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 significantly predict future stock returns. 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 competing explanations for this predictability, including the style-chasing hypothesis and the limited-attention theory. Empirical evidence shows that the AG-based style momentum profit is induced because investors neglect to use AG as an investment style, consistent with the limited-attention explanation but not the style-chasing hypothesis. Furthermore, we find that the profitability of the AG-based style momentum is robust to different time periods partitioned by several time-series predictors, including business cycles, market states, market transitions, market volatilities, and investor sentiment.

JEL Classification: G11; G12; G14.
Keywords: Asset growth; Style investing; Style momentum; Limited attention.

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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: can a firm characteristic that is associated with stock returns be a potential (or better) investment style that generates higher profitability to investors?

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 profitability and has become an important anomaly in academic research.[1]

We consider AG as an investment style and hypothesize that this "new" style generates subsequent return profitability for several reasons. First, prior literature on long-run event studies shows that corporate events associated with asset expansion (i.e., acquisitions and public equity/debt offerings) tend to be followed by abnormally low returns, while events associated with asset contraction (i.e., share repurchases, debt prepayments, and dividend initiations) 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 high AG stocks have lower BM and past 36-month returns; they also have higher earnings-to-price ratio, return on assets, accruals, and past 6-month returns than low AG stocks, indicating 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

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[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).

on stock returns than size and BM and exhibits a long-lasting effect on stock returns. 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), we hypothesize that AG as a style can generate higher and more consistent momentum profits than traditional styles such as size and BM.

To confirm our conjecture, 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 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-sorted style returns is eliminated by the inclusion of AG-size-sorted style returns. This evidence suggests that the AG-based style plays the dominant role in generating the positive return predictability over the intermediate horizons.

We next propose the AG-based style momentum based on Jegadeesh and Titman's (1993) portfolio-based procedures and examine the properties of its profits. Several 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 0.916% and 0.767% 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, unlike other conventional momentum strategies, the AG-based style momentum is not subject to January seasonality.[3] The January returns of the AG-based style momentum strategy are remarkably high and remain positive when Fama and French's (1993) risk adjustments are taken into consideration. Third, 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-based style momentum dominates price momentum and size-BM style momentum in generating momentum returns. Finally, the intermediate-term momentum return of the AG-based strategy is followed by long-term return persistence rather than reversals, implying that the AG-based style momentum profit is unlikely to be driven by investors' overreaction.

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-based style can provide incremental information to investors when making investment decisions.

We propose two potential explanations for AG-based style momentum profits. First, as illustrated in Barberis and Shleifer's (2003) model, momentum profits are induced because of investors' style-chasing behavior in which all stocks are correctly classified into styles, and, within a style, all stocks are subject to the same level of investors' style flows. As such, style

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[3] For example, price momentum in Jegadeesh and Titman's (1993), earnings momentum in Chan, Jegadeesh, and Lakonishok (1996) and Chordia and Shivakumar (2006), and the 52-week high momentum in George and Hwang (2004) all exhibit pronounced reversals in January.

chasing generates not only momentum but also excess comovement of a stock with its style. Motivated by this notion, the effect of style chasing predicts that the AG-based style momentum profit will be higher among stocks with higher comovement associated with its style if investors consider AG a style when making investment decisions in reality. Second, if investors do not perceive AG as a potential investment style, they may neglect the relative performance of stocks with a different magnitude of AG and thus underreact to the information embedded in this neglected investment style. According to the limited-attention theory, we hypothesize that the AG-based style momentum profit is higher among stocks with a limited capacity in drawing investors' attention.

We first examine whether the style-chasing hypothesis accounts for our results. Following Wahal and Yavuz (2013), we measure a stock's comovement with its style by estimating its beta with respect to style returns over the prior three months. We allocate all stocks into three groups based on these style betas within each of the three style return groups. If the profitability of the AG-based style momentum is due to investors' style-chasing behavior, we expect that a momentum strategy that buys style winners with high comovement and short sells style losers with high comovement should generate higher returns than a momentum portfolio that buys style winners with low comovement and short sells style losers with low comovement. However, our empirical results reveal that differences in AG-based style momentum profits between high and low comovement groups are insignificant and that momentum profits are all significantly positive with quantitatively similar magnitude across comovement groups. Hence we document no evidence for the style-chasing hypothesis in explaining the profitability of the AG-based style momentum.

If investors neglect to use AG as an investment style, on the contrary, the AG-based style momentum is profitable when investor underreaction to the information embedded in the style. If this hypothesis holds true, we expect higher profits to the AG-based style momentum among styles that have delayed reaction to the 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-based 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-based 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 is a neglected style that draws limited investor attention and further induces underreaction-oriented momentum profits.

We next examine the time-series patterns of AG-based style momentum profits conditional on several predictive variables that explain the momentum effect in the literature. In particular, Chordia and Shivakumar (2002) show that momentum profits are higher in expansions than in recessions. Cooper, Gutierrez, and Hameed (2004) suggest that the momentum strategy is profitable only following positive market returns because investor biases are more accentuated after market gains. Furthermore, Asem and Tian (2010) show that momentum profits are sensitive not only to market states but also to market transitions. Wang and Xu (2015), on the other hand, document higher momentum profits following low market volatility. Finally, Antoniou, Doukas, and Subrahmanyam (2013) and Stambaugh, Yu, and Yuan (2012) both relate the momentum effect to investor sentiment. By taking these conditioning variables into account, we show that AG-based style momentum profits are quantitatively and statistically similar across different time periods. This finding leads to an important implication, namely, that smart investors can take advantage of the market by searching for possible neglected 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-based style returns and properties of the AG-based style momentum. Section 4 discusses possible explanations based on style-chasing hypothesis and limited-attention theory. We investigate the time-varying patterns of the AG-based style momentum conditional on several predictive variables 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 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 and AG-BM style returns as alternative strategies for comparisons, which are constructed in a similar way.

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[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.

3. AG 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 and AG-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 profitability, we conduct George and Hwang's (2004) cross-sectional regressions to compare the relative performance of alternative momentum strategies in both intermediate and long terms.

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 as dependent variables. To gain a complete picture of the predictability of the AG-size style returns, we do not skip a month between the formation and holding periods to observe the short- and intermediate-term patterns. Our results remain virtually unchanged if we skip one month before the holding period to avoid potential problems of microstructure biases.

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, AG-size, and AG-BM style 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, 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. Coefficients on AG-BM style returns (*Sret*(*A*,*B*)), however, are significantly positive for the first to the third (Panel A) and to the sixth (Panel B) holding months, but the significance disappears when the holding horizon is extended to 12 months. 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 1-month future stock returns. The inclusion of firm characteristics weakens the significance of size-BM and AG-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 three 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*) are negative and those on ln(*BM*) and *AG* 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 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-based 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 is sufficient to observe the overall time-varying patterns of AG-based style portfolios and trade according to the information embedded in these style return patterns.

