anomalies are in general considered possible candidates for styles (Bernstein, 1995). Indeed, starting from the 1980s, value/growth (measured by BM), size (measured by market capitalizations), and industry classifications are widespread descriptors of styles in the mutual fund industry and academic research (e.g., Haugen and Baker, 1996; Moskowitz and Grinblatt, 1999; Chan, Chen, and Lakonishok, 2002; Lewellen, 2002; Chen and De Bondt, 2004; Wahal and Yavuz, 2013). As market anomalies have been extensively proposed afterward, a fundamental question in regard to style investing arises: while classifying stocks into styles enables investors to simply investment decision making, can they benefit from a newly-documented anomaly by considering it as an investment style?

The investment style of our interest in exploring this issue is a firm's total asset growth (AG). This anomaly is initiated by Cooper, Gulen, and Schill (2008), who use AG to measure the synergistic effect of firms' investment and financing activities and show that firms experiencing rapid investment growth have lower subsequent stock returns. They also show that AG emerges as a more important predictor of stock returns compared with previously documented determinants of the cross-section of stock returns. After the publication of Cooper, Gulen, and

Schill in 2008, AG has received substantial attention in exploring the sources and robustness of its predictability and has become an important anomaly in academic research.[1]

We consider AG as an investment style for several reasons. First, prior literature on long-run event studies shows that corporate events associated with asset expansion tend to be followed by abnormally low returns, while events associated with asset contraction are generally followed by abnormally high returns.[2] As a broad measure that captures these asset-expansionary events, AG exhibits a certain familiarity to investors who seek potential investment targets with such event-oriented mispricing. Second, Cooper, Gulen, and Schill (2008) find that stocks with similar AG tend to share some common characteristics, hence AG conforms to the definition of investment styles. Finally, AG has more robust explanatory ability on stock returns than size and BM and exhibits a long-lasting effect on stock returns. Fama and French (2015) also demonstrate that firm investment is an important predictor of stock returns and can be a priced factor. Motivated by the ample evidence that style rotation provides potential benefits in enhancing investment profits (e.g., Chen and De Bondt, 2004; Kao and Shumaker, 1999; Levis and Liodakis, 1999; Lucas, van Dijk, and Kloek, 2002) and Fama and French's (2015) recent evidence, we examine whether AG could be an investment style to investors.

To enhance the information content in predicting future stock returns, we augment AG with firm size as the investment style. This is motivated by Fama and French (2008), who document that size provides incremental information in dissecting the AG anomaly. Since style investing refers to the process of categorizing stocks that perform analogously, a style formed on the intersection of AG and size can better differentiate the relative performance across style portfolios.[3]

We first apply Fama and MacBeth's (1973) cross-sectional regressions to show that past style returns constructed based on the interactions of AG and size have significant predictive power on stock returns over subsequent 1-, 3-, 6-, and 12-month horizons. This predictability is sustained when past stock returns, size-BM-sorted style returns, and firm characteristics such as

[1] Titman, Wei, and Xie (2013) and Watanabe, Xu, Yao, and Yu (2013) extend this line of research to international markets, whereas Lam and Wei (2011), Li and Zhang (2010) and Lipson, Mortal, and Schill (2011) investigate the role of the q-theory with investment frictions and the limits-to-arbitrage theory in explaining the AG effect.

[2] For a detailed list of references, please refer to footnote 1 of Cooper, Gulen, and Schill (2008).

[3] Whether the AG-size style generates better return predictability is actually an empirical issue. We show in Tables 1 and A1 that styles formed on AG or size alone and the AG-BM style do not generate consistent return predictability, while the AG-size style performs well in predicting future stock returns. This evidence is consistent with Fama and French's (2008) finding that conditioning on size enhances the explanatory power of AG.

size, BM, and AG are incorporated into the regressions. Furthermore, when stock returns are adjusted using Fama and French's (1993) three-factor model, the explanatory power of past returns and size-BM style returns is eliminated by the inclusion of AG-size style returns. This evidence suggests that the AG-size style plays a dominant role in generating the positive return predictability over the intermediate horizons.

Given the fact that AG-size style generates return predictability, it is of interest to identify whether AG-size serves as a style to investors. Barberis and Shleifer (2003) show theoretically that style investing generates excess comovement of stocks within a style. Wahal and Yavuz (2013) further show that if stocks are correctly classified into styles, the excess comovement within styles due to investors' style-chasing behavior could generate return predictability. To verify AG-size as a useful style to investors, we measure comovement with the AG-size style following Wahal and Yavuz's (2013) approach and show that this comovement generates variations in return predictability.

We next propose an AG-size style momentum strategy based on Jegadeesh and Titman's (1993) portfolio-based procedures and examine the properties of its profits. Two interesting findings emerge. First, for the 6-month formation and holding periods, the average monthly profit obtained from buying the winner style decile and short selling the loser style decile is 0.909% and is still 0.764% under Fama and French's (1993) risk adjustments. This significant profit is robust regardless of the lengths of formation (6 and 12 months) and holding (1, 3, 6, and 12 months) horizons and is not sensitive to the cutoff points used to identify winner and loser portfolios. Second, using George and Hwang's (2004) regression approach, which enables us to compare the relative performance of several momentum strategies simultaneously, we find that our AG-size style momentum dominates price momentum and size-BM style momentum in generating momentum returns.

Our findings are related to Nyberg and Pöyry (2014), who provide the first linkage between firm-level asset changes and the price momentum. They document a U-shaped AG-momentum relation; that is, momentum profits are higher and more significant for firms that experience large asset expansions or contractions. We extend their results by showing that, in addition to being a conditioning variable in grouping stocks to distinguish the magnitude of momentum profits, AG can also be a potential investment style in generating momentum profits. Our evidence suggests that not only the level of asset changes but also the past performance of a stock's corresponding AG-associated style can provide incremental information to investors when making investment decisions.

We propose two potential explanations for AG-size style momentum profits. First, Fama and French (2015) and Hou, Xue, and Zhang (2015) both demonstrate that AG represents a form of common risk factor, thus the AG-size style momentum profit might be the result of higher risk exposure to an AG related factor. Second, if investors neglect the relative performance of stocks with a different magnitude of AG, they might underreact to the information embedded in this investment style. According to the limited-attention theory, we hypothesize that the AG-size style momentum profit is higher among stocks with a limited capacity in drawing investors' attention.

We first examine the risk-based explanation for the AG-size style momentum profit. If AG-size style momentum is induced because it has higher risk exposure to AG, its profit shall be higher among stocks with higher investment betas. Using Fama and French's (2015) five-factor model to estimate the investment beta for each individual stock, we show that AG-size style winners consistently outperform AG-size style losers even after controlling for investment betas. Thus the profit of AG-size style momentum is unaffected by the risk exposure to the investment factor.

If investors neglect the AG-size style performance, they will underreact to the information embedded in the style, thus contributing to AG-size style momentum profit. If this hypothesis holds true, we expect higher AG-size style momentum profit among styles that exhibit stronger delayed reaction to market information. To explore this possibility, we follow Chordia and Swaminathan (2000) to construct the measure of price delay (PD) for each style portfolio. The analysis based on the double-sorting procedure by style returns and style PDs shows that the AG-size style momentum profits are higher among style portfolios with higher PDs.

Investor inattention is another important channel for underreaction because limited attention causes investors to ignore useful information and results in subsequent underreaction (Dellavigna and Pollet, 2007, 2009; Hirshleifer, Lim, and Teoh, 2009; Hou, Peng, and Xiong, 2009). In this channel, it is important to identify the flow of information and justify how investors perceive and react to it. To examine this issue, we follow Da, Gurun, and Warachka (2014) to construct the information discreteness (ID) to proxy for individual stocks' information flows and examine whether a stock's ID is associated with future returns. The construction of ID is based on the notion that investors underreact to information arriving continuously in small amounts than to information arriving in large amounts at discrete time intervals. Specifically, we show that the AG-size style momentum profits are stronger among stocks with more continuous information than those with more discrete information. In short, these findings confirm our conjecture that AG-size style performance draws limited attention from investors and further induces underreaction-oriented momentum profits.

While Subrahmanyam (2018) claims that the source of momentum is still debating, our findings contributes to this emerging debate by providing support for the underreaction story of momentum. Our evidence is also in line with Conrad and Yavuz's (2017) research, which documents that conditioning on firm characteristics such as size and BM helps separating reversals from momentum. We show further that sorting on AG and size enables us to facilitate momentum profits through style investing, which could be a more useful trading strategy to generate momentum.

We further explore why investors underreact to AG-size style past performance. Motivated by Mullainathan's (2002) theory of categorical thinking that there is underreaction within categories and overreaction when category switching occurs, we propose that investors' underreact to style performance among stocks that do not migrate across styles. We confirm this prediction by showing that investors tend to underreact to the style performance of stocks staying in the same AG-size style, thus contributing to the AG-size style momentum profit. When stocks experience style migration, the AG-size style momentum profit is irrelevant to investor underreaction.

As robustness tests, we examine the time-series patterns of AG-size style momentum profits conditional on several predictive variables that explain the momentum effect in the literature, including business cycles, market states, market volatilities, and investor sentiment. By taking these conditioning variables into account, we show that the traditional size-BM style momentum displays considerable variations over time while AG-size style momentum profits are quantitatively and statistically similar across different time periods. This evidence indicates that size-BM and AG-size style momentum strategies exhibit distinct time-varying patterns and further leads to an important implication, namely, that smart investors can take advantage of the market by searching for possible styles (like AG) to invest before professional traders pay attention to such new investment strategies. By doing so, they can generate significant and consistent profits over time.

The remainder of this paper is organized as follows. Section 2 describes the data and style identification. In Section 3, we examine the predictability of AG-size style returns and properties of the AG-size style momentum. Section 4 discusses possible risk-based explanations and limited-attention theory in explaining our results. We investigate the time-series pattern of AG-size style momentum profits in Section 5. Finally, Section 6 concludes.

2. Data and constructions of style returns

Our sample consists of all common stocks with shares codes of 10 and 11 trading on NYSE, AMEX, and Nasdaq between January 1963 and December 2012. Daily and monthly market data of individual stocks are retrieved from the Center for Research in Security Prices (CRSP) database. We also obtain accounting data from the COMPUSTAT database. To be included in our sample, a stock must have sufficient market and accounting data.

We consider three investment styles, including size, BM, and AG. The calculation of size and BM is the same as in Fama and French (1992). From July of year T to June of year T+1, we define size as the market value of common equity at the end of June in year T. BM is calculated as the ratio of book value of equity at the end of year T–1 divided by market capitalization at the end of year T–1. As in Fama and French (1992), we exclude stocks with negative BM ratios and winsorize size and BM at the 1st and the 99th percentiles to avoid the influence of outliers. To measure the degree of a stock's asset expansion, we follow Cooper, Gulen, and Schill (2008) and other follow-up studies by calculating the changes in total assets. Specifically, at the beginning of July in year T, we calculate AG as

$$AG_{i,T} \equiv \frac{TA_{i,T-1} - TA_{i,T-2}}{TA_{i,T-2}}, \tag{1}$$

where $TA_{i,T-1}$ is stock i's total assets in fiscal year T–1.

We construct AG-size style returns by allocating individual stocks into 5×5 portfolios based on their values of AG and size in an independent way.[4] For each of the 25 style portfolios, we

[4] We compute size breakpoints using the full set of all individual stocks. In unreported results, we demonstrate the robustness of our findings using size breakpoints based on NYSE stocks only. The results are similar and are available upon request. Also, an alternative way is to construct AG-BM style returns by forming 5×5 portfolios

calculate monthly value-weighted style returns using the market capitalizations of stocks in the previous month as the weights. In addition to AG-size style returns, we also consider size-BM style returns as alternative strategies for comparisons, which are constructed in a similar way.

3. AG-size as a style in momentum investing

We first examine whether AG-size style returns have predictive power in explaining the cross section of stock returns based on Fama and MacBeth's (1973) regressions controlling for past returns, size-BM style returns, and firm characteristics. Next we follow Jegadeesh and Titman's (1993) portfolio-based procedures to observe the patterns of AG-size style momentum profits. To ensure the validity of the AG-size style momentum profit, we conduct George and Hwang's (2004) cross-sectional regressions to compare the relative performance of alternative momentum strategies.

3.1. Fama and MacBeth (1973) regressions

We first provide Fama and MacBeth's (1973) regressions to examine the predictability of the AG-size style returns on future stock returns. To investigate whether past performance predicts future stock performance, we calculate average style returns and past stock returns over the past 6 or 12 months as the independent variables. We also incorporate the logarithm of size and the logarithm of BM and AG as independent variables to control for the explanatory power of these anomalies in the cross section. As in Wahal and Yavuz (2013), we calculate the cumulative returns of individual stocks over the subsequent 1-, 3-, 6-, and 12-months holding horizons with a one-month skip as dependent variables.[5]

Once we construct all dependent and independent variables, we perform cross-sectional regressions every month and report average coefficients and corresponding *t*-statistics that are adjusted by Newey and West's (1987) robust standard errors. For each holding period, we report two specifications: (i) a model that includes past stock returns, size-BM, and AG-size style

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based on values of AG and BM. We show in Table A1 that AG-BM style returns do not generate consistent predictive power for future stock returns.