3.2. Profitability of the style momentum based on AG and size

The results from cross-sectional regressions discussed above are suggestive. Our further interest is just how much investors can earn if they implement the trading strategy suggested by the AG-based 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 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. 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. 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 2 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 2 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 0.854% (t-statistic = 5.18), 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 observable 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, if winners and losers are identified using 10% cutoff points.

Prior literature widely documents that traditional momentum strategies exhibit reversals in January months due to investors' tax consideration, known as the tax-loss-selling effect. 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-based style momentum involves trading based on past performance of AG-size style portfolios, we expect that its profitability is free from such tax-loss-selling behavior. That is, the AG-based style momentum should not display significant reversals in January months. To confirm this conjecture, we split the full sample into January-only and non-January observations and report the profits of the AG-size style momentum separately for the two subsamples in Table 3.

[Insert Table 3 about here]

As expected, the average January returns of the AG-size style momentum are positive across all holding horizons and even significant when past performance is measured over prior 6 months (Panel A of Table 3). The January momentum returns remain positive under Fama-French risk adjustments, with the only exception of the insignificantly negative returns for the very short-term holding horizon of K = 1. Without January observations, the momentum profits are still significantly positive in the non-January subsample. Taking the 12-month formation period as an example, the risk-adjusted momentum profit ranges from 0.452% to 0.854% across all holding horizons. In sum, Table 3 reveals that the profitability of the AG-size style momentum is not subject to the January seasonality. To have a complete understanding of the time-varying patterns of the AG-size style momentum profitability, we conduct several tests conditional on different time-series predictors in Section 5.

3.3. 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:[5]

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

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.[6]

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[5] Although Tables 1 and 2 show that style momentum does not exhibit short-term return reversals, we still skip 1 month between formation and holding periods to alleviate potential problems associated with bid-ask bounce and nonsynchronous trading of the price momentum. The empirical results are robust regardless of the 1-month skip.

[6] 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.

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 $\bar{b}_{7t} = \frac{1}{12}\sum_{j=2}^{13} b_{7jt}$ ($\bar{b}_{8t} = \frac{1}{12}\sum_{j=2}^{13} b_{8jt}$). 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 with January months included, 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 profitability 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 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.

3.4. Long-term persistence of style momentum profits

Behavioral theories generally predict that the intermediate-term momentum return is followed by long-term reversals.[7] Chen and De Bondt (2004), however, find no return reversal for the size-BM style momentum within the component stocks of the Standard and Poor's 500 index. Before turning our attention to the driving forces behind the profitability of the AG-size style momentum, it is interesting to observe the long-term performance of the strategy. To this end, we perform the cross-sectional regressions of Equation (2) for the holding periods of the second to the fifth years, that is, for j = 14,..., 25 to j = 50,..., 61. Table 5 reports risk-adjusted returns from the estimations separately for the second to the fifth years after the portfolio formation.

[Insert Table 5 about here]

Surprisingly, we find that the AG-size style momentum exhibits significant long-term continuations. With January included, the monthly risk-adjusted returns of the AG-size style momentum are 0.339%, 0.273%, 0.245%, and 0.223% for the second- to the fifth-year holding periods, respectively. These profits are all significant at the 1% level and robust to the Fama-French risk adjustments. Like intermediate-term profits, long-term returns of the AG-size style momentum come from both outperformance of style winners and underperformance of style losers. Although the size-BM style momentum also generates positive returns in the long term,

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[7] Possible behavioral theories include the model of investor sentiment (Barberis, Shleifer, and Vishny, 1998), the theory of overconfidence and self-attribution (Daniel, Hirshleifer, and Subrahmanyam, 1998), and the theory of gradual information diffusion (Hong and Stein, 1999).

they are lower in magnitude and mostly insignificant (the corresponding returns are 0.158%, 0.091%, 0.188%, and 0.087%, respectively). As for the price momentum, we observe negative returns across the second- to the fifth-year holding periods, consistent with prior evidence that the momentum strategy constructed based on stock levels generates both intermediate-term continuations and long-term reversals.

4. Sources of style momentum profits

To understand the driving forces behind the AG-size style momentum profits, we propose two alternative explanations in this section. The first is built based on the hypothesis of style chasing, and the second provides a linkage between limited attention and style momentum profits. We discuss the details and provide corresponding tests sequentially.

4.1. Style-chasing explanation: The role of comovement

Barberis and Shleifer (2003) propose a theoretical model to illustrate that style investing generates not only intermediate-term momentum but also comovement of a stock with its style. Comovement is an outcome of investors' style-chasing behavior, which implies that all stocks are correctly classified into styles and that all stocks within a style are subject to the same level of style investor flows. As a result, if style chasing generates return predictability, comovement should play an important role in accounting for this 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:

$$r_{i,s,d} = \alpha_i + \beta_{i,s} r_{s,d} + \varepsilon_{i,d}, \tag{3}$$

where $r_{i,s,d}$ is the return of stock i belonging to style s 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 (3), we follow Wahal and Yavuz (2013) by using the past three months of daily returns with at least 20 available observations as the estimation window. The regression is estimated rolling forward one month at a time, generating time series estimates of $\beta_{i,s}$.

Once we obtain the estimations of $\beta_{i,s}$ every month, we form portfolios based on the interactions of style returns and style 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 3.2. Within each of the three style 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. Similarly, we calculate monthly returns for each portfolio with the overlapping procedure across the K positions. We hypothesize that if the AG-size style momentum profit is induced due to investors' style-chasing behavior, higher momentum profits will be prevalent in the C3 group rather than in the C1 group. Table 6 shows the average momentum profits sorted by comovement.

[Insert Table 6 about here]

Surprisingly, we do not observe an increasing pattern of momentum returns across comovement groups. As shown in Panel A of Table 6, the momentum profits based on the 6-month holding horizon are 0.726%, 0.600%, and 0.723% for C1, C2, and C3 portfolios, respectively. The difference between C3 and C1 is insignificant at –0.003% (t-statistic = –0.01). This evidence is robust to different holding periods and Fama-French risk adjustments (as shown in Panel B). Our finding of an insignificant difference in momentum profits between high and low comovement groups suggests that the style-chasing hypothesis fails to explain the profitability of the AG-size style momentum.

4.2. Limited-attention explanation: Is AG a neglected style?

We next examine whether the profitability of the AG-size style momentum is induced because of investors' inattention in recognizing AG as a potential investment style. 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 profitability 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:

$$r_{s,d} = \alpha_s + \sum_{k=-5}^{5} \beta_{s,k} r_{m,d-k} + \varepsilon_{s,d}, \tag{4}$$

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

$$PD_s = \frac{1}{1+e^{-x_s}}. \tag{5}$$

The advantage of the log transformation moderates the influence of outliers and yields values between zero and one. In particular, values closer to zero imply a faster speed of adjustment to the market information and values closer to one imply 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 (5) 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 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 7.

[Insert Table 7 about here]

We 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 0.319%, 0.536%, and 0.620% for D1, D2, and D3 groups with a significant difference of 0.301% (t-statistic = 2.66) 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-based style momentum is profitable because AG is a neglected style to investors.