[5] The one-month skip between formation and holding periods is imposed to avoid potential problems of microstructure biases (Jegadeesh, 1990; Lo and MacKinlay, 1990). The significance of coefficients on style returns remains virtually unchanged without the imposition of the one-month skip. In particular, unlike past stock returns, style returns exhibit no short-term return reversals, a phenomenon that is observable from the significantly positive coefficients in explaining the one-month future stock returns.

returns and (ii) a full model that includes ln(*Size*), ln(*BM*), *AG*, past stock returns, and all sets of style returns. Table 1 presents the estimation results. Panels A and B correspond to past performance measured over the prior 6 and 12 months, respectively.

[Insert Table 1 about here]

Our primary interest is in the predictability of past style returns. For the first specification without including firm characteristics, the coefficients on size-BM and AG-size style returns (i.e., *Sret*(*S*,*B*) and *Sret*(*A*,*S*)) are all significantly positive regardless of the lengths of formation and holding horizons. The inclusion of firm characteristics weakens the significance of size-BM style returns but not that of AG-size style returns. Specifically, the explanatory power of size-BM style returns totally disappears in the second specification, whereas coefficients on *Sret*(*A*,*S*) remain significantly positive across all holding horizons. This evidence indicates that the predictability of AG-size style returns is the most prominent among the two measures of past style returns.

Notably, in the second specification coefficients on ln(*Size*), ln(*BM*) and *AG* are all significant across all holding horizons. In particular, coefficients on ln(*Size*) and *AG* are negative and those on ln(*BM*) are positive, consistent with the literature that the three anomalies are important to the U.S. stock market. As pointed out in Wahal and Yavuz (2013), the explanatory power of size and BM as styles is not subsumed by their characteristics. Our evidence suggests that the predictability of the size-BM style can be simply attenuated by the AG effect. AG-size as a style, however, offers incremental information in explaining future stock returns beyond the AG anomaly, which again confirms the importance of AG in style investing.

Another interesting finding from Table 1 is that past stock returns fail to account for future stock return predictability when AG-size style returns are incorporated in the regressions. This evidence indicates that the predictability of stock returns and style returns may not be exclusive and may be correlated. More important, our results imply that investors do not need to pay attention to the past performance of all stocks when making investment decisions. Rather, it suffices to observe the overall time-varying patterns of AG-size style portfolios and trade according to the information embedded in these style return patterns.

Because the style returns are constructed based on the interaction of AG and size, it is important to clarify whether the predictability comes sorely from AG or size. To this end, we construct AG (size) style returns, denoted as *Sret*(*A*) (*Sret*(*S*)), by allocating individual stocks into 10 portfolios based on their values of AG (size) and perform Fama and MacBeth's (1973) regressions by including the two style returns. Panels C and D of Table 1 correspond to past performance measured over the prior 6 and 12 months, respectively.

It is notable that *Sret*(*S*) significantly predicts future stock returns in all holding lengths while the predictability of *Sret*(*A*) exists for 3- and 6-month holding periods in the first model specification. When firm characteristics are included, as presented in the second specification, the significance of the two style returns disappears. Thus the return predictability is induced by AG and size jointly as a style, rather than separately.

3.2. Do stocks comove within the AG-size style?

Before we formally examine whether the AG-size style could be a profitable trading strategy, it is important to confirm the validity of this style. In particular, Barberis and Shleifer (2003) propose a theoretical model to illustrate that style investing generates not only intermediate-term momentum but also comovement of stocks within a style. To verify AG-size as a useful style, it is important to demonstrate that comovement of stocks with this style generates variations in price momentum profits.[6]

If stocks are correctly classified into styles and all stocks within a style are subject to the same level of style investor flows, investors' style-chasing behavior could result in excess comovement with styles. As a result, comovement should play an important role in accounting for this predictability if style chasing generates return predictability. One way to measure a stock's comovement with its style is the style beta, which can be obtained from the univariate time-series regression of daily stock returns on daily style returns, expressed as follows:

$$r_{i,s,d} = \alpha_i + \beta_{i,s} r_{s,d} + \varepsilon_{i,d}, \tag{2}$$

where $r_{i,s,d}$ is the return of stock *i* belonging to style *s* based on AG and size on day *d*, and $r_{s,d}$ is the value-weighted return of style *s* on day *d*. As in Barberis, Shleifer, and Wurgler (2005) and Wahal and Yavuz (2013), we exclude stock *i* in calculating the style return ($r_{s,d}$) to avoid any mechanical correlation between stock *i* and the style portfolio. $\beta_{i,s}$ is thus stock *i*'s style beta (comovement) with its style. To estimate Equation (2), we follow Wahal and Yavuz (2013) by using the past three months of daily returns with at least 20 available observations as the

[6] We thank a referee for suggesting this analysis.

estimation window. The regression is estimated rolling forward one month at a time, generating time series estimates of $\beta_{i,s}$.

Once the estimates of $\beta_{i,s}$ are obtained every month, we form portfolios based on the interactions of price momentum and style betas. In each month *t*, we first sort individual stocks into three groups based on past 12-month stock returns. Within each of the three portfolios, we allocate all stocks into three comovement groups (denoted as C1, C2, and C3), with C3 being the group of the highest comovement. Each of the nine portfolios is constructed with equal weights and held for subsequent *K* months (where *K* = 3, 6, and 12) with the one-month skip.[7] We calculate monthly returns for each portfolio with the overlapping procedure across the *K* positions. In addition to raw returns, we also show risk-adjusted returns by obtaining the intercepts from time-series regressions on Fama and French's (1993) factors. Data on the factors are downloaded from Kenneth French's website.[8] We hypothesize that if the AG-size style generates momentum profit, higher momentum profits will be prevalent in the C3 group rather than in the C1 group.

Table 2 shows that price momentum profits increase with style betas. Taking the 6-month holding horizon for example, the price momentum generates an average raw returns of 0.143%, 0.447%, and 0.595% for C1 to C3 groups, resulting in a significant difference of 0.452% (*t*-statistic = 4.30) between C3 and C1 groups. This finding is robust to different holding lengths and risk-adjusted returns. In line with Barberis and Shleifer's (2003) model and Wahal and Yavuz's (2013) argument that all stocks within a style are subject to the same level of style flows, our results suggest that AG-size serves as a useful investment style to investors.

[Insert Table 2 about here]

3.3. Profit of the style momentum based on AG and size

The results from above analyses are suggestive. Our next interest is just how much investors can earn if they implement the trading strategy suggested by the AG-size style predictability. We investigate this issue by calculating the AG-size style momentum profits based on the portfolio-based procedures proposed by Jegadeesh and Titman (1993), which has been widely

[7] We do not report the results for *K* = 1 to conserve space. They are robust and are available upon request.
[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

adopted in the literature (e.g., Chan, Jegadeesh, and Lakonishok, 1996; Griffin, Ji, and Martin, 2002; Grundy and Martin, 2001; Gutierrez and Pirinsky, 2007; Jegadeesh and Titman, 2001). In each month *t*, we first rank the 25 AG-size style portfolios based on their average value-weighted returns over prior 6 or 12 months.[9] We then classify style portfolios ranked at the top 10% or 30% (the top two or seven style portfolios that performed best, respectively) as the winner styles, and those ranked at the bottom 10% or 30% (the bottom two or seven style portfolios that performed worst, respectively) as the loser styles. We then hold the stocks that belong to the winner styles and short sell those that belong to the loser styles over the following 1, 3, 6, and 12 months with the one-month skip between formation and holding periods. These portfolios are equally weighted. In each month *t*, the return on the AG-size style momentum is calculated as the difference between the winner and loser portfolio returns, averaged across K separate positions (K = 1, 3, 6, 12), each formed in one of the K consecutive prior months from $t-K$ to $t-1$. Table 3 reports and tests average momentum returns with *t*-statistics adjusted for autocorrelation and heteroskedasticity using Newey and West's (1987) standard errors. In addition to raw returns, the table reports risk-adjusted returns by obtaining the intercepts from time-series regressions on Fama and French's (1993) factors.

[Insert Table 3 about here]

The momentum profits are remarkably high regardless of the lengths of formation (6 and 12 months) and holding (1, 3, 6, and 12 months) periods. The results are also robust to the cutoff points used to identify winner and loser styles. Taking past 12-month style returns with 30% cutoff points as an example, the momentum profits are 0.761% (*t*-statistic = 4.83), 0.670% (*t*-statistic = 4.87), 0.626% (*t*-statistic = 4.64), and 0.480% (*t*-statistic = 3.74) for the 1-, 3-, 6-, and 12-month holding periods, respectively. These returns remain significantly positive at the 1% significance level when they are adjusted by Fama and French's (1993) three-factor model. Similar patterns are observed when past performance is evaluated by past 6-month style returns. In addition, momentum profits are slightly higher when we focus on relatively extreme observations; that is, when winners and losers are identified using 10% cutoff points.[10]

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[9] In addition to AG, Li and Zhang (2010) illustrate five additional variables that are related to the investment-based anomaly. We replicate the same analysis for each of the five variables using the 30% cutoffs to identify style winners and losers and report the results in Table A2. The detailed definitions of the five variables are provided in the Appendix. The overall evidence suggests that our findings are not special to AG but also hold true for all asset expansion related variables that have been demonstrated to explain the cross section of stock returns.

[10] Prior literature widely documents that traditional momentum strategies exhibit reversals in January months due to

3.4. Style momentum profits conditional on other momentum strategies

In addition to the portfolio analysis, we also perform the Fama and MacBeth (1973) style cross-sectional regression developed by George and Hwang (2004) to examine the relative performance of the AG-size style momentum compared with other momentum strategies. We simultaneously consider the price momentum of Jegadeesh and Titman (1993) and the size-BM style momentum as comparisons. A major advantage of this approach is that we can isolate the confounding effects due to microstructure problems such as the bid-ask bounce and the interactions of different momentum strategies. As a result, we can facilitate the estimation of the net premium related to each momentum strategy. In each month t, we perform the following cross-sectional regressions for j = 2 to j = 7 or j = 2 to j = 13:

$$\begin{aligned} r_{i,t} = {} & b_{ojt} + b_{1jt} r_{i,t-1} + b_{2jt} \ln(Size)_{i,t-1} + b_{3jt} PRW_{i,t-j} + b_{4jt} PRL_{i,t-j} + b_{5jt} SRW(S,B)_{i,t-j} \\ & + b_{6jt} SRL(S,B)_{i,t-j} + b_{7jt} SRW(A,S)_{i,t-j} + b_{8jt} SRL(A,S)_{i,t-j} + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $r_{i,t}$ is the return of stock i in month t; $\ln(Size)_{i,t-1}$ is the natural logarithm of stock i's market capitalization at the end of previous month; $PRW_{i,t-j}$ ($PRL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past return over the prior 12 months is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $SRW(S,B)_{i,t-j}$ ($SRL(S,B)_{i,t-j}$) is a dummy variable that equals 1 if the prior 12-month return of the size-BM style portfolio to which stock i belongs is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise; and $SRW(A,S)_{i,t-j}$ ($SRL(A,S)_{i,t-j}$) is a dummy variable that equals 1 if the prior 12-month return of the AG-size style portfolio to which stock i belongs is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise.[11]

In each month t, we estimate 6 (12) cross-sectional regressions for j = 2 to j = 7 (j = 2 to j = 13) and average the corresponding coefficient estimates. For example, the return of pure AG-size style winner (loser) portfolio with the 12-month holding period in month t is calculated as

investors' tax consideration, known as the tax-loss-selling effect (Jegadeesh and Titman, 1993; Chan, Jegadeesh, and Lakonishok, 1996; Chordia and Shivakumar, 2006). George and Hwang (2004) point out that such phenomenon is a consequence of investors evaluating their capital losses of individual stocks rather than portfolios. As the AG-size style momentum involves trading based on past performance of AG-size style portfolios, we also show in untabulated results that its predictability is not subject to January reversals.

[11] To conserve space, we conduct the remaining analyses based on style portfolios' past 12-month performance. The results based on past 6-month style returns are quantitatively and statistically similar and are available upon request.

$\bar{b}_{7t} = \frac{1}{12}\sum_{j=2}^{13} b_{7jt}$ ($\bar{b}_{8t} = \frac{1}{12}\sum_{j=2}^{13} b_{8jt}$). The difference between $\bar{b}_{7t}$ and $\bar{b}_{8t}$ is thus the net return of the AG-size style momentum controlling for other confounding effects. We test the coefficients using Newey and West's (1987) standard errors to adjust for autocorrelation and heteroskedasticity. In addition to raw returns, we also obtain the intercepts from a time-series regression of monthly returns of the portfolio on the contemporaneous Fama-French factor realizations as risk-adjusted returns. Table 4 gives the estimation results.

[Insert Table 4 about here]

We find that the three strategies all generate significantly positive momentum profits and that the AG-size style momentum has the highest profits among the three strategies in most cases. For example, for the 6-month holding periods, the AG-size style momentum yields an average monthly return of 0.452% (t-statistic = 6.30), which is higher than 0.281% (t-statistic = 1.92) of the price momentum and 0.249% (t-statistic = 3.02) of the size-BM style momentum. The higher t-statistic of the AG-size style momentum indicates that its profit is relative stable and less volatile over time. Taking a closer look, we find that the AG-size style winners and losers both contribute to the profit of the AG-size style momentum. Furthermore, the magnitude of the AG-size style momentum profit remains roughly the same when the Fama-French risk adjustment is taken into account. As a comparison, the Fama-French risk adjustment enhances the profit of the price momentum but not those associated with the style momentum strategies. In sum, evidence from Table 4 indicates that the significantly positive returns of the AG-size style momentum are robust when controlling for the effects of other momentum strategies and that the AG-size style momentum plays the dominant role in generating intermediate-term return continuation, which is relatively consistent over time.[12]

4. Sources of style momentum profits

To understand the driving forces behind the AG-size style momentum profits, we explore two alternative explanations in this section. The first is related to the risk-based explanation the second provides a linkage between limited attention and style momentum profits. We discuss the details and provide corresponding tests sequentially.

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[12] In untabulated results, we also show that the AG-size style momentum is not subject to long-term reversals while the price momentum has negative returns across the second- to the fifth-year holding periods. Thus the profit of the AG-size style momentum is more persistent over investment horizons.

4.1. Risk explanation: Is it risk exposure to the investment factor?

Although the results from Table 4 indicate that the AG-size style momentum generates significant abnormal returns after controlling for Fama and French's (1993) risk factors, we cannot rule out the possibility of risk-based explanation for the momentum profit. In particular, as Fama and French (2015) and Hou, Xue, and Zhang (2015) both include AG as a common risk factor, a plausible conjecture is to link the AG-size style momentum profit with risk exposure to AG.[13] To measure risk exposure to AG, we estimate the investment betas for individual stocks using the time-series regression on Fama and French's (2015) five-factor model, expressed as:

$$r_{i,t} - r_{f,t} = \beta_0 + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_{i,t}, \qquad (4)$$

where MKT_t, SMB_t, HML_t, RMW_t, and CMA_t represent factor risk premiums associated with the market, size, value, operating profitability, and investment, respectively, in month *t*. Data on the factor risk premiums are again obtained from Kenneth French's website. For each month *t*, the regression is estimated using past five-year data with at least 24 available observations as the estimation window. β_{CMA} is thus the stock's investment beta.

Once we obtain the estimations of β_{CMA} every month, we form portfolios based on the interactions of style returns and investment betas. In each month *t*, we first sort individual stocks into three groups based on past 12-month AG-size style returns as described in Section 3.3. Within each of the three style portfolios, we allocate all stocks into three investment beta groups (denoted as B1, B2, and B3), with B3 being the group of the highest investment beta. Each of the nine portfolios is constructed with equal weights and held for subsequent *K* months (where *K* = 3, 6, and 12) with the one-month skip. Similarly, we calculate monthly returns for each portfolio with the overlapping procedure across the *K* positions. If the AG-size style momentum profit is due to higher risk exposure to the investment factor, higher momentum profits will be prevalent in the B3 group rather than in the B1 group.

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[13] We thank a referee for suggesting this hypothesis. In unreported results, we also show that the long-term persistency of the AG-size style momentum is explained by Fama and French's (2015) five-factor model. The AG-size style momentum profit in the intermediate term, however, remains significant when the returns are adjusted by Fama and French's (2015) five-factor model. The evidence suggests that the sources of the AG-size style momentum in intermediate and long terms might be different. Here we focus on the intermediate-term holding periods only.

Panel A of Table 5 shows that the AG-size style momentum profits exhibit indistinguishable patterns across investment beta groups. The difference in momentum profits between B3 and B1 groups are insignificant at −0.002%, 0.037%, and −0.058% for 3-, 6-, and 12-month holding periods. Similar patterns are observed for risk-adjusted returns in Panel B. Thus the AG-size style momentum profit is unlikely to be induced by higher risk exposure to the investment factor.

[Insert Table 5 about here]

4.2. Limited-attention explanation: Do investors neglect AG-size style performance?

We next examine whether the profit of the AG-size style momentum is induced because of investors' inattention in reacting to AG-size past performance. Based on this conjecture, we expect that investors tend to underreact to the information embedded in the prices of certain styles, which further induces subsequent continuation patterns associated with these styles. That is, the profit would be stronger among styles that display delayed reaction to the market information. To examine this conjecture, we first follow Chordia and Swaminathan (2000) to construct the price delay measure for each of the 25 AG-size style portfolios, which involves the estimation as follows:

$$r_{s,d} = \alpha_s + \sum_{k=-5}^{5} \beta_{s,k} r_{m,d-k} + \varepsilon_{s,d}, \tag{5}$$

where $r_{s,d}$ is the return of style s on day d, $r_{m,d}$ is the daily return of the NYSE, AMEX, and Nasdaq value-weighted market index on day d, and $\beta_{s,k}$ is the beta of style s with respect to the market return at lag k.

The speed of price adjustment is defined as $x_s = \sum_{k=1}^{5} \beta_{s,k} / \beta_{s,0}$. Chordia and Swaminathan (2000) adopt a log transformation of this ratio to identify the magnitude of price delay (denoted as PD), expressed as

$$PD_s = \frac{1}{1+e^{-x_s}}. \tag{6}$$

The advantage of the log transformation moderates the influence of outliers and yields values between zero and one, with lower values signifying a faster speed of adjustment to the market information and higher values signifying a slower speed of adjustment. Thus, higher values of PD imply higher magnitude of delay reaction for the style portfolio. At the beginning of each month t in constructing the momentum strategy, we estimate Equation (6) by using the daily returns over the past one year with at least 20 available observations as the estimation window.

Once we obtain the estimation of PD for every style portfolio every month, we form 3 by 3 dependent-sorted portfolios according to past 12-month AG-size style returns and style PDs. We then construct three PD groups (denoted as D1, D2, and D3) within each of the three style portfolios, with D3 being the group of the highest PD. Each of the nine portfolios is constructed with equal weights and held for subsequent K months (where K = 3, 6, and 12) with a month skip. We hypothesize that if the AG-size style momentum profit is induced because of investors' inattention in recognizing AG-size as a potential investment style, higher momentum profits in the D3 group is expected. We report the average momentum profits conditional on PD in Panel A of Table 6.

[Insert Table 6 about here]

The results show that the average return of the AG-size style momentum monotonically increases with style PD. For the 6-month holding period, the momentum profits are 0.307%, 0.520%, and 0.630% for D1, D2, and D3 groups with a significant difference of 0.323% (t-statistic = 2.81) between D3 and D1 groups. This pattern is robust to different lengths of holding horizons and Fama-French risk adjustments and confirms our conjecture that the AG-size style momentum is profitable because investors have delayed reaction to AG-size style performance.

In addition to the PD measure, Da, Gurun, and Warachka (2014) construct another information measure by isolating the information flow into continuous information and discrete information to capture the degree of investors' limited attention. In particular, they propose a frog-in-the-pan hypothesis, which asserts that a series of frequent gradual changes attracts less attention than infrequent dramatic changes, to explain momentum profits. We hypothesize that if the past performance of stocks in the winner and loser styles is generated by frequent gradual changes, such information may be neglected by investors, resulting in subsequent return continuations of stocks. That is, the theory of limited attention implies that investors are more likely to underreact to the information flow of stocks within the AG-size style winner and loser portfolios.

We first follow Da, Gurun, and Warachka (2014) to construct the ID measure for individual stocks (denoted as ID_i), which is defined as

$$ID_i = \text{sgn}(PRET_i) \times [\%neg_i - \%pos_i], \tag{7}$$

where $PRET_i$ is the cumulative return of stock i during the formation period of past 12 months, and $\%neg_i$ and $\%pos_i$ denote the percentages of days with negative and positive returns of stock i during the formation period. The sign of $PRET_i$ is denoted as sgn($PRET_i$), which equals +1 when $PRET_i > 0$ and –1 when $PRET_i < 0$. For the estimation of ID, we require stocks having at least 20 observations.

By construction, a higher value of ID_i signifies discrete information, and a lower value of ID_i signifies continuous information. According to Equation (7), higher percentages of positive (negative) returns culminating in positive (negative) $PRET_i$ yield lower values of ID_i. A higher value of ID_i, however, implies that the positive (negative) $PRET_i$ is generated by a few large positive (negative) past returns whereas the majority of daily returns are negative (positive). Such small amounts of large positive (negative) returns in generating the positive (negative) $PRET_i$ tend to be discrete information.

To examine the importance of ID_i to style momentum, we form double-sorted portfolios sequentially that are first conditioned on past style returns and then on ID_i. Specifically, we sort style portfolios into three groups according to their past 12-month returns and then subdivide these groups into ID_i subgroups. Each of the nine portfolios is constructed with equal weights and held for subsequent K months (where K = 3, 6, and 12) with a month skip. Panel B of Table 6 reports raw and Fama-French risk-adjusted returns of these portfolios.

Consistent with the limited-attention explanation, we observe monotonic decreasing patterns of momentum profits from low ID_i (D1) to high ID_i (D3) groups. The differences in the AG-size style momentum between D3 and D1 are –0.249% (t-statistic = –3.07), –0.259% (t-statistic = –3.37), and –0.133% (t-statistic = –1.71) for 3-, 6-, and 12-month holding periods, respectively. These differences increase in magnitude to –0.254%, –0.286%, and –0.184%; they are all significant at the 1% level under Fama-French risk adjustments. This finding suggests that AG-size style momentum is more pronounced among stocks that attract little investor attention, strengthening our evidence that information implied in the AG-size style is neglected by investors and that investor underreaction plays a role in generating such style-oriented return predictability.

4.3. Why do investors neglect the AG-size style performance?

Our analyses from Section 3.2 indicate that investors chase AG-size as an investment style, a further question is why investors pay limited attention to the AG-size style performance. Mullainathan's (2002) theoretical model of categorical thinking, a manifestation of representativeness heuristics and mental accounting, provides a plausible answer to this question. Based on the assumption that people can only hold a finite set of posteriors rather than every possible posteriors, his model predicts that investors tend to underreact when stocks stay in a group or style, while overreact when stocks switch across groups or styles. An important implication of Mullainathan's model to our results is that investors underreact to the information embedded in style performance when stocks stay in the same style. Style migration, however, mitigates the magnitude of underreaction. Several studies also demonstrate that stocks experiencing style migrations are subject to changes in equity valuation. For example, Fama and French (2007) attribute size and value premiums to migrations of stocks across size and BM portfolios. Chen and Wermers (2010) propose that investors require higher returns to compensate for higher risk associated with style migration. Ibbotson, Chen, Kim, and Hu (2013) show that as illiquid (liquid) stocks become more liquid (illiquid), they are subject to return increases (declines). These studies all point out the linkage between investors' attention and style migration.

We thus propose that investors' underreaction to style performance occurs when stocks experienced style stability. More specifically, if a stock remains in the same style, investors are more likely to ignore its style performance because their attention capacity is limited to stocks migrating across style portfolios. Style migration, however, is more likely to capture investors' attention and thus mitigates the magnitude of underreaction. We thus partition the sample into two subsamples, one containing stocks remaining in the same AG-size style and the other containing stocks migrating to another AG-size style. We replicate the methodology described in Section 3.3 to construct two AG-size style momentum strategies by partitioning style winners and losers into two subgroups that contain stocks staying in the same AG-size style and those belonging to two different AG-size styles for two subsequent years prior to the portfolio formation.

Panels A and B of Table 7 report the AG-size style momentum profits for subsamples of stocks with style stability and migration, respectively. We find that both subsamples generate significant momentum profits, despite the fact that stocks with style stability generate higher momentum profits than those with style migration. In particular, the raw momentum profit of the style stability group ranges from 0.604% to 1.098% while the momentum profit of the style migration group ranges from 0.265% to 0.354%.

[Insert Table 7 about here]

We further apply the analyses associated with ID in Section 4.3 for the two subsamples of style stability and migration, respectively. Panel A of Table 8 reveals the AG-size style momentum profits conditional on ID measures for the style stability group. The momentum profit monotonically decreases as ID increases. Taking 6-month holding horizon for example, the average momentum profits are 0.976%, 0.856%, and 0.587% for D1 to D3 groups, resulting in a significant difference of −0.389% (*t*-statistic = −3.35) between D3 and D1 groups. This pattern remains for risk-adjusted returns.

Panel B shows the AG-size style momentum profits conditional on ID measures for the style migration group. Across all holding horizons, we observe no significant difference in momentum profits between low and high ID groups. The 6-month momentum profits D1 to D3 groups are 0.427%, 0.224%, and 0.367%, with an insignificant difference of −0.060% (*t*-statistic = −0.40) between D3 and D1 groups. The overall evidence confirms our prediction that style migration mitigates investors' underreaction. Rather, investors tend to underreact to the style performance of stocks staying in the same AG-size style, further inducing the AG-size style momentum profit.

[Insert Table 8 about here]

5. Robustness of style momentum profits

To examine whether the AG-size style momentum displays predictable time-varying patterns or whether its profit is stable and persistent over time, we provide further tests conditional on several time-series predictors in this section.