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-based 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

$$ID_i = \text{sgn}(PRET_i) \times [\%neg_i - \%pos_i], \tag{4}$$

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 $PRET_i < 0$.

By construction, a higher value of ID_i signifies discrete information, and a lower value of ID_i signifies continuous information. According to Equation (4), 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 7 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 0.247% (t-statistic = 3.07), 0.257% (t-statistic = 3.38), and 0.135% (t-statistic = 1.77) for 3-, 6-, and 12-month holding periods, respectively. These return differences increase to 0.251%, 0.283%, and 0.186% and 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 style are neglected by investors and that investor underreaction plays a role in generating such style-oriented return predictability.

5. Robustness of style momentum profits conditional on time-series predictors

In Section 3.2, we document that the profitability of the AG-size style momentum is not subject to the January seasonality. To examine whether the AG-size style momentum displays predictable time-varying patterns or whether its profitability 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 profitability 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.[8] We then calculate average momentum profits estimated as in Equation (2) separately for the two periods and report the results based on 6- and 12-month holding periods in Table 8.

[Insert Table 8 about here]

Unsurprisingly, 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 profitability is more stable and less volatile during expansions than during recessions.

[8] 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.

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, Table 8 shows 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 accentuated after market gains, further inducing the profitability 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).[9] After identifying the market state of each month *t*, we average coefficients estimated from Equation (2) separately for UP and DOWN markets, respectively. Table 9 provides the results.

[Insert Table 9 about here]

[9] 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.

Among the three momentum strategies examined, we find that only the AG-size style momentum displays consistent profitability 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 profitability of the AG-size style momentum.

5.3. Momentum profits conditional on market dynamics

Extending Cooper, Gutierrez, and Hameed's (2004) finding, Asem and Tian (2010) propose that the dynamic of market states, rather than the market state itself, predicts momentum profits. Their investigation is motivated by Daniel, Hirshleifer, and Subrahmanyam's (1998) model of investor overconfidence in driving momentum profits. Specifically, they propose that the degree of overconfidence on the buying (selling) behavior is enhanced when the markets continue in the UP (DOWN) market state. As a result, the model predicts that momentum profits should be higher when the markets continue in the same state (from UP to UP or from DOWN to DOWN) than when they transit to a different state (from UP to DOWN or from DOWN to UP).

Because we demonstrate in Section 4 that AG-size style momentum profits are better driven by investor underreaction, we expect the behavior model based on investor overconfidence to be rejected by our findings. That is, we hypothesize that AG-size style momentum profits are robust to different market dynamics. To explore this hypothesis, we first define a given month as market continuation or transition as in Asem and Tian (2010). At the beginning of each month *t*, we define past market performance by calculating past 12-month CRSP value-weighted index and classify the month as past UP (DOWN) if this return is nonnegative (negative). Following past UP markets, we further classify month *t* as market continuation (transition) if the CRSP value-weighted return in the subsequent month is nonnegative (negative). Analogously, a market continuation (transition) following DOWN markets is identified if the CRSP value-weighted return in the subsequent month is negative (nonnegative). Table 10 reports the momentum profits separately for periods of market continuations and transitions.

[Insert Table 10 about here]

Table 10 reveals several interesting findings. First, consistent with Asem and Tian (2010), the price momentum generates significantly positive profits when the market continues in the same state and insignificantly negative profits during market transitions. The significantly positive momentum profits during market continuations are robust regardless of the length of holding horizons and risk adjustments, whereas the negative momentum profits during market transitions become significant when Fama-French risk adjustments are considered. Second, style momentum strategies in general yield higher raw returns during market transitions than during market continuations. This pattern reverses when returns are adjusted by the Fama-French three-factor model. For example, the average 6-month profit of the AG-size momentum is 0.295% (*t*-statistic = 3.97) during market continuations and 0.663% (*t*-statistic = 5.11) during market transitions. The corresponding risk adjusted returns are 0.426% (*t*-statistic = 5.39) and 0.379% (*t*-statistic = 3.57), respectively. Similar patterns are observable for the size-BM style momentum. Finally, despite these particular patterns, the AG-size momentum profits are significantly positive in all scenarios, including different market dynamics. This finding confirms our prediction that because the profitability of the AG-size style momentum is better driven by investor underreaction, it is not affected by the dynamics of market states.

5.4. 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 profitability 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 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. Table 11 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 profitability 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.

[Insert Table 11 about here]

5.5. 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 profitability 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.[10] 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 month are those with below-median values. We then examine the momentum profits separately for periods of high and low sentiment.

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

Table 12 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 profitability of the AG-size style momentum.

[Insert Table 12 about here]

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 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 in the intermediate term, and that this profitability is not subject to January seasonality and is not followed by long-term reversals.

We test two competing explanations for our findings. The first explanation is based on Barberis and Shleifer's (2003) model, which predicts that investors' style-chasing behavior induces both momentum and excess comovement of a stock with its style. The second explanation is related to the limited-attention theory, which hypothesizes that investors do not perceive AG as a potential investment style and thus underreact to the information embedded in this neglected investment style. We provide evidence in support of the limited-attention explanation but our evidence is inconsistent with the style-chasing hypothesis, suggesting that investor underreaction better accounts for the profitability of the AG-based style momentum.

We also study the time-series patterns of AG-based style momentum profits by considering several conditioning variables that prior studies show are related to the momentum effect. In general we find that the AG-based style momentum generates consistent profits over time. To conclude, our 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 attention to this new strategy. AG is at least a starting point.