5.1. Momentum profits conditional on business cycles

From a risk-based perspective, Chordia and Shivakumar (2002) propose that momentum profits are explained by common macroeconomic variables that are associated with business cycles. Specifically, their empirical evidence indicates that profits to Jegadeesh and Titman's (1993) price momentum are significantly positive during periods of expansion but negative (although insignificant) during periods of recession. As firm expansion on aggregate is highly related to business cycles, it is important to examine the impact of business cycles on our results. Nevertheless, because the AG-size style momentum is constructed based on past style returns, its predictability should be neutral to the overall AG of the market and is thus unrelated to business cycles. To examine our conjecture, we follow Chordia and Shivakumar (2002) to classify each holding month into expansionary and recessionary periods based on the definition of the National Bureau of Economic Research.[14] We then calculate average momentum profits estimated as in Equation (3) separately for the two periods and report the results based on 6- and 12-month holding periods in Panel A of Table 9.

[Insert Table 9 about here]

Unsurprisingly, the coefficients on the difference between *SRW*(*A*,*S*) and *SRL*(*A*,*S*) are significantly positive at the 1% level during both periods of expansion and recession regardless of the length of holding horizons and the Fama-French risk adjustments. The AG-size style momentum profit is even slightly higher during recessions. Taking the 6-month raw returns as an example, coefficients on *SRW*(*A*,*S*)–*SRL*(*A*,*S*) are 0.429% (*t*-statistic = 5.70) and 0.591% (*t*-statistic = 2.91) for expansions and recessions, respectively. Despite the relatively lower momentum returns during expansions, its higher corresponding *t*-statistic indicates that this profit is more stable and less volatile during expansions than during recessions.

The return patterns of the size-BM style momentum (i.e., *SRW*(*S*,*B*)–*SRL*(*S*,*B*)) are similar to those of the AG-size style momentum but with wider dispersions between expansionary and recessionary periods. The corresponding coefficients in columns 1 and 5 (i.e., the 6-month raw returns) are 0.176% (*t*-statistic = 2.13) and 0.695% (*t*-statistic = 2.67) for expansions and recessions, respectively. Finally, consistent with the literature, the profit to the price momentum is pronounced only during expansions but becomes insignificantly negative during recessions. To summarize, the results show that style momentum profits are in general robust to different conditions of business cycles.

5.2. Momentum profits conditional on market states

Another important time-series predictor of momentum is the state of the market, which is proposed by Cooper, Gutierrez, and Hameed (2004). They suggest that investor biases are more

[14] The reference dates of business cycles and the definition of expansions and recessions are obtained from the website of National Bureau of Economic Research. See http://www.nber.org/cycles/cyclesmain.html.

accentuated after market gains, further inducing the profit of the price momentum following positive market returns. To address whether the state of the market influences our results, we follow Cooper, Gutierrez, and Hameed (2004) to classify each formation period into different market states. At the beginning of each month *t*, we calculate the buy-and-hold return on the CRSP value-weighted index over the past 36 months prior to the holding period of the momentum strategies. If this return is nonnegative (negative), we classify the market state of month *t* as UP (DOWN).[15] After identifying the market state of each month *t*, we average coefficients estimated from Equation (3) separately for UP and DOWN markets, respectively. Panel B of Table 9 provides the results.

Among the three momentum strategies examined, we find that only the AG-size style momentum displays consistent profit across different market states. The 6-month AG-size style momentum profits are 0.424% and 0.598% for UP and DOWN markets, respectively. This pattern remains unchanged when the holding period is extended to 12 months or when the returns are adjusted using the Fama-French three-factor model. The price momentum, however, displays considerable variations across different market states, consistent with the vast literature on momentum. Specifically, the coefficients on *PRW–PRL* are significantly positive following UP markets and are significantly negative following DOWN markets (although the significance following DOWN markets disappears when risk adjustments are taken into account). Thus, even though the state of the market has strong predictive power on price momentum profits, it does not influence the profit of the AG-size style momentum.

5.3. Momentum profits conditional on market volatilities

Prior literature shows that, in addition to the first moment of past market returns, the second moment also can predict future performance of momentum strategies. Motivated by the notion that the extreme market volatility during the financial crisis is followed by dramatic losses of momentum strategies, Wang and Xu (2015) hypothesize that market volatility has significant power to forecast momentum profits. Specifically, they show that the profit of the price momentum is concentrated following periods of low market volatility but not following periods of high market volatility and that this effect is robust after controlling for market states and

[15] We also use past 12- or 24-month cumulative market returns to identify market states and obtain similar results. These unreported results are available upon request.

business cycles. To examine the impact of market volatilities on our findings, we follow Wang and Xu (2015) and divide our sample into periods of high and low market volatilities to examine the AG-size style momentum profits separately for the two subperiods.

To this end, we calculate two sets of past market volatility. For each month *t* of the holding period, we calculate the short-term (long-term) market volatility by computing the standard deviation of CRSP value-weighted daily returns over month $t-12$ to month $t-1$ (month $t-36$ to month $t-1$). If the short-term market volatility is larger (smaller) than the long-term market volatility, we define month *t* as high (low) volatility. Panel C of Table 9 reports profits to the momentum strategies separately for periods of high and low market volatilities. Again, we find that the coefficients on *SRW*(*A*,*S*)–*SRL*(*A*,*S*) are quantitatively and statistically similar in both states of market volatilities. This evidence suggests that the AG-size style momentum is unlikely to suffer from large losses even when the market is experiencing dramatic declines, and thus its profit is more consistent over time. In addition, we confirm Wang and Xu's (2015) finding by showing that the coefficient on *PRW*–*PRL* is significant and higher following periods of low volatilities and insignificant following periods of high volatilities.

5.4. Momentum profits conditional on investor sentiment

Antoniou, Doukas, and Subrahmanyam (2013) and Stambaugh, Yu, and Yuan (2012) both propose that market-wide investor sentiment should be related to momentum profits. They show that momentum profits are higher following periods of high (i.e., optimistic) sentiment and insignificant following periods of low (i.e., pessimistic) sentiment. Because we document a potential behavior explanation for AG-size style momentum profits based on the limited-attention argument, such behaviorally driven predictability may be related to investor sentiment. To explore this possibility, we use the monthly sentiment index constructed by Baker and Wurgler (2006, 2007) to measure the degree of investor sentiment for each month. We obtain the data on the sentiment index from Jeffrey Wurgler's website for the sample period from July 1965 to December 2010.[16] As in Stambaugh, Yu, and Yuan (2012), we classify each month *t* of the holding period as following a high-sentiment month if the value of the sentiment index in month $t-1$ is above the median value for the sample period, and the low-sentiment

[16] See http://pages.stern.nyu.edu/~jwurgler/. We adopt the orthogonalized sentiment index with respect to a set of macroeconomic conditions.

month are those with below-median values. We then examine the momentum profits separately for periods of high and low sentiment.

Panel D of Table 9 shows that the coefficient on *SRW*(*A*,*S*)–*SRL*(*A*,*S*) following periods of high sentiment is about double that of the corresponding values following periods of low sentiment. For example, the 6-month raw return of the AG-size momentum is 0.613% (*t*-statistic = 5.44) following high investor sentiment and 0.318% (*t*-statistic = 3.46) following low investor sentiment. This evidence indicates that investor sentiment is perhaps the most useful predictor of AG-size style momentum profits. As behavioral biases arise because sentiment traders exert greater influence during high-sentiment periods (Stambaugh, Yu, and Yuan, 2012), the effect of limited attention may be strengthened when sentiment is high. However, despite the distinct magnitudes of AG-size style momentum profits following high and low sentiment periods, they are both only significant at the 1% level. This result suggests that investor sentiment cannot fully explain the profit of the AG-size style momentum.

6. Conclusion

We establish a significant and robust connection between individual stocks' AG and style investing. Given that previous long-run event studies demonstrate a linkage between asset expansion/contraction and follow-up abnormal stock returns, AG exhibits a certain familiarity to investors who seek potential investment targets with such event-oriented mispricing. Also, AG serves as a good candidate of investment style to investors, as Cooper, Gulen, and Schill (2008) point out, AG exhibits a long-lasting effect on stock returns beyond size and BM, and firms with similar AG share some common characteristics. Motivated by this notion, we hypothesize that AG-size as a style can generate higher and more consistent profits than traditional styles such as size and BM.

We confirm this hypothesis by showing that past style returns constructed based on the interactions of AG and size significantly predict future stock returns over 1-, 3-, 6-, and 12-month horizons in the cross section. This predictability is robust after controlling for the effects of past stock returns, size-BM-sorted style returns, and firm characteristics such as size, BM, and AG. We thus propose a style momentum strategy based on AG and size and find that it dominates the price momentum and the size-BM style momentum in generating momentum profits.

We test two competing explanations for our findings. The first explanation examines whether the AG-size momentum profit is due to higher risk exposure to the investment factor. The second one is related to the limited-attention theory, which hypothesizes that investors underreact to the information embedded in the AG-size style performance. We provide evidence in support of the limited-attention explanation but not risk-based hypotheses, suggesting that investor underreaction better accounts for the profit of the AG-size style momentum.

We also investigate the time-series patterns of AG-size style momentum profits by considering several conditioning variables that are documented in prior studies to be related to the momentum effect. In general we find that the AG-size style momentum generates consistent profits over time. To conclude, our overall results have important implications to the literature that style investing based on newly proposed asset-pricing anomalies can generate significant and consistent profits when investors have yet paid sufficient attention to this new strategy.

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Table 1: Fama-MacBeth regressions of future stock returns

This table reports the average coefficients from the Fama-MacBeth regressions of future 1-, 3-, 6-, and 12-month cumulative returns on stock and style returns measured over past 6 (Panels A and C) and 12 (Panels B and D) months and firm characteristics including ln(*Size*), ln(*BM*), and *AG*. We exclude stocks with negative BM ratios and winsorize size and BM at the 1st and the 99th percentiles to avoid the influence of outliers. Past stock returns are calculated as the average monthly returns of individual stocks over the past 6 or 12 months (*Pret6* or *Pret12*). We form the AG-size style returns (*Sret*(*A,S*)) by allocating individual stocks into 5×5 portfolios based on their values of AG and size in an independent way. *Sret*(*S,B*), *Sret*(*S*), and *Sret*(*A*) are constructed in a similar way. For each of the 25 style portfolios, we calculate the average value-weighted style returns over the past 6 or 12 months. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	1-month future return		3-month future return		6-month future return		12-month future return	
Panel A: Style and stock returns measured over prior 6 months								
Pret6	0.109	0.091	0.742 **	0.689 **	1.667 **	1.657 ***	0.926	0.742
	(0.79)	(0.69)	(2.11)	(2.09)	(2.56)	(2.74)	(0.87)	(0.79)
Sret(*S,B*)	0.197 ***	–0.018	0.520 ***	–0.081	1.028 ***	–0.173	1.867 ***	–0.208
	(3.48)	(–0.46)	(3.49)	(–0.75)	(3.79)	(–0.88)	(3.65)	(–0.65)
Sret(*A,S*)	0.250 ***	0.139 ***	0.863 ***	0.487 ***	1.706 ***	0.864 ***	2.505 ***	0.951 ***
	(4.19)	(3.40)	(4.94)	(3.97)	(5.45)	(3.79)	(5.23)	(2.78)
ln(*Size*)		–0.183 ***		–0.541 ***		–1.211 ***		–2.804 ***
		(–3.86)		(–4.00)		(–4.98)		(–6.28)
ln(*BM*)		0.143 ***		0.466 ***		0.916 ***		1.658 ***
		(2.62)		(2.96)		(3.36)		(3.68)
AG		–0.396 ***		–1.108 ***		–2.068 ***		–3.268 ***
		(–7.80)		(–8.63)		(–8.87)		(–8.46)
Panel B: Style and stock returns measured over prior 12 months								
Pret12	0.108	0.089	0.755 **	0.683 **	1.771 ***	1.654 ***	1.278	0.734
	(0.78)	(0.67)	(2.16)	(2.06)	(2.74)	(2.72)	(1.22)	(0.77)
Sret(*S,B*)	0.264 ***	0.003	0.726 ***	0.008	1.291 ***	0.038	2.381 ***	–0.053
	(3.70)	(0.05)	(3.44)	(0.06)	(3.15)	(0.16)	(3.39)	(–0.14)
Sret(*A,S*)	0.345 ***	0.162 ***	1.052 ***	0.497 ***	1.956 ***	0.854 ***	2.840 ***	0.908 **
	(5.35)	(3.23)	(5.30)	(3.41)	(5.49)	(3.17)	(4.78)	(2.26)
ln(*Size*)		–0.210 ***		–0.606 ***		–1.319 ***		–2.931 ***
		(–4.30)		(–4.33)		(–5.24)		(–6.48)
ln(*BM*)		0.145 ***		0.486 ***		0.941 ***		1.596 ***
		(2.77)		(3.21)		(3.49)		(3.45)
AG		–0.395 ***		–1.090 ***		–2.012 ***		–3.258 ***
		(–7.71)		(–8.57)		(–8.85)		(–8.75)

Table 1 continued

Variable	1-month future return		3-month future return		6-month future return		12-month future return	
Panel C: Styles returns identified by size or AG alone over prior 6 months								
Pret6	0.133	0.088	0.827 **	0.673 **	1.826 ***	1.627 ***	1.172	0.647
	(0.99)	(0.67)	(2.42)	(2.05)	(2.91)	(2.69)	(1.19)	(0.69)
Sret(*S*,*B*)	0.186 ***	0.033	0.550 ***	0.026	0.985 ***	–0.053	1.553 ***	0.177
	(2.96)	(0.83)	(3.18)	(0.25)	(3.51)	(–0.28)	(3.45)	(0.56)
Sret(*A*)	0.098	0.044	0.465 *	0.244	1.086 **	0.664 *	1.196	1.001
	(1.00)	(0.53)	(1.83)	(1.16)	(2.43)	(1.81)	(1.55)	(1.47)
Sret(*S*)	0.531 ***	–0.173	1.269 ***	–0.424	2.335 **	–0.555	4.260 **	–0.940
	(3.05)	(–1.24)	(2.67)	(–1.18)	(2.53)	(–0.87)	(2.23)	(–0.83)
ln(*Size*)		–0.249 ***		–0.720 ***		–1.601 ***		–3.626 ***
		(–4.75)		(–4.88)		(–6.05)		(–7.45)
ln(*BM*)		0.140 ***		0.439 ***		0.879 ***		1.586 ***
		(2.71)		(2.90)		(3.37)		(3.74)
AG		–0.367 ***		–1.022 ***		–1.953 ***		–2.994 ***
		(–6.70)		(–7.37)		(–7.80)		(–7.38)
Panel D: Style returns identified by size or AG alone over prior 12 months								
Pret12	0.130	0.086	0.808 **	0.665 **	1.809 ***	1.616 ***	1.209	0.643
	(0.97)	(0.65)	(2.35)	(2.02)	(2.87)	(2.66)	(1.22)	(0.68)
Sret(*S*,*B*)	0.199 **	0.079	0.544 **	0.189	1.025 **	0.345	1.702 **	0.670 *
	(2.57)	(1.54)	(2.30)	(1.36)	(2.53)	(1.44)	(2.49)	(1.74)
Sret(*A*)	0.076	–0.035	0.420 *	0.023	1.036 **	0.225	1.133	0.509
	(0.78)	(–0.44)	(1.65)	(0.11)	(2.30)	(0.63)	(1.46)	(0.80)
Sret(*S*)	0.563 ***	–0.271 **	1.363 **	–0.710 **	2.279 **	–1.058	4.362 **	–1.371
	(2.91)	(–2.00)	(2.54)	(–2.00)	(2.20)	(–1.64)	(2.08)	(–1.12)
ln(*Size*)		–0.244 ***		–0.705 ***		–1.576 ***		–3.578 ***
		(–4.56)		(–4.66)		(–5.83)		(–7.21)
ln(*BM*)		0.143 ***		0.457 ***		0.899 ***		1.539 ***
		(2.86)		(3.18)		(3.53)		(3.52)
AG		–0.370 ***		–1.007 ***		–1.908 ***		–2.971 ***
		(–6.67)		(–7.20)		(–7.72)		(–7.54)

Table 2: Profits to the price momentum conditional on comovement with the AG-size style

In each month t, we estimate style betas for each stock with respect to its style portfolio using the equation $r_{i,s,d} = \alpha_i + \beta_{i,s} r_{s,d} + \varepsilon_{i,d}$, where $r_{i,s,t}$ is the return of stock i belonging to style s on day d; $r_{s,t}$ is the value-weighted return of style s on day d. The regression is estimated using the past three months of daily returns with at least 20 available observations as the estimation window. We first sort individual stocks into three groups based on past 12-month stock returns. Within each of the three portfolios, we allocate all stocks into three comovement groups (denoted as C1, C2, and C3), with C3 being the group of the highest comovement. Each of the nine portfolios is constructed with equal weights and held for subsequent K months (where K = 3, 6, and 12) with a month skip. We calculate raw and risk-adjusted returns for each portfolio in Panels A and B. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	K=3				*K*=6				*K*=12			
	C1	C2	C3	C3−C1	C1	C2	C3	C3−C1	C1	C2	C3	C3−C1
Panel A: Raw returns												
Winner	1.502 ***	1.493 ***	1.484 ***	–0.018	1.560 ***	1.496 ***	1.479 ***	–0.081	1.453 ***	1.364 ***	1.302 ***	–0.151
	(6.39)	(6.17)	(4.66)	(–0.13)	(6.43)	(5.88)	(4.41)	(–0.57)	(5.82)	(5.24)	(3.83)	(–1.14)
Loser	1.457 ***	1.078 ***	0.851 **	–0.606 ***	1.417 ***	1.048 ***	0.884 **	–0.533 ***	1.500 ***	1.172 ***	1.118 ***	–0.382 ***
	(4.67)	(3.54)	(2.30)	(–4.78)	(4.45)	(3.35)	(2.32)	(–4.18)	(4.64)	(3.66)	(2.87)	(–3.10)
Winner–Loser	0.045	0.415 ***	0.633 ***	0.588 ***	0.143	0.447 ***	0.595 ***	0.452 ***	–0.047	0.192	0.184	0.231 ***
	(0.28)	(2.64)	(3.50)	(5.20)	(0.93)	(3.02)	(3.49)	(4.30)	(–0.34)	(1.44)	(1.25)	(2.85)
Panel B: Fama-French risk-adjusted returns												
Winner	1.063 ***	1.042 ***	1.004 ***	–0.059	1.000 ***	0.913 ***	0.841 ***	–0.159	0.851 ***	0.738 ***	0.598 ***	–0.253 ***
	(8.70)	(9.36)	(6.41)	(–0.52)	(10.65)	(11.59)	(7.04)	(–1.57)	(10.36)	(11.19)	(6.00)	(–2.82)
Loser	0.956 ***	0.569 ***	0.275	–0.682 ***	0.780 ***	0.380 ***	0.133	–0.647 ***	0.786 ***	0.403 ***	0.250 *	–0.536 ***
	(4.81)	(3.38)	(1.34)	(–6.17)	(4.50)	(2.74)	(0.80)	(–5.77)	(4.93)	(3.30)	(1.66)	(–5.14)
Winner–Loser	0.107	0.473 ***	0.729 ***	0.623 ***	0.220	0.533 ***	0.708 ***	0.488 ***	0.065	0.336 ***	0.348 ***	0.283 ***
	(0.69)	(3.24)	(4.20)	(5.59)	(1.53)	(3.91)	(4.46)	(4.70)	(0.51)	(2.86)	(2.65)	(3.62)

Table 3: Returns to the AG-size style momentum based on portfolio analyses

In each month *t*, we rank the 25 AG-size style portfolios based on their average value-weighted returns over prior 6 (Panel A) or 12 (Panel B) months. We then classify style portfolios ranked at the top 10% or 30% as the winner styles, and those ranked at the bottom 10% or 30% as the loser styles. We hold the stocks that belong to the winner styles and short sell those that belong to the loser styles over the following 1, 3, 6, and 12 months. These portfolios are equally weighted. We calculate raw and risk-adjusted momentum profits based on the difference between the winner and loser portfolio returns, averaged across K separate positions (K = 1, 3, 6, 12), each formed in one of the K consecutive prior months from $t-K$ to $t-1$. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns				Risk-adjusted returns			
Portfolio	*K*=1	*K*=3	*K*=6	*K*=12	*K*=1	*K*=3	*K*=6	*K*=12
Panel A: Style returns measured over prior 6 months								
10% cutoffs to identify winner and loser styles								
Winner	1.819 ***	1.764 ***	1.766 ***	1.628 ***	1.890 ***	1.285 ***	1.148 ***	0.962 ***
	(5.94)	(6.41)	(6.19)	(5.77)	(6.04)	(8.27)	(8.73)	(9.02)
Loser	0.912 ***	0.907 ***	0.850 ***	0.919 ***	1.059 ***	0.559 ***	0.372 ***	0.364 ***
	(3.21)	(3.67)	(3.35)	(3.54)	(3.51)	(3.87)	(3.15)	(3.46)
Winner–Loser	0.907 ***	0.857 ***	0.916 ***	0.709 ***	0.831 ***	0.726 ***	0.776 ***	0.597 ***
	(4.11)	(4.67)	(4.88)	(4.30)	(3.50)	(4.22)	(4.42)	(4.04)
30% cutoffs to identify winner and loser styles								
Winner	1.582 ***	1.586 ***	1.620 ***	1.557 ***	1.676 ***	1.100 ***	0.992 ***	0.873 ***
	(5.44)	(6.11)	(5.98)	(5.66)	(5.64)	(8.48)	(9.86)	(10.26)
Loser	0.945 ***	0.957 ***	0.959 ***	1.028 ***	1.067 ***	0.569 ***	0.440 ***	0.427 ***
	(3.38)	(3.90)	(3.78)	(3.93)	(3.65)	(4.21)	(4.15)	(4.61)
Winner–Loser	0.636 ***	0.629 ***	0.661 ***	0.529 ***	0.609 ***	0.531 ***	0.551 ***	0.445 ***
	(3.92)	(4.52)	(4.70)	(4.18)	(3.54)	(4.12)	(4.31)	(3.99)
Panel B: Style returns measured over prior 12 months								
10% cutoffs to identify winner and loser styles								
Winner	1.758 ***	1.677 ***	1.599 ***	1.486 ***	1.862 ***	1.238 ***	1.025 ***	0.854 ***
	(5.66)	(6.19)	(5.86)	(5.55)	(5.82)	(7.75)	(8.24)	(8.43)
Loser	0.855 ***	0.857 ***	0.860 ***	0.966 ***	0.975 ***	0.465 ***	0.340 ***	0.365 ***
	(2.95)	(3.41)	(3.30)	(3.57)	(3.20)	(3.09)	(2.68)	(3.06)
Winner–Loser	0.903 ***	0.820 ***	0.739 ***	0.520 ***	0.887 ***	0.772 ***	0.685 ***	0.489 ***
	(3.95)	(4.21)	(3.99)	(3.03)	(3.62)	(3.99)	(3.89)	(3.03)
30% cutoffs to identify winner and loser styles								
Winner	1.677 ***	1.633 ***	1.612 ***	1.535 ***	1.774 ***	1.164 ***	1.006 ***	0.871 ***
	(5.73)	(6.32)	(6.05)	(5.71)	(5.94)	(8.82)	(9.97)	(10.28)
Loser	0.915 ***	0.962 ***	0.987 ***	1.056 ***	1.024 ***	0.545 ***	0.434 ***	0.424 ***
	(3.27)	(3.84)	(3.77)	(3.91)	(3.53)	(3.98)	(3.95)	(4.24)
Winner–Loser	0.761 ***	0.670 ***	0.626 ***	0.480 ***	0.751 ***	0.619 ***	0.572 ***	0.448 ***
	(4.83)	(4.87)	(4.64)	(3.74)	(4.50)	(4.68)	(4.52)	(3.74)

Table 4: Cross-sectional regressions based on style returns measured over prior 12 months

In each month t, we perform the following 6 or 12 cross-sectional regressions (for j = 2 to j = 7 or j = 2 to j = 13):

$$r_{i,t} = b_{ojt} + b_{1jt} r_{i,t-1} + b_{2jt} \ln(Size)_{i,t-1} + b_{3jt} PRW_{i,t-j} + b_{4jt} PRL_{i,t-j} + b_{5jt} SRW(S,B)_{i,t-j} + b_{6jt} SRL(S,B)_{i,t-j}$$
$$+ b_{7jt} SRW(A,S)_{i,t-j} + b_{8jt} SRL(A,S)_{i,t-j} + \varepsilon_{i,t},$$