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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 (Panel A) and 12 (Panel B) 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*) and *Sret*(*A*,*B*) 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	–0.588 ***	–0.681 ***	–0.032	–0.188	0.776	0.725	0.895	0.918
	(–3.45)	(–4.04)	(–0.09)	(–0.51)	(1.19)	(1.11)	(0.83)	(0.92)
Sret(*S*,*B*)	0.202 ***	–0.056	0.532 ***	–0.125	0.910 ***	–0.248	1.877 ***	–0.318
	(3.97)	(–1.37)	(3.66)	(–1.19)	(3.61)	(–1.29)	(3.94)	(–1.09)
Sret(*A*,*S*)	0.238 ***	0.095 **	0.719 ***	0.376 ***	1.660 ***	0.775 ***	2.631 ***	0.945 ***
	(4.32)	(2.16)	(4.34)	(3.10)	(5.30)	(3.37)	(5.62)	(2.70)
Sret(*A*,*B*)	0.116 ***	0.057 **	0.307 ***	0.130 **	0.374 **	0.119	0.271	0.148
	(3.67)	(2.57)	(3.61)	(2.31)	(2.40)	(1.17)	(0.96)	(0.82)
ln(*Size*)		–0.173 ***		–0.508 ***		–1.120 ***		–2.592 ***
		(–3.61)		(–3.73)		(–4.63)		(–5.91)
ln(*BM*)		0.204 ***		0.583 ***		1.277 ***		2.372 ***
		(2.85)		(2.76)		(3.50)		(3.98)
AG		–0.386 ***		–1.048 ***		–1.972 ***		–3.161 ***
		(–7.47)		(–8.66)		(–8.99)		(–8.34)
Panel B: Style and stock returns measured over prior 12 months								
Pret12	–0.093	–0.114	0.300	0.270	0.522	0.545	–0.206	–0.331
	(–0.82)	(–1.02)	(1.08)	(0.97)	(1.06)	(1.10)	(–0.29)	(–0.44)
Sret(*S*,*B*)	0.316 ***	0.001	0.824 ***	–0.034	1.406 ***	–0.037	2.659 ***	–0.031
	(4.89)	(0.03)	(4.19)	(–0.28)	(3.57)	(–0.17)	(3.61)	(–0.09)
Sret(*A*,*S*)	0.329 ***	0.119 **	1.011 ***	0.422 ***	2.099 ***	0.874 ***	3.188 ***	1.003 **
	(5.09)	(2.16)	(5.42)	(2.82)	(5.87)	(3.13)	(5.44)	(2.33)
Sret(*A*,*B*)	0.117 ***	0.060 **	0.195 *	0.068	0.170	–0.019	–0.043	0.038
	(3.08)	(2.05)	(1.90)	(0.91)	(0.92)	(–0.14)	(–0.12)	(0.16)
ln(*Size*)		–0.195 ***		–0.576 ***		–1.220 ***		–2.730 ***
		(–3.96)		(–4.04)		(–4.85)		(–5.98)
ln(*BM*)		0.188 ***		0.586 ***		1.277 ***		2.302 ***
		(2.71)		(2.88)		(3.54)		(3.76)
AG		–0.362 ***		–1.021 ***		–1.904 ***		–3.097 ***
		(–7.07)		(–8.11)		(–8.41)		(–8.48)

Table 2: 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 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. 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	1.812 ***	1.764 ***	1.766 ***	1.628 ***	1.040 ***	1.267 ***	1.129 ***	0.942 ***
	(5.80)	(6.41)	(6.19)	(5.77)	(7.48)	(8.23)	(8.75)	(9.03)
Loser	0.822 ***	0.907 ***	0.850 ***	0.919 ***	0.183	0.547 ***	0.362 ***	0.355 ***
	(2.94)	(3.67)	(3.35)	(3.54)	(1.46)	(3.78)	(3.06)	(3.38)
Winner–Loser	0.990 ***	0.857 ***	0.916 ***	0.709 ***	0.857 ***	0.720 ***	0.767 ***	0.587 ***
	(4.46)	(4.67)	(4.88)	(4.30)	(3.96)	(4.20)	(4.41)	(4.02)
30% cutoffs to identify winner and loser styles								
Winner	1.619 ***	1.586 ***	1.620 ***	1.557 ***	0.836 ***	1.082 ***	0.973 ***	0.854 ***
	(5.60)	(6.11)	(5.98)	(5.66)	(9.01)	(8.35)	(9.74)	(10.12)
Loser	0.870 ***	0.957 ***	0.959 ***	1.028 ***	0.174 *	0.557 ***	0.430 ***	0.417 ***
	(3.11)	(3.90)	(3.78)	(3.93)	(1.68)	(4.09)	(4.01)	(4.45)
Winner–Loser	0.748 ***	0.629 ***	0.661 ***	0.529 ***	0.662 ***	0.525 ***	0.544 ***	0.437 ***
	(4.74)	(4.52)	(4.70)	(4.18)	(4.30)	(4.10)	(4.28)	(3.96)
Panel B: Style returns measured over prior 12 months								
10% cutoffs to identify winner and loser styles								
Winner	1.730 ***	1.677 ***	1.599 ***	1.486 ***	0.973 ***	1.222 ***	1.009 ***	0.837 ***
	(5.61)	(6.19)	(5.86)	(5.55)	(6.93)	(7.71)	(8.23)	(8.33)
Loser	0.770 ***	0.857 ***	0.860 ***	0.966 ***	0.141	0.454 ***	0.330 ***	0.355 ***
	(2.71)	(3.41)	(3.30)	(3.57)	(1.01)	(3.00)	(2.59)	(2.98)
Winner–Loser	0.960 ***	0.820 ***	0.739 ***	0.520 ***	0.832 ***	0.769 ***	0.679 ***	0.482 ***
	(4.17)	(4.21)	(3.99)	(3.03)	(3.67)	(4.00)	(3.89)	(3.00)
30% cutoffs to identify winner and loser styles								
Winner	1.685 ***	1.633 ***	1.612 ***	1.535 ***	0.903 ***	1.148 ***	0.989 ***	0.853 ***
	(5.76)	(6.32)	(6.05)	(5.71)	(9.30)	(8.69)	(9.84)	(10.08)
Loser	0.831 ***	0.962 ***	0.987 ***	1.056 ***	0.144	0.534 ***	0.423 ***	0.412 ***
	(2.99)	(3.84)	(3.77)	(3.91)	(1.33)	(3.87)	(3.82)	(4.09)
Winner–Loser	0.854 ***	0.670 ***	0.626 ***	0.480 ***	0.760 ***	0.614 ***	0.566 ***	0.442 ***
	(5.18)	(4.87)	(4.64)	(3.74)	(4.75)	(4.67)	(4.50)	(3.71)

Table 3: January seasonality of the AG-size style momentum using 30% cutoffs

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 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. 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 $t-1$. We report the momentum profits separately for January-only and non-January observations. 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								
January months								
Winner	5.448 ***	4.795 ***	5.650 ***	5.770 ***	2.012 ***	2.303 ***	2.572 ***	2.560 ***
	(4.48)	(5.39)	(5.10)	(4.91)	(4.51)	(5.08)	(5.47)	(5.67)
Loser	4.704 ***	3.367 ***	3.579 ***	4.081 ***	2.128 ***	1.964 ***	1.830 ***	1.882 ***
	(4.13)	(4.83)	(4.46)	(4.30)	(4.18)	(4.23)	(4.32)	(4.58)
Winner–Loser	0.744	1.429 **	2.071 ***	1.689 **	–0.116	0.339	0.742	0.678
	(0.83)	(2.43)	(2.81)	(2.30)	(–0.19)	(0.70)	(1.29)	(1.19)
Non-January months								
Winner	1.270 ***	1.293 ***	1.252 ***	1.180 ***	0.740 ***	0.962 ***	0.822 ***	0.700 ***
	(4.43)	(5.01)	(4.66)	(4.30)	(7.92)	(7.32)	(8.48)	(8.90)
Loser	0.521 *	0.737 ***	0.720 ***	0.755 ***	–0.010	0.427 ***	0.307 ***	0.290 ***
	(1.82)	(2.99)	(2.81)	(2.88)	(–0.10)	(3.25)	(3.01)	(3.25)
Winner–Loser	0.749 ***	0.556 ***	0.532 ***	0.425 ***	0.750 ***	0.535 ***	0.515 ***	0.410 ***
	(5.01)	(4.15)	(4.03)	(3.50)	(5.12)	(4.21)	(4.11)	(3.68)
Panel B: Style returns measured over prior 12 months								
January months								
Winner	5.448 ***	4.538 ***	5.184 ***	5.349 ***	2.012 ***	2.065 ***	2.327 ***	2.438 ***
	(4.48)	(5.14)	(4.86)	(4.74)	(4.51)	(4.53)	(4.89)	(5.61)
Loser	4.704 ***	3.690 ***	4.106 ***	4.657 ***	2.128 ***	1.961 ***	1.971 ***	2.045 ***
	(4.13)	(4.61)	(4.52)	(4.40)	(4.18)	(3.89)	(4.42)	(4.38)
Winner–Loser	0.744	0.848	1.078	0.692	–0.116	0.105	0.356	0.392
	(0.83)	(1.38)	(1.51)	(0.89)	(–0.19)	(0.22)	(0.62)	(0.66)
Non-January months								
Winner	1.342 ***	1.368 ***	1.287 ***	1.195 ***	0.812 ***	1.048 ***	0.863 ***	0.715 ***
	(4.61)	(5.32)	(4.85)	(4.43)	(8.54)	(7.88)	(8.93)	(9.01)
Loser	0.478 *	0.714 ***	0.702 ***	0.734 ***	–0.042	0.397 ***	0.282 ***	0.264 ***
	(1.70)	(2.88)	(2.70)	(2.75)	(–0.42)	(2.95)	(2.62)	(2.75)
Winner–Loser	0.864 ***	0.654 ***	0.585 ***	0.461 ***	0.854 ***	0.651 ***	0.581 ***	0.452 ***
	(5.74)	(4.88)	(4.41)	(3.66)	(5.74)	(4.97)	(4.59)	(3.76)

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 (one for each average) 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: Persistence of momentum strategies based on style returns

In each month *t*, we perform the following 6 or 12 cross-sectional regressions (for *j* = 14,..., 25 to *j* = 50,..., 61):

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

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 12 cross-sectional regressions for *j* = 14,..., 25 to *j* = 50,..., 61 and average the corresponding coefficient estimates. We report risk-adjusted returns by performing time-series regressions of these averages (one for each average) 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.

	FF-adj. returns (14,25)		FF-adj. returns (26,37)		FF-adj. returns (38,49)		FF-adj. returns (50,61)	
Variable	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.	Jan. incl.	Jan. excl.
Intercept	1.545 ***	0.853 ***	1.447 ***	0.741 ***	1.414 ***	0.740 ***	1.275 ***	0.627 ***
	(6.52)	(4.04)	(6.35)	(3.73)	(6.43)	(3.81)	(5.98)	(3.31)
$r_{i,t-1}$	–0.053 ***	–0.047 ***	–0.053 ***	–0.047 ***	–0.053 ***	–0.047 ***	–0.054 ***	–0.047 ***
	(–14.42)	(–14.11)	(–14.62)	(–14.33)	(–14.46)	(–13.96)	(–14.43)	(–13.77)
ln(*Size*)	–0.158 ***	–0.040	–0.154 ***	–0.038	–0.144 ***	–0.034	–0.119 ***	–0.014
	(–4.03)	(–1.16)	(–4.08)	(–1.13)	(–3.96)	(–1.06)	(–3.46)	(–0.45)
PRW	–0.193 ***	–0.191 ***	–0.131 ***	–0.146 ***	–0.080 **	–0.111 ***	–0.140 ***	–0.174 ***
	(–4.42)	(–4.42)	(–2.93)	(–3.17)	(–2.06)	(–2.85)	(–3.64)	(–4.60)
PRL	–0.031	–0.119 **	–0.060	–0.105 **	–0.047	–0.081 **	–0.005	–0.029
	(–0.63)	(–2.58)	(–1.41)	(–2.58)	(–1.30)	(–2.27)	(–0.15)	(–0.87)
SRW(*S*,*B*)	–0.017	–0.069	0.034	0.009	0.084 *	0.072 *	0.017	–0.014
	(–0.36)	(–1.48)	(0.86)	(0.23)	(1.90)	(1.67)	(0.45)	(–0.40)
SRL(*S*,*B*)	–0.175 ***	–0.212 ***	–0.057	–0.102 **	–0.105 **	–0.138 ***	–0.070 *	–0.117 ***
	(–4.22)	(–5.18)	(–1.24)	(–2.28)	(–2.53)	(–3.45)	(–1.88)	(–3.21)
SRW(*A*,*S*)	0.093 **	0.049	0.090 ***	0.061 *	0.074 **	0.056 *	0.080 ***	0.069 **
	(2.50)	(1.42)	(2.63)	(1.86)	(2.37)	(1.83)	(2.60)	(2.39)
SRL(*A*,*S*)	–0.246 ***	–0.291 ***	–0.183 ***	–0.227 ***	–0.171 ***	–0.210 ***	–0.142 ***	–0.176 ***
	(–6.85)	(–8.38)	(–5.34)	(–6.53)	(–5.06)	(–6.22)	(–4.66)	(–5.81)
PRW–PRL	–0.163 **	–0.072	–0.070	–0.042	–0.032	–0.030	–0.135 ***	–0.145 ***
	(–2.44)	(–1.12)	(–1.21)	(–0.70)	(–0.68)	(–0.62)	(–2.85)	(–3.03)
SRW(*S*,*B*)	0.158 **	0.143 **	0.091	0.111 *	0.188 ***	0.210 ***	0.087	0.103 **
–*SRL*(*S*,*B*)	(2.36)	(2.16)	(1.51)	(1.85)	(3.11)	(3.52)	(1.59)	(2.01)
SRW(*A*,*S*)	0.339 ***	0.341 ***	0.273 ***	0.287 ***	0.245 ***	0.266 ***	0.223 ***	0.245 ***
–*SRL*(*A*,*S*)	(6.79)	(6.78)	(5.90)	(6.24)	(5.77)	(6.12)	(5.60)	(6.34)