where $r_{i,t}$ is the return of stock i in month t; $\ln(Size)_{i,t-1}$ is the natural logarithm of stock i's market capitalization at the end of previous month; and $PRW_{i,t-j}$ ($PRL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past return over prior 12 months is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $SRW(S,B)_{i,t-j}$ ($SRL(S,B)_{i,t-j}$) is a dummy variable that equals 1 if the prior 12-month return of the size-BM style portfolio to which stock i belongs is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $SRW(A,S)_{i,t-j}$ ($SRL(A,S)_{i,t-j}$) is a dummy variable that equals 1 if the prior 12-month return of the AG-size style portfolio to which stock i belongs is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise. In each month t, we estimate 6 (12) cross-sectional regressions for j = 2 to j = 7 (j = 2 to j = 13) and average the corresponding coefficient estimates. To obtain risk-adjusted returns, we perform time-series regressions of these averages on the contemporaneous Fama-French factor realizations to hedge out the factor exposure. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns (2,7)		FF-adj. returns (2,7)		Raw returns (2,13)		FF-adj. returns (2,13)	
Variable	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.
Intercept	2.436 ***	1.459 ***	1.501 ***	0.853 ***	2.486 ***	1.490 ***	1.519 ***	0.855 ***
	(5.85)	(3.64)	(6.72)	(4.25)	(5.81)	(3.60)	(6.61)	(4.15)
$r_{i,t-1}$	–0.054 ***	–0.046 ***	–0.050 ***	–0.044 ***	–0.055 ***	–0.046 ***	–0.051 ***	–0.045 ***
	(–13.51)	(–12.24)	(–14.32)	(–13.81)	(–13.67)	(–12.42)	(–14.39)	(–13.88)
ln(*Size*)	–0.215 ***	–0.070	–0.173 ***	–0.061 *	–0.212 ***	–0.065	–0.165 ***	–0.051
	(–4.55)	(–1.60)	(–4.64)	(–1.85)	(–4.40)	(–1.43)	(–4.36)	(–1.52)
PRW	0.149	0.176 *	0.205 ***	0.226 ***	–0.013	0.009	0.044	0.056
	(1.65)	(1.83)	(2.93)	(3.18)	(–0.17)	(0.10)	(0.78)	(0.99)
PRL	–0.132	–0.316 ***	–0.230 ***	–0.386 ***	–0.049	–0.225 **	–0.149 **	–0.291 ***
	(–1.17)	(–2.74)	(–2.85)	(–4.99)	(–0.49)	(–2.22)	(–2.18)	(–4.47)
SRW(*S*,*B*)	0.023	–0.039	0.057	–0.009	0.036	–0.031	0.058	–0.014
	(0.37)	(–0.60)	(1.04)	(–0.16)	(0.67)	(–0.54)	(1.27)	(–0.31)
SRL(*S*,*B*)	–0.225 ***	–0.240 ***	–0.168 ***	–0.186 ***	–0.273 ***	–0.277 ***	–0.209 ***	–0.222 ***
	(–3.95)	(–4.04)	(–3.77)	(–4.24)	(–5.02)	(–4.87)	(–5.13)	(–5.53)
SRW(*A*,*S*)	0.137 **	0.077	0.139 ***	0.094 **	0.095 **	0.037	0.105 **	0.053
	(2.40)	(1.44)	(2.87)	(2.00)	(2.04)	(0.83)	(2.53)	(1.31)
SRL(*A*,*S*)	–0.316 ***	–0.340 ***	–0.272 ***	–0.306 ***	–0.333 ***	–0.367 ***	–0.286 ***	–0.331 ***
	(–5.88)	(–6.05)	(–6.73)	(–7.83)	(–6.84)	(–6.80)	(–7.74)	(–9.40)
PRW–*PRL*	0.281 *	0.492 ***	0.435 ***	0.612 ***	0.037	0.233 *	0.193 **	0.347 ***
	(1.92)	(3.29)	(3.59)	(5.16)	(0.31)	(1.95)	(2.02)	(3.70)
SRW(*S*,*B*)	0.249 ***	0.200 **	0.225 ***	0.178 ***	0.309 ***	0.247 ***	0.267 ***	0.208 ***
–*SRL*(*S*,*B*)	(3.02)	(2.41)	(3.30)	(2.61)	(3.80)	(3.02)	(4.17)	(3.33)
SRW(*A*,*S*)	0.452 ***	0.417 ***	0.411 ***	0.401 ***	0.429 ***	0.404 ***	0.391 ***	0.384 ***
–*SRL*(*A*,*S*)	(6.30)	(5.81)	(7.15)	(7.18)	(6.88)	(6.27)	(7.52)	(7.61)

Table 5: Profits to the AG-size style momentum conditional on CMA loadings

In each month t, we estimate CMA loadings for each stock using the time-series regression on Fama and French's (2015) five-factor model. The regression is estimated using the past five years of monthly returns with at least 24 available observations as the estimation window. We first sort individual stocks into three groups based on past 12-month AG-size style returns. Within each of the three style portfolios, we allocate all stocks into three CMA loading groups (denoted as B1, B2, and B3), with P3 being the group of the highest CMA loading. Each of the nine portfolios is constructed with equal weights and held for subsequent K months (where K = 3, 6, and 12) with a month skip. We calculate raw and risk-adjusted returns for each portfolio in Panels A and B. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	K=3				*K*=6				*K*=12			
	B1	B2	B3	B3−B1	B1	B2	B3	B3−B1	B1	B2	B3	B3−B1
Panel A: Raw returns												
Winner	1.680 ***	1.562 ***	1.668 ***	–0.012	1.653 ***	1.541 ***	1.678 ***	0.025	1.535 ***	1.448 ***	1.535 ***	–0.001
	(5.66)	(6.61)	(6.02)	(–0.13)	(5.40)	(6.29)	(5.84)	(0.28)	(5.00)	(5.78)	(5.34)	(–0.01)
Loser	0.954 ***	0.934 ***	0.943 ***	–0.010	0.973 ***	0.969 ***	0.962 ***	–0.011	0.995 ***	1.006 ***	1.052 ***	0.057
	(3.40)	(4.00)	(3.58)	(–0.14)	(3.32)	(3.96)	(3.49)	(–0.15)	(3.31)	(3.95)	(3.64)	(0.79)
Winner–Loser	0.726 ***	0.628 ***	0.724 ***	–0.002	0.680 ***	0.573 ***	0.716 ***	0.037	0.540 ***	0.442 ***	0.483 ***	–0.058
	(4.48)	(5.12)	(4.46)	(–0.02)	(4.26)	(4.67)	(4.64)	(0.40)	(3.66)	(3.75)	(3.31)	(–0.69)
Panel B: Fama-French risk-adjusted returns												
Winner	1.187 ***	1.101 ***	1.199 ***	0.012	1.008 ***	0.938 ***	1.057 ***	0.049	0.866 ***	0.816 ***	0.898 ***	0.032
	(7.06)	(9.53)	(8.27)	(0.13)	(7.24)	(10.93)	(9.31)	(0.53)	(7.14)	(10.85)	(9.22)	(0.36)
Loser	0.517 ***	0.524 ***	0.551 ***	0.034	0.385 ***	0.424 ***	0.422 ***	0.037	0.356 ***	0.410 ***	0.453 ***	0.098
	(3.24)	(4.18)	(3.60)	(0.48)	(2.90)	(4.22)	(3.40)	(0.51)	(2.92)	(4.54)	(3.92)	(1.34)
Winner–Loser	0.670 ***	0.577 ***	0.648 ***	–0.022	0.623 ***	0.514 ***	0.635 ***	0.012	0.510 ***	0.406 ***	0.445 ***	–0.065
	(4.28)	(5.00)	(4.17)	(–0.23)	(4.06)	(4.54)	(4.45)	(0.13)	(3.57)	(3.70)	(3.30)	(–0.76)

Table 6: Profits to the AG-size style momentum conditional on price delay and information discreteness

In each month *t*, we construct the style-level price delay (PD) and individual-level information discreteness (ID) measures for individual stocks. We first sort individual stocks into three groups based on past 12-month AG-size style returns. Within each of the three style portfolios, we allocate all stocks into three PD (or ID) groups (denoted as D1, D2, and D3), with D3 being the group of the highest PD (or ID) values. Each of the nine portfolios is constructed with equal weights and held for subsequent *K* months (where *K* = 3, 6, and 12) with a month skip. We calculate raw and risk-adjusted returns for each portfolio. Panel A reports the momentum profits conditional on PD, whereas Panel B reports the momentum profits conditional on ID. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	K=3				*K*=6				*K*=12			
	D1	D2	D3	D3−D1	D1	D2	D3	D3−D1	D1	D2	D3	D3−D1
Panel A: Momentum profits conditional on price delay at the style level												
Raw returns												
Winner	1.236 ***	1.444 ***	1.774 ***	0.537 ***	1.222 ***	1.429 ***	1.739 ***	0.517 ***	1.178 ***	1.404 ***	1.644 ***	0.465 ***
	(5.89)	(6.08)	(6.18)	(3.58)	(5.56)	(5.72)	(5.91)	(3.44)	(5.16)	(5.44)	(5.57)	(3.27)
Loser	0.930 ***	0.884 ***	1.096 ***	0.167	0.915 ***	0.909 ***	1.109 ***	0.194	0.953 ***	0.964 ***	1.173 ***	0.220 *
	(4.37)	(3.59)	(4.09)	(1.37)	(4.08)	(3.54)	(3.97)	(1.53)	(4.10)	(3.64)	(4.06)	(1.79)
Winner–Loser	0.307 **	0.560 ***	0.677 ***	0.371 ***	0.307 **	0.520 ***	0.630 ***	0.323 ***	0.225 *	0.439 ***	0.470 ***	0.245 **
	(2.52)	(4.05)	(5.08)	(3.11)	(2.51)	(3.68)	(5.01)	(2.81)	(1.94)	(3.15)	(4.03)	(2.40)
Fama-French risk-adjusted returns												
Winner	0.830 ***	0.981 ***	1.263 ***	0.433 ***	0.693 ***	0.834 ***	1.092 ***	0.399 ***	0.597 ***	0.745 ***	0.942 ***	0.345 ***
	(7.58)	(8.44)	(8.11)	(3.43)	(7.74)	(9.12)	(8.92)	(3.31)	(7.05)	(8.68)	(9.14)	(3.17)
Loser	0.573 ***	0.480 ***	0.632 ***	0.060	0.440 ***	0.373 ***	0.514 ***	0.074	0.410 ***	0.350 ***	0.495 ***	0.086
	(4.84)	(3.46)	(4.25)	(0.56)	(4.62)	(3.36)	(4.26)	(0.69)	(4.95)	(3.46)	(4.45)	(0.86)
Winner–Loser	0.258 **	0.501 ***	0.631 ***	0.373 ***	0.253 **	0.461 ***	0.578 ***	0.325 ***	0.187	0.395 ***	0.446 ***	0.259 **
	(2.18)	(3.88)	(4.93)	(3.14)	(2.12)	(3.53)	(4.88)	(2.74)	(1.62)	(3.02)	(4.12)	(2.43)
Panel B: Momentum profits conditional on information discreteness at the individual level												
Raw returns												
Winner	1.623 ***	1.743 ***	1.532 ***	0.091	1.629 ***	1.706 ***	1.494 ***	0.135	1.571 ***	1.597 ***	1.427 ***	0.144 **
	(5.93)	(6.85)	(5.84)	(1.04)	(5.70)	(6.52)	(5.53)	(1.63)	(5.48)	(6.01)	(5.18)	(2.12)
Loser	0.831 ***	1.057 ***	0.989 ***	–0.157	0.866 ***	1.080 ***	0.990 ***	–0.124	1.008 ***	1.107 ***	0.997 ***	0.010
	(2.91)	(4.27)	(4.22)	(–1.50)	(2.89)	(4.18)	(4.04)	(–1.22)	(3.21)	(4.15)	(3.95)	(0.10)
Winner–Loser	0.792 ***	0.686 ***	0.543 ***	–0.249 ***	0.763 ***	0.626 ***	0.504 ***	–0.259 ***	0.563 ***	0.490 ***	0.429 ***	–0.133 *
	(5.34)	(4.73)	(3.87)	(–3.07)	(5.24)	(4.36)	(3.70)	(–3.37)	(3.95)	(3.61)	(3.35)	(–1.71)
Fama-French risk-adjusted returns												
Winner	1.120 ***	1.253 ***	1.078 ***	0.042	0.981 ***	1.084 ***	0.911 ***	0.070	0.865 ***	0.929 ***	0.784 ***	0.081
	(7.61)	(9.63)	(7.83)	(0.51)	(8.44)	(11.06)	(8.55)	(0.97)	(8.65)	(11.13)	(8.82)	(1.35)
Loser	0.380 **	0.630 ***	0.591 ***	–0.212 **	0.264 *	0.527 ***	0.479 ***	–0.215 **	0.317 **	0.477 ***	0.420 ***	–0.103
	(2.12)	(4.69)	(4.91)	(–2.01)	(1.76)	(4.84)	(5.03)	(–2.21)	(2.26)	(4.83)	(5.00)	(–1.14)
Winner–Loser	0.740 ***	0.623 ***	0.486 ***	–0.254 ***	0.718 ***	0.558 ***	0.432 ***	–0.286 ***	0.549 ***	0.453 ***	0.365 ***	–0.184 ***
	(5.05)	(4.65)	(3.64)	(–3.17)	(5.04)	(4.32)	(3.46)	(–3.78)	(3.98)	(3.69)	(3.12)	(–2.59)

Table 7: Returns to the AG-size style momentum conditional on style migration

In each month *t*, we rank the 25 AG-size style portfolios based on their average value-weighted returns over prior 6 (Panel A) or 12 (Panel B) months. We then classify style portfolios ranked at the top 30% as the winner styles, and those ranked at the bottom 30% as the loser styles. We hold the stocks that belong to the winner styles and short sell those that belong to the loser styles over the following 1, 3, 6, and 12 months. These portfolios are equally weighted. We calculate raw and risk-adjusted momentum profits based on the difference between the winner and loser portfolio returns, averaged across K separate positions (K = 1, 3, 6, 12), each formed in one of the K consecutive prior months from $t-K$ to $t-1$. In Panel A, we include style winners and losers that remained in the same AG-size style. In Panel B, we include style winners and losers that experienced migration in the AG-size style. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns				Risk-adjusted returns			
Portfolio	K=1	K=3	K=6	K=12	K=1	K=3	K=6	K=12
Panel A: Stocks remained in the same AG-size style								
Winner	1.804 ***	1.721 ***	1.681 ***	1.576 ***	1.031 ***	1.246 ***	1.074 ***	0.912 ***
	(6.08)	(6.56)	(6.31)	(5.90)	(8.22)	(8.33)	(9.08)	(9.23)
Loser	0.706 **	0.847 ***	0.878 ***	0.973 ***	0.027	0.420 ***	0.317 **	0.326 ***
	(2.55)	(3.37)	(3.34)	(3.60)	(0.22)	(2.78)	(2.53)	(2.94)
Winner–Loser	1.098 ***	0.874 ***	0.803 ***	0.604 ***	1.004 ***	0.826 ***	0.757 ***	0.586 ***
	(5.27)	(4.80)	(4.66)	(3.86)	(4.89)	(4.58)	(4.58)	(3.97)
Panel B: Stocks experienced style migrations								
Winner	1.386 ***	1.453 ***	1.452 ***	1.405 ***	0.587 ***	0.972 ***	0.823 ***	0.707 ***
	(4.56)	(5.38)	(5.14)	(4.95)	(5.76)	(6.96)	(7.81)	(7.76)
Loser	1.121 ***	1.127 ***	1.098 ***	1.093 ***	0.385 ***	0.694 ***	0.503 ***	0.409 ***
	(3.45)	(4.02)	(3.78)	(3.70)	(3.14)	(4.45)	(4.19)	(3.86)
Winner–Loser	0.265 *	0.326 ***	0.354 ***	0.312 ***	0.202	0.278 **	0.320 ***	0.297 ***
	(1.86)	(2.93)	(3.22)	(3.03)	(1.49)	(2.53)	(2.99)	(2.95)