Table 6: Profits to the AG-size style momentum conditional on comovement

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 AG-size style returns. Within each of the three style 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. 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	2.604 ***	1.712 ***	1.757 ***	–0.848 *	1.794 ***	1.607 ***	1.639 ***	–0.155	1.629 ***	1.491 ***	1.517 ***	–0.112
	(5.14)	(7.02)	(5.50)	(–1.89)	(5.98)	(6.36)	(4.91)	(–0.54)	(6.92)	(5.70)	(4.46)	(–0.63)
Loser	1.097 ***	1.071 ***	0.993 ***	–0.104	1.068 ***	1.007 ***	0.916 ***	–0.152	1.091 ***	1.037 ***	0.972 ***	–0.118
	(5.06)	(4.56)	(3.32)	(–0.74)	(4.65)	(4.11)	(2.91)	(–1.06)	(4.52)	(3.99)	(2.92)	(–0.80)
Winner–Loser	1.508 ***	0.641 ***	0.764 ***	–0.744 *	0.726 ***	0.600 ***	0.723 ***	–0.003	0.538 ***	0.454 ***	0.545 ***	0.007
	(3.25)	(4.65)	(4.99)	(–1.65)	(2.90)	(4.38)	(4.68)	(–0.01)	(3.58)	(3.52)	(3.75)	(0.05)
Panel B: Fama-French risk-adjusted returns												
Winner	1.979 ***	1.153 ***	1.126 ***	–0.853 **	1.228 ***	0.953 ***	0.915 ***	–0.314	1.046 ***	0.811 ***	0.763 ***	–0.283 **
	(4.79)	(9.40)	(6.63)	(–2.10)	(5.40)	(9.88)	(6.67)	(–1.37)	(9.66)	(10.07)	(6.57)	(–2.24)
Loser	0.658 ***	0.580 ***	0.440 ***	–0.219 **	0.550 ***	0.433 ***	0.268 **	–0.282 **	0.526 ***	0.412 ***	0.263 **	–0.263 **
	(4.66)	(4.32)	(2.68)	(–2.05)	(4.36)	(3.91)	(1.98)	(–2.58)	(4.53)	(4.28)	(2.12)	(–2.41)
Winner–Loser	1.320 ***	0.573 ***	0.687 ***	–0.634	0.679 ***	0.520 ***	0.647 ***	–0.032	0.520 ***	0.399 ***	0.500 ***	–0.020
	(3.17)	(4.52)	(4.70)	(–1.54)	(2.87)	(4.22)	(4.50)	(–0.14)	(3.61)	(3.45)	(3.71)	(–0.16)

Table 7: 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	1.225 ***	1.420 ***	1.762 ***	0.537 ***	1.235 ***	1.403 ***	1.725 ***	0.490 ***	1.197 ***	1.355 ***	1.650 ***	0.453 ***
	(5.87)	(6.11)	(6.26)	(3.57)	(5.70)	(5.78)	(5.99)	(3.37)	(5.35)	(5.44)	(5.72)	(3.28)
Loser	0.935 ***	0.875 ***	1.067 ***	0.132	0.915 ***	0.866 ***	1.105 ***	0.189	0.955 ***	0.950 ***	1.183 ***	0.228 *
	(4.52)	(3.65)	(4.01)	(1.08)	(4.20)	(3.49)	(4.00)	(1.50)	(4.24)	(3.70)	(4.17)	(1.87)
Winner–Loser	0.290 **	0.545 ***	0.694 ***	0.404 ***	0.319 ***	0.536 ***	0.620 ***	0.301 ***	0.242 **	0.405 ***	0.467 ***	0.225 **
	(2.42)	(3.96)	(5.22)	(3.36)	(2.70)	(3.89)	(4.96)	(2.66)	(2.18)	(2.99)	(4.00)	(2.18)
Fama-French risk-adjusted returns												
Winner	0.817 ***	0.961 ***	1.252 ***	0.435 ***	0.703 ***	0.809 ***	1.075 ***	0.372 ***	0.612 ***	0.704 ***	0.937 ***	0.325 ***
	(7.41)	(8.53)	(8.23)	(3.43)	(8.07)	(9.15)	(9.12)	(3.22)	(7.51)	(8.49)	(9.49)	(3.12)
Loser	0.586 ***	0.475 ***	0.599 ***	0.012	0.440 ***	0.335 ***	0.499 ***	0.059	0.411 ***	0.344 ***	0.494 ***	0.084
	(4.96)	(3.49)	(4.07)	(0.12)	(4.73)	(3.10)	(4.22)	(0.57)	(5.18)	(3.45)	(4.54)	(0.84)
Winner–Loser	0.231 *	0.486 ***	0.653 ***	0.422 ***	0.263 **	0.474 ***	0.576 ***	0.313 ***	0.202 *	0.361 ***	0.443 ***	0.242 **
	(1.96)	(3.80)	(5.03)	(3.51)	(2.28)	(3.70)	(4.84)	(2.70)	(1.82)	(2.82)	(4.06)	(2.23)
Panel B: Momentum profits conditional on information discreteness at the individual level												
Raw returns												
Winner	1.626 ***	1.743 ***	1.530 ***	–0.096	1.635 ***	1.708 ***	1.496 ***	–0.138 *	1.576 ***	1.599 ***	1.433 ***	–0.143 **
	(5.98)	(6.89)	(5.87)	(-1.10)	(5.79)	(6.60)	(5.61)	(-1.69)	(5.61)	(6.14)	(5.31)	(–2.14)
Loser	0.838 ***	1.060 ***	0.989 ***	0.151	0.874 ***	1.092 ***	0.993 ***	0.119	1.025 ***	1.128 ***	1.017 ***	–0.008
	(2.95)	(4.31)	(4.25)	(1.44)	(2.95)	(4.27)	(4.10)	(1.18)	(3.33)	(4.31)	(4.10)	(–0.08)
Winner–Loser	0.788 ***	0.682 ***	0.541 ***	–0.247 ***	0.760 ***	0.617 ***	0.503 ***	–0.257 ***	0.551 ***	0.471 ***	0.416 ***	–0.135 *
	(5.35)	(4.73)	(3.88)	(–3.07)	(5.28)	(4.33)	(3.74)	(–3.38)	(3.94)	(3.53)	(3.30)	(–1.77)
Fama-French risk-adjusted returns												
Winner	1.120 ***	1.250 ***	1.074 ***	-0.045	0.980 ***	1.079 ***	0.908 ***	-0.071	0.860 ***	0.921 ***	0.780 ***	-0.079
	(7.65)	(9.65)	(7.83)	(-0.55)	(8.49)	(11.10)	(8.58)	(-0.99)	(8.73)	(11.22)	(8.93)	(-1.34)
Loser	0.383 **	0.629 ***	0.589 ***	0.206 *	0.264 *	0.529 ***	0.475 ***	0.211 **	0.322 **	0.485 ***	0.429 ***	0.107
	(2.15)	(4.71)	(4.91)	(1.96)	(1.78)	(4.91)	(5.03)	(2.19)	(2.34)	(5.00)	(5.18)	(1.20)
Winner–Loser	0.737 ***	0.620 ***	0.486 ***	-0.251 ***	0.716 ***	0.550 ***	0.433 ***	-0.283 ***	0.537 ***	0.436 ***	0.352 ***	-0.186 ***
	(5.05)	(4.65)	(3.65)	(-3.15)	(5.07)	(4.30)	(3.50)	(-3.77)	(3.97)	(3.61)	(3.06)	(-2.65)

Table 8: Cross-sectional regressions conditional on business cycles

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 expansionary and recessionary periods. The expansionary and recessionary periods are identified based on the definition of National Bureau of Economic Research. To obtain risk-adjusted returns, we perform time-series regressions of these averages (one for each average) 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.

	Expansionary periods				Recessionary periods			
	Monthly returns (2,7)		Monthly returns (2,13)		Monthly returns (2,7)		Monthly returns (2,13)	
Variable	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.
Intercept	2.612 ***	1.519 ***	2.633 ***	1.517 ***	1.365	1.239 *	1.593	1.462 *
	(6.29)	(6.39)	(6.30)	(6.29)	(1.08)	(1.85)	(1.16)	(1.98)
$r_{i,t-1}$	–0.048 ***	–0.044 ***	–0.049 ***	–0.045 ***	–0.089 ***	–0.090 ***	–0.089 ***	–0.090 ***
	(–12.64)	(–12.34)	(–12.75)	(–12.41)	(–6.70)	(–8.43)	(–6.72)	(–8.29)
ln(*Size*)	–0.225 ***	–0.184 ***	–0.219 ***	–0.174 ***	–0.152	–0.056	–0.170	–0.075
	(–4.42)	(–4.60)	(–4.32)	(–4.31)	(–1.16)	(–0.53)	(–1.19)	(–0.65)
PRW	0.200 **	0.190 ***	0.026	0.032	–0.164	–0.028	–0.250	–0.088
	(2.09)	(2.77)	(0.31)	(0.57)	(–0.66)	(–0.13)	(–1.28)	(–0.53)
PRL	–0.162	–0.264 ***	–0.070	–0.181 ***	0.051	0.126	0.078	0.143
	(–1.63)	(–3.28)	(–0.77)	(–2.64)	(0.11)	(0.42)	(0.20)	(0.57)
SRW(*S*,*B*)	0.001	0.073	0.012	0.046	0.162	0.093	0.179	0.129
	(0.01)	(1.28)	(0.24)	(0.97)	(0.88)	(0.57)	(1.02)	(0.81)
SRL(*S*,*B*)	–0.175 ***	–0.115 **	–0.218 ***	–0.158 ***	–0.533 ***	–0.428 ***	–0.605 ***	–0.494 ***
	(–2.87)	(–2.43)	(–3.85)	(–3.77)	(–3.47)	(–3.17)	(–3.66)	(–3.64)
SRW(*A*,*S*)	0.140 **	0.137 ***	0.100 **	0.103 **	0.113	0.117	0.066	0.094
	(2.29)	(2.64)	(2.04)	(2.33)	(0.80)	(0.89)	(0.49)	(0.78)
SRL(*A*,*S*)	–0.289 ***	–0.260 ***	–0.290 ***	–0.260 ***	–0.478 ***	–0.367 ***	–0.596 ***	–0.499 ***
	(–4.94)	(–6.01)	(–5.56)	(–6.60)	(–3.55)	(–3.18)	(–4.81)	(–4.82)
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)

Table 9: Cross-sectional regressions conditional on market states

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 different market states:

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

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 separately for UP and DOWN markets. 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 month *t*. If this return is nonnegative (negative), we classify the market state of month *t* as UP (DOWN). To obtain risk-adjusted returns, we perform time-series regressions of these averages (one for each average) 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.

	UP markets				DOWN markets			
	Monthly returns (2,7)		Monthly returns (2,13)		Monthly returns (2,7)		Monthly returns (2,13)	
Variable	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.
Intercept	2.101 ***	1.294 ***	2.095 ***	1.272 ***	4.155 ***	2.429 ***	4.490 ***	2.676 ***
	(5.28)	(5.59)	(5.21)	(5.45)	(3.42)	(3.58)	(3.49)	(3.64)
$r_{i,t-1}$	–0.050 ***	–0.047 ***	–0.051 ***	–0.048 ***	–0.077 ***	–0.067 ***	–0.077 ***	–0.067 ***
	(–12.64)	(–12.70)	(–12.79)	(–12.79)	(–6.57)	(–6.70)	(–6.54)	(–6.60)
ln(*Size*)	–0.189 ***	–0.150 ***	–0.176 ***	–0.134 ***	–0.348 ***	–0.276 ***	–0.398 ***	–0.315 ***
	(–3.75)	(–3.75)	(–3.51)	(–3.33)	(–3.14)	(–2.72)	(–3.29)	(–2.88)
PRW	0.250 ***	0.286 ***	0.041	0.081	–0.372 *	–0.232	–0.287 *	–0.159
	(2.61)	(4.06)	(0.48)	(1.41)	(–1.74)	(–1.20)	(–1.78)	(–1.11)
PRL	–0.325 ***	–0.342 ***	–0.210 ***	–0.238 ***	0.858 **	0.465	0.774 **	0.411
	(–3.89)	(–4.80)	(–2.69)	(–3.90)	(2.00)	(1.50)	(2.09)	(1.59)
SRW(*S*,*B*)	0.040	0.095	0.011	0.042	–0.062	–0.041	0.164	0.201
	(0.61)	(1.61)	(0.20)	(0.86)	(–0.38)	(–0.31)	(1.11)	(1.57)
SRL(*S*,*B*)	–0.229 ***	–0.163 ***	–0.271 ***	–0.199 ***	–0.209 *	–0.144	–0.283 **	–0.220 **
	(–3.45)	(–3.43)	(–4.52)	(–4.56)	(–1.88)	(–1.20)	(–2.33)	(–2.00)
SRW(*A*,*S*)	0.120 **	0.144 ***	0.098 **	0.117 ***	0.221	0.189	0.082	0.083
	(2.02)	(2.84)	(2.04)	(2.77)	(1.52)	(1.36)	(0.62)	(0.61)
SRL(*A*,*S*)	–0.304 ***	–0.269 ***	–0.315 ***	–0.280 ***	–0.377 ***	–0.299 **	–0.428 ***	–0.340 ***
	(–5.20)	(–6.34)	(–5.77)	(–7.05)	(–3.11)	(–2.61)	(–4.13)	(–3.64)
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)

Table 10: Cross-sectional regressions conditional on market dynamics

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 different market dynamics:

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

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 separately for different market dynamics. If the sign of the buy-and-hold return on the CRSP value-weighted index over the past 12 months prior to month *t* is the same with the sign of the CRSP value-weighted index in month *t*, we classify month *t* as "market continuations", otherwise it is classified as "market transitions". To obtain risk-adjusted returns, we perform time-series regressions of these averages (one for each average) 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.