Table 8: Profits to the AG-size style momentum conditional on style migration and information discreteness

In each month t, we construct the individual-level ID measures for individual stocks. We first sort individual stocks into three groups based on past 12-month AG-size style returns. Within each of the three style portfolios, we allocate all stocks into three ID groups (denoted as D1, D2, and D3), with D3 being the group of the highest ID values. Each of the nine portfolios is constructed with equal weights and held for subsequent K months (where K = 3, 6, and 12) with a month skip. We calculate raw and risk-adjusted returns for each portfolio. In Panel A, we include style winners and losers that remained in the same AG-size style. In Panel B, we include style winners and losers that experienced migration in the AG-size style. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	K=3				K=6				K=12			
	D1	D2	D3	D3−D1	D1	D2	D3	D3−D1	D1	D2	D3	D3−D1
Panel A: Stocks remained in the same AG-size style												
Raw returns												
Winner	1.685 ***	1.921 ***	1.539 ***	−0.146	1.733 ***	1.830 ***	1.476 ***	−0.257 ***	1.616 ***	1.682 ***	1.435 ***	−0.181 **
	(6.48)	(7.27)	(5.60)	(−1.43)	(6.43)	(6.95)	(5.31)	(−2.88)	(6.01)	(6.39)	(5.20)	(−2.45)
Loser	0.680 **	0.924 ***	0.929 ***	0.249 **	0.757 **	0.975 ***	0.889 ***	0.132	0.947 ***	1.042 ***	0.926 ***	−0.021
	(2.34)	(3.75)	(4.00)	(2.14)	(2.49)	(3.80)	(3.71)	(1.15)	(3.02)	(3.99)	(3.77)	(−0.19)
Winner–Loser	1.005 ***	0.997 ***	0.610 ***	−0.394 ***	0.976 ***	0.856 ***	0.587 ***	−0.389 ***	0.669 ***	0.640 ***	0.509 ***	−0.160
	(5.23)	(5.14)	(3.23)	(−3.19)	(5.24)	(4.70)	(3.38)	(−3.35)	(3.84)	(3.84)	(3.29)	(−1.38)
Fama-French risk-adjusted returns												
Winner	1.214 ***	1.433 ***	1.073 ***	−0.141	1.118 ***	1.219 ***	0.877 ***	−0.242 ***	0.938 ***	1.021 ***	0.778 ***	−0.161 **
	(7.76)	(9.41)	(6.56)	(−1.41)	(8.67)	(10.33)	(6.75)	(−2.88)	(8.74)	(10.24)	(7.20)	(−2.20)
Loser	0.220	0.502 ***	0.530 ***	0.310 ***	0.146	0.426 ***	0.367 ***	0.221 **	0.237	0.412 ***	0.333 ***	0.095
	(1.13)	(3.32)	(4.13)	(2.64)	(0.88)	(3.38)	(3.48)	(2.10)	(1.60)	(3.68)	(3.54)	(0.98)
Winner–Loser	0.994 ***	0.931 ***	0.543 ***	−0.451 ***	0.973 ***	0.793 ***	0.509 ***	−0.463 ***	0.701 ***	0.609 ***	0.445 ***	−0.256 ***
	(5.07)	(5.01)	(2.92)	(−3.88)	(5.22)	(4.71)	(3.09)	(−4.41)	(4.15)	(4.00)	(3.08)	(−2.59)
Panel B: Stocks experienced style migrations												
Raw returns												
Winner	1.532 ***	1.489 ***	1.318 ***	−0.214	1.494 ***	1.497 ***	1.356 ***	−0.138	1.498 ***	1.399 ***	1.243 ***	−0.256 **
	(5.08)	(5.50)	(5.05)	(−1.45)	(4.82)	(5.37)	(5.02)	(−1.12)	(4.90)	(5.05)	(4.52)	(−2.29)
Loser	1.082 ***	1.269 ***	1.058 ***	−0.024	1.067 ***	1.273 ***	0.989 ***	−0.078	1.139 ***	1.212 ***	0.936 ***	−0.203
	(3.26)	(4.46)	(4.07)	(−0.13)	(3.17)	(4.40)	(3.73)	(−0.47)	(3.36)	(4.18)	(3.53)	(−1.38)
Winner–Loser	0.450 ***	0.221	0.260 *	−0.190	0.427 ***	0.224	0.367 ***	−0.060	0.359 ***	0.187	0.306 ***	−0.052
	(2.98)	(1.44)	(1.90)	(−1.09)	(3.08)	(1.57)	(2.94)	(−0.40)	(2.76)	(1.51)	(2.66)	(−0.39)
Fama-French risk-adjusted returns												
Winner	1.014 ***	1.023 ***	0.875 ***	−0.138	0.808 ***	0.896 ***	0.771 ***	−0.037	0.742 ***	0.729 ***	0.592 ***	−0.150
	(5.65)	(6.54)	(6.44)	(−0.96)	(6.04)	(7.40)	(7.18)	(−0.32)	(6.29)	(7.33)	(6.41)	(−1.38)
Loser	0.577 ***	0.852 ***	0.678 ***	0.101	0.375 **	0.702 ***	0.470 ***	0.095	0.362 **	0.549 ***	0.342 ***	−0.020
	(2.65)	(5.35)	(4.49)	(0.57)	(2.20)	(5.75)	(3.99)	(0.61)	(2.34)	(5.35)	(3.56)	(−0.15)
Winner–Loser	0.437 ***	0.170	0.197	−0.240	0.433 ***	0.194	0.301 **	−0.132	0.380 ***	0.180	0.249 **	−0.130
	(2.90)	(1.14)	(1.43)	(−1.37)	(3.21)	(1.39)	(2.37)	(−0.89)	(3.00)	(1.47)	(2.18)	(−0.99)

Table 9: Cross-sectional regressions conditional on time-varying predictors

In each month t, we perform the following 6 or 12 cross-sectional regressions (for j = 2 to j = 7 or j = 2 to j = 13) separately for expansionary and recessionary periods:

$$r_{i,t} = b_{ojt} + b_{1jt} r_{i,t-1} + b_{2jt} \ln(Size)_{i,t-1} + b_{3jt} PRW_{i,t-j} + b_{4jt} PRL_{i,t-j} + b_{5jt} SRW(S,B)_{i,t-j} + b_{6jt} SRL(S,B)_{i,t-j}$$
$$+ b_{7jt} SRW(A,S)_{i,t-j} + b_{8jt} SRL(A,S)_{i,t-j} + \varepsilon_{i,t},$$

where $r_{i,t}$ is the return of stock i in month t; $\ln(Size)_{i,t-1}$ is the natural logarithm of stock i's market capitalization at the end of previous month; and $PRW_{i,t-j}$ ($PRL_{i,t-j}$) is a dummy variable that equals 1 if stock i's past return over prior 12 months is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $SRW(S,B)_{i,t-j}$ ($SRL(S,B)_{i,t-j}$) is a dummy variable that equals 1 if the prior 12-month return of the size-BM style portfolio to which stock i belongs is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise; $SRW(A,S)_{i,t-j}$ ($SRL(A,S)_{i,t-j}$) is a dummy variable that equals 1 if the prior 12-month return of the AG-size style portfolio to which stock i belongs is in the top (bottom) 30% at the end of month $t-j$, and zero otherwise. In each month t, we estimate 6 (or 12) cross-sectional regressions for j = 2 to j = 7 (or j = 2 to j = 13) and average the corresponding coefficient estimates separately for different periods implied by business cycles (Panel A), market states (Panel B), market volatilities (Panel C), and investor sentiment (Panel D). To obtain risk-adjusted returns, we perform time-series regressions of these averages on the contemporaneous Fama-French factor realizations to hedge out the factor exposure. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Monthly returns (2,7)		Monthly returns (2,13)		Monthly returns (2,7)		Monthly returns (2,13)	
	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.
Panel A: Periods partitioned by business cycles								
	Expansionary periods				Recessionary periods			
PRW–PRL	0.362 ***	0.453 ***	0.097	0.214 **	–0.215	–0.154	–0.328	–0.231
	(2.97)	(3.92)	(0.92)	(2.29)	(–0.34)	(–0.34)	(–0.69)	(–0.67)
SRW(S,B)	0.176 **	0.188 ***	0.231 ***	0.204 ***	0.695 ***	0.521 **	0.784 ***	0.624 **
–SRL(S,B)	(2.13)	(2.67)	(2.98)	(3.24)	(2.67)	(2.32)	(2.82)	(2.53)
SRW(A,S)	0.429 ***	0.398 ***	0.391 ***	0.364 ***	0.591 ***	0.484 ***	0.662 ***	0.592 ***
–SRL(A,S)	(5.70)	(6.52)	(6.12)	(6.67)	(2.91)	(2.74)	(3.52)	(3.54)
Panel B: Periods partitioned by market states								
	UP markets				DOWN markets			
PRW–PRL	0.575 ***	0.628 ***	0.251 ***	0.319 ***	–1.229 **	–0.697	–1.062 **	–0.569
	(5.93)	(6.08)	(3.21)	(3.96)	(–2.06)	(–1.53)	(–2.16)	(–1.59)
SRW(S,B)	0.269 ***	0.258 ***	0.282 ***	0.241 ***	0.147	0.103	0.447 *	0.421 **
–SRL(S,B)	(3.09)	(3.53)	(3.66)	(3.70)	(0.72)	(0.55)	(1.84)	(2.01)
SRW(A,S)	0.424 ***	0.413 ***	0.413 ***	0.397 ***	0.598 ***	0.489 ***	0.509 ***	0.423 ***
–SRL(A,S)	(5.72)	(6.78)	(6.44)	(7.27)	(3.36)	(3.15)	(3.08)	(2.83)
Panel C: Periods partitioned by market volatilities								
	Low market volatilities				High market volatilities			
PRW–PRL	0.617 ***	0.622 ***	0.295 ***	0.172	–0.076	0.336 ***	–0.238	–0.012
	(5.38)	(5.86)	(3.00)	(0.82)	(–0.29)	(3.70)	(–1.15)	(–0.08)
SRW(S,B)	0.300 ***	0.292 ***	0.344 ***	0.172	0.194	0.289 ***	0.271 **	0.242 **
–SRL(S,B)	(2.97)	(3.67)	(3.84)	(1.53)	(1.48)	(4.18)	(2.09)	(2.20)
SRW(A,S)	0.472 ***	0.424 ***	0.425 ***	0.406 ***	0.431 ***	0.374 ***	0.433 ***	0.411 ***
–SRL(A,S)	(5.09)	(5.50)	(5.43)	(4.77)	(4.25)	(5.75)	(4.68)	(5.03)
Panel D: Periods partitioned by investor sentiment								
	High sentiment				Low sentiment			
PRW–PRL	0.609 ***	0.697 ***	0.236 *	0.348 ***	–0.077	0.147	–0.212	–0.001
	(3.87)	(4.22)	(1.82)	(2.68)	(–0.30)	(0.75)	(–1.04)	(–0.01)
SRW(S,B)	0.383 ***	0.347 ***	0.408 ***	0.333 ***	0.178	0.191 **	0.271 **	0.264 ***
–SRL(S,B)	(3.28)	(3.29)	(3.59)	(3.47)	(1.42)	(1.97)	(2.18)	(2.73)
SRW(A,S)	0.613 ***	0.583 ***	0.564 ***	0.532 ***	0.318 ***	0.275 ***	0.309 ***	0.269 ***
–SRL(A,S)	(5.44)	(6.48)	(5.87)	(6.71)	(3.46)	(3.40)	(3.65)	(3.58)

Appendix: Alternative investment-based styles

In addition to AG, Li and Zhang (2010) illustrate five additional variables that are related to the investment-based anomaly, including investment-to-assets (I/A) and net stock issues (NSI) of Lyandres, Sun, and Zhang (2008), investment growth (IG) of Xing (2008), capital investment (CI) of Titman, Wei, and Xie (2004), and net operating assets (NOA) of Hirshleifer, Hou, Teoh, and Zhang (2004). As AG is one of the investment-based anomalies and our results point to the underreaction explanation to account for this new style investing, one may reasonably conjecture that our results can be applicable to these alternative investment-based measures. To examine this possibility, we replicate our portfolio-based analyses described in Section 3.2 by using each of the five additional variables combined with size to construct alternative investment-based style momentum strategies and investigate whether they display pronounced profits.

The constructions of the five investment-based variables are described as follows. I/A is the change in gross property, plant, and equipment (Compustat data item PPEGT) plus the change in inventories (item INVT) divided by lagged total assets (Compustat data item AT). NSI is the ratio of the split-adjusted shares outstanding (Compustat data item CSHO times item ADJEX_C) ending in year T–1 divided by the split-adjusted shares outstanding ending in year T–2. IG is the growth rate of capital expenditures (Compustat data item CAPX). CI is defined as $3CE_{T-1}/(CE_{T-2}+CE_{T-3}+CE_{T-4})-1$, where CE_{T-1} is capital expenditures (Compustat data item CAPX) divided by sales (Compustat data item SALE) ending in year T–1. NOA is the difference between operating assets and operating liabilities scaled by lagged total assets, where operating assets is total assets minus cash and short-term investment (Compustat data item CHE), and operating liabilities is defined as Compustat data item TA–DLC–DLTT–MIB–PSTK–CEQ.

Table A1: Fama-MacBeth regressions of future stock returns on AG-BM style returns

This table reports the average coefficients from the Fama-MacBeth regressions of future 1-, 3-, 6-, and 12-month cumulative returns on stock and style returns measured over past 6 (Panels A and C) and 12 (Panels B and D) months and firm characteristics including ln(*Size*), ln(*BM*), and *AG*. We exclude stocks with negative BM ratios and winsorize size and BM at the 1st and the 99th percentiles to avoid the influence of outliers. Past stock returns are calculated as the average monthly returns of individual stocks over the past 6 or 12 months (*Pret6* or *Pret12*). We form the AG-BM style returns (*Sret*(*A*,*B*)) by allocating individual stocks into 5×5 portfolios based on their values of AG and BM in an independent way. *Sret*(*S*,*B*), *Sret*(*B*), and *Sret*(*A*) are constructed in a similar way. For each of the 25 style portfolios, we calculate the average value-weighted style returns over the past 6 or 12 months. Numbers in the parentheses are the *t*-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	1-month future return		3-month future return		6-month future return		12-month future return	
Panel A: Style and stock returns measured over prior 6 months								
Pret6	0.122	0.095	0.786 **	0.705 **	1.734 ***	1.668 ***	1.101	0.769
	(0.88)	(0.72)	(2.22)	(2.13)	(2.65)	(2.75)	(1.04)	(0.81)
Sret(*S*,*B*)	0.277 ***	0.006	0.821 ***	0.018	1.711 ***	0.041	2.860 ***	0.028
	(3.92)	(0.13)	(4.17)	(0.16)	(4.96)	(0.20)	(4.79)	(0.08)
Sret(*A*,*B*)	0.115 ***	0.055 **	0.290 ***	0.154 **	0.404 **	0.197 *	0.374	0.138
	(3.54)	(2.29)	(3.33)	(2.29)	(2.54)	(1.73)	(1.29)	(0.73)
ln(*Size*)		−0.191 ***		−0.570 ***		−1.245 ***		−2.752 ***
		(−3.85)		(−3.95)		(−4.80)		(−6.04)
ln(*BM*)		0.128 **		0.426 ***		0.820 ***		1.495 ***
		(2.41)		(2.75)		(3.03)		(3.40)
AG		−0.418 ***		−1.150 ***		−2.117 ***		−3.433 ***
		(−7.81)		(−8.66)		(−8.82)		(−8.61)
Panel B: Style and stock returns measured over prior 12 months								
Pret12	0.125	0.093	0.788 **	0.694 **	1.807 ***	1.654 ***	1.390	0.734
	(0.89)	(0.70)	(2.23)	(2.09)	(2.77)	(2.71)	(1.32)	(0.77)
Sret(*S*,*B*)	0.382 ***	0.022	1.077 ***	0.067	1.901 ***	0.171	3.410 ***	0.176
	(4.51)	(0.42)	(4.29)	(0.46)	(4.12)	(0.66)	(4.13)	(0.42)
Sret(*A*,*B*)	0.086 **	0.042	0.236 **	0.114	0.387 *	0.115	0.272	0.017
	(2.25)	(1.45)	(2.30)	(1.39)	(1.95)	(0.79)	(0.75)	(0.07)
ln(*Size*)		−0.204 ***		−0.587 ***		−1.261 ***		−2.798 ***
		(−4.03)		(−4.02)		(−4.87)		(−6.11)
ln(*BM*)		0.123 **		0.422 ***		0.826 ***		1.378 ***
		(2.46)		(2.91)		(3.17)		(3.06)
AG		−0.419 ***		−1.152 ***		−2.087 ***		−3.358 ***
		(−7.90)		(−8.68)		(−8.75)		(−8.59)

Table A1 continued

Variable	1-month future return		3-month future return		6-month future return		12-month future return	
Panel C: Style and stock returns measured over prior 6 months								
Pret6	0.119	0.091	0.776 **	0.691 **	1.722 ***	1.648 ***	1.028	0.740
	(0.86)	(0.69)	(2.20)	(2.10)	(2.66)	(2.72)	(0.98)	(0.78)
Sret(*S*,*B*)	0.278 ***	0.009	0.808 ***	0.032	1.676 ***	0.060	2.705 ***	−0.098
	(3.73)	(0.21)	(3.88)	(0.28)	(4.63)	(0.29)	(4.35)	(−0.28)
Sret(*A*)	0.114	0.018	0.535 *	0.159	1.283 **	0.510	1.589 *	0.615
	(1.11)	(0.22)	(1.95)	(0.73)	(2.58)	(1.40)	(1.83)	(1.03)
Sret(*B*)	−0.032	−0.058	0.012	−0.109	0.205	0.098	0.152	0.820
	(−0.27)	(−0.69)	(0.04)	(−0.47)	(0.36)	(0.25)	(0.15)	(1.48)
ln(*Size*)		−0.190 ***		−0.574 ***		−1.216 ***		−2.683 ***
		(−3.85)		(−3.96)		(−4.71)		(−5.99)
ln(*BM*)		0.135 ***		0.443 ***		0.885 ***		1.372 ***
		(2.82)		(3.28)		(3.64)		(3.51)
AG		−0.374 ***		−1.049 ***		−1.993 ***		−3.156 ***
		(−6.58)		(−7.45)		(−7.86)		(−7.61)
Panel D: Style and stock returns measured over prior 12 months								
Pret12	0.118	0.087	0.775 **	0.679 **	1.767 ***	1.635 ***	1.270	0.719
	(0.85)	(0.66)	(2.20)	(2.05)	(2.75)	(2.69)	(1.23)	(0.76)
Sret(*S*,*B*)	0.417 ***	0.056	1.160 ***	0.146	1.957 ***	0.292	3.228 ***	0.161
	(4.71)	(1.01)	(4.47)	(0.96)	(4.11)	(1.11)	(3.78)	(0.39)
Sret(*A*)	0.095	0.022	0.496 *	0.214	1.202 **	0.685 *	1.457 *	1.000 *
	(0.93)	(0.27)	(1.80)	(0.97)	(2.43)	(1.83)	(1.75)	(1.68)
Sret(*B*)	−0.130	−0.102	−0.323	−0.227	−0.159	0.017	−0.238	0.979
	(−1.11)	(−1.12)	(−1.06)	(−0.94)	(−0.27)	(0.04)	(−0.22)	(1.63)
ln(*Size*)		−0.201 ***		−0.582 ***		−1.223 ***		−2.731 ***
		(−4.00)		(−3.98)		(−4.78)		(−6.11)
ln(*BM*)		0.135 ***		0.463 ***		0.940 ***		1.363 ***
		(2.89)		(3.51)		(3.90)		(3.44)
AG		−0.375 ***		−1.050 ***		−1.982 ***		−3.155 ***
		(−6.62)		(−7.51)		(−8.02)		(−7.70)

Table A2: Returns to alternative investment-based style momentum

In each month t, we form 25 investment-based style portfolios based on their values of investment-based measures and size in an independent way. We rank the 25 investment-based style portfolios based on their average value-weighted returns over prior 12 months. We then classify style portfolios ranked at the top 30% as the winner styles, and those ranked at the bottom 30% as the loser styles. We hold the stocks that belong to the winner styles and short sell those that belong to the loser styles over the following 1, 3, 6, and 12 months. These portfolios are equally weighted. We calculate raw and risk-adjusted momentum profits based on the difference between the winner and loser portfolio returns, averaged across K separate positions (K = 1, 3, 6, 12), each formed in one of the K consecutive prior months from $t-K$ to $t-1$. In Panels A to F, the corresponding investment-based measures are I/A, NSI, IG, CI, and NOA, respectively. Numbers in the parentheses are the t-statistics calculated using Newey and West's (1987) robust standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Raw returns				Risk-adjusted returns			
Portfolio	*K*=1	*K*=3	*K*=6	*K*=12	*K*=1	*K*=3	*K*=6	*K*=12
Panel A: I/A as a style								
Winner	1.581 ***	1.429 ***	1.364 ***	1.324 ***	0.825 ***	0.962 ***	0.754 ***	0.646 ***
	(5.43)	(5.62)	(5.19)	(4.90)	(7.89)	(7.47)	(7.42)	(6.73)
Loser	0.675 **	0.827 ***	0.899 ***	0.964 ***	0.085	0.471 ***	0.402 ***	0.392 ***
	(2.41)	(3.39)	(3.48)	(3.62)	(0.70)	(3.43)	(3.41)	(3.45)
Winner–Loser	0.906 ***	0.602 ***	0.465 ***	0.360 **	0.740 ***	0.491 ***	0.351 **	0.254 *
	(5.23)	(4.14)	(3.04)	(2.33)	(4.34)	(3.58)	(2.46)	(1.75)
Panel B: NSI as a style								
Winner	1.612 ***	1.504 ***	1.479 ***	1.438 ***	0.831 ***	1.021 ***	0.862 ***	0.758 ***
	(5.53)	(6.02)	(5.77)	(5.50)	(8.24)	(8.07)	(8.36)	(7.70)
Loser	0.833 ***	0.932 ***	0.937 ***	0.997 ***	0.222 **	0.569 ***	0.450 ***	0.435 ***
	(3.25)	(4.01)	(3.82)	(3.99)	(2.26)	(4.59)	(4.35)	(4.59)
Winner–Loser	0.779 ***	0.572 ***	0.542 ***	0.441 ***	0.609 ***	0.453 ***	0.411 ***	0.323 **
	(4.41)	(3.61)	(3.29)	(2.71)	(3.77)	(3.11)	(2.70)	(2.16)
Panel C: IG as a style								
Winner	1.565 ***	1.460 ***	1.446 ***	1.419 ***	0.820 ***	1.002 ***	0.848 ***	0.753 ***
	(5.50)	(6.08)	(5.81)	(5.52)	(8.33)	(7.98)	(8.23)	(7.62)
Loser	0.855 ***	0.962 ***	0.953 ***	1.016 ***	0.236 **	0.595 ***	0.467 ***	0.453 ***
	(3.26)	(4.07)	(3.83)	(4.00)	(2.45)	(4.80)	(4.56)	(4.85)
Winner–Loser	0.710 ***	0.498 ***	0.493 ***	0.404 **	0.584 ***	0.407 ***	0.382 **	0.300 **
	(4.27)	(3.26)	(3.13)	(2.57)	(3.79)	(2.86)	(2.56)	(2.03)
Panel D: CI as a style								
Winner	1.593 ***	1.460 ***	1.470 ***	1.435 ***	0.810 ***	0.988 ***	0.862 ***	0.761 ***
	(5.82)	(6.04)	(5.94)	(5.66)	(8.84)	(8.25)	(9.10)	(8.42)
Loser	0.932 ***	0.992 ***	0.973 ***	1.022 ***	0.317 ***	0.620 ***	0.485 ***	0.456 ***
	(3.68)	(4.39)	(4.11)	(4.24)	(3.47)	(5.41)	(5.16)	(5.38)
Winner–Loser	0.661 ***	0.468 ***	0.497 ***	0.414 ***	0.493 ***	0.368 ***	0.377 ***	0.305 **
	(4.13)	(3.31)	(3.44)	(2.92)	(3.38)	(2.84)	(2.80)	(2.33)
Panel E: NOA as a style								
Winner	1.578 ***	1.481 ***	1.475 ***	1.458 ***	0.816 ***	1.000 ***	0.856 ***	0.772 ***
	(5.45)	(5.95)	(5.71)	(5.51)	(8.04)	(7.71)	(7.94)	(7.52)
Loser	0.808 ***	0.887 ***	0.911 ***	0.980 ***	0.225 **	0.523 ***	0.433 ***	0.427 ***
	(3.14)	(3.79)	(3.68)	(3.86)	(2.31)	(4.36)	(4.29)	(4.49)
Winner–Loser	0.771 ***	0.594 ***	0.564 ***	0.477 ***	0.591 ***	0.477 ***	0.423 ***	0.345 **
	(4.46)	(3.80)	(3.47)	(2.91)	(3.70)	(3.30)	(2.80)	(2.26)