	Market continuations				Market transitions			
	Monthly returns (2,7)		Monthly returns (2,13)		Monthly returns (2,7)		Monthly returns (2,13)	
Variable	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.
Intercept	3.488 ***	1.376 ***	3.535 ***	1.428 ***	1.025	1.974 ***	1.078	2.054 ***
	(7.72)	(3.86)	(7.83)	(3.95)	(1.53)	(5.71)	(1.52)	(5.63)
$r_{i,t-1}$	–0.059 ***	–0.049 ***	–0.060 ***	–0.050 ***	–0.048 ***	–0.060 ***	–0.048 ***	–0.060 ***
	(–11.21)	(–8.77)	(–11.26)	(–8.78)	(–7.78)	(–11.25)	(–7.88)	(–11.13)
ln(*Size*)	–0.143 **	–0.165 ***	–0.144 **	–0.170 ***	–0.311 ***	–0.221 ***	–0.304 ***	–0.223 ***
	(–2.32)	(–2.78)	(–2.36)	(–2.83)	(–4.72)	(–3.82)	(–4.36)	(–3.72)
PRW	0.720 ***	0.432 ***	0.559 ***	0.303 ***	–0.618 ***	–0.263 **	–0.781 ***	–0.344 ***
	(5.96)	(4.64)	(5.72)	(4.09)	(–4.23)	(–2.09)	(–5.86)	(–3.41)
PRL	0.036	–0.351 ***	0.107	–0.283 ***	–0.358	0.167	–0.259	0.194
	(0.31)	(–3.38)	(1.01)	(–3.16)	(–1.55)	(1.09)	(–1.31)	(1.52)
SRW(*S*,*B*)	–0.003	0.083	0.024	0.193 ***	0.058	0.003	0.051	–0.008
	(–0.04)	(1.05)	(0.40)	(2.97)	(0.52)	(0.03)	(0.54)	(–0.10)
SRL(*S*,*B*)	–0.063	–0.134 *	–0.127 **	–0.202 ***	–0.444 ***	–0.150 **	–0.469 ***	–0.165 **
	(–0.89)	(–1.93)	(–1.97)	(–3.27)	(–4.78)	(–2.10)	(–4.96)	(–2.43)
SRW(*A*,*S*)	0.157 **	0.206 ***	0.148 ***	0.208 ***	0.109	0.057	0.024	–0.027
	(2.30)	(3.11)	(2.72)	(3.80)	(1.21)	(0.63)	(0.30)	(–0.34)
SRL(*A*,*S*)	–0.138 **	–0.220 ***	–0.147 ***	–0.212 ***	–0.554 ***	–0.322 ***	–0.583 ***	–0.353 ***
	(–2.57)	(–4.12)	(–3.03)	(–4.17)	(–5.67)	(–4.15)	(–6.44)	(–5.17)
PRW–*PRL*	0.684 ***	0.784 ***	0.452 ***	0.586 ***	–0.261	–0.430 *	–0.521 **	–0.539 ***
	(4.63)	(5.23)	(3.78)	(4.95)	(–0.92)	(–1.89)	(–2.32)	(–3.07)
SRW(*S*,*B*)	0.060	0.217 **	0.152	0.395 ***	0.502 ***	0.153	0.520 ***	0.157
–*SRL*(*S*,*B*)	(0.62)	(2.15)	(1.56)	(4.25)	(3.50)	(1.28)	(3.79)	(1.38)
SRW(*A*,*S*)	0.295 ***	0.426 ***	0.296 ***	0.420 ***	0.663 ***	0.379 ***	0.608 ***	0.326 ***
–*SRL*(*A*,*S*)	(3.97)	(5.39)	(4.58)	(5.82)	(5.11)	(3.57)	(5.05)	(3.42)

Table 11: Cross-sectional regressions conditional on market volatilities

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 high and low market volatilities:

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

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 separately for periods of high and low market volatilities. To identify whether a given month belongs to high or low market volatilities, we first calculate the standard deviation of daily market returns separately for past 12 and 36 months. Each holding period of month t is classified as high (low) volatility if the lagged 12-month volatility is larger (smaller) than the lagged 36-month volatility. To obtain risk-adjusted returns, we perform time-series regressions of these averages (one for each average) 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.

	Low market volatilities				High market volatilities			
	Monthly returns (2,7)		Monthly returns (2,13)		Monthly returns (2,7)		Monthly returns (2,13)	
Variable	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.
Intercept	2.139 ***	1.249 ***	2.130 ***	1.727 ***	2.752 ***	1.216 ***	2.864 ***	1.800 ***
	(4.50)	(4.98)	(4.45)	(4.64)	(4.16)	(4.79)	(4.18)	(4.67)
$r_{i,t-1}$	–0.047 ***	–0.041 ***	–0.048 ***	–0.057 ***	–0.062 ***	–0.042 ***	–0.063 ***	–0.058 ***
	(–10.61)	(–10.64)	(–10.66)	(–10.18)	(–9.59)	(–10.69)	(–9.73)	(–10.23)
ln(*Size*)	–0.189 ***	–0.147 ***	–0.175 ***	–0.188 ***	–0.242 ***	–0.130 ***	–0.251 ***	–0.191 ***
	(–3.19)	(–3.47)	(–2.95)	(–3.08)	(–3.34)	(–3.05)	(–3.36)	(–3.04)
PRW	0.217 **	0.170 **	0.041	0.180	0.075	0.017	–0.070	0.018
	(2.10)	(2.37)	(0.47)	(1.58)	(0.53)	(0.29)	(–0.56)	(0.20)
PRL	–0.399 ***	–0.452 ***	–0.254 ***	0.007	0.151	–0.320 ***	0.169	0.031
	(–4.42)	(–6.76)	(–2.89)	(0.05)	(0.77)	(–5.19)	(0.98)	(0.25)
SRW(*S*,*B*)	0.121 *	0.158 ***	0.104 *	–0.049	–0.080	0.099 **	–0.037	–0.003
	(1.67)	(2.81)	(1.90)	(–0.53)	(–0.81)	(2.20)	(–0.42)	(–0.04)
SRL(*S*,*B*)	–0.179 ***	–0.135 ***	–0.240 ***	–0.221 ***	–0.275 ***	–0.190 ***	–0.308 ***	–0.245 ***
	(–3.02)	(–2.60)	(–4.54)	(–3.04)	(–2.96)	(–4.26)	(–3.36)	(–3.60)
SRW(*A*,*S*)	0.207 **	0.189 ***	0.141 **	0.078	0.062	0.124 **	0.047	0.070
	(2.52)	(2.89)	(2.37)	(1.10)	(0.91)	(2.50)	(0.72)	(1.05)
SRL(*A*,*S*)	–0.265 ***	–0.234 ***	–0.284 ***	–0.329 ***	–0.369 ***	–0.250 ***	–0.386 ***	–0.341 ***
	(–4.49)	(–4.71)	(–5.49)	(–5.20)	(–4.40)	(–5.85)	(–4.86)	(–5.71)
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)

Table 12: Cross-sectional regressions conditional on investor sentiment

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 high and low sentiment:

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

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 separately for periods of high and low sentiment. We measure the level of investor sentiment based on the value of the monthly market-based sentiment series constructed by Baker and Wurgler (2006, 2007). A given month t is identified as high (low) sentiment if the value of the Baker-Wurgler sentiment index in month *t*−1 is above (below) the median value for the sample period. Note that the sentiment index spans the period from July 1965 to December 2010. To obtain risk-adjusted returns, we perform time-series regressions of these averages (one for each average) 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.

	High sentiment				Low sentiment			
	Monthly returns (2,7)		Monthly returns (2,13)		Monthly returns (2,7)		Monthly returns (2,13)	
Variable	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.	Raw	FF-adj.
Intercept	1.781 ***	1.137 ***	1.807 ***	1.153 ***	3.228 ***	1.904 ***	3.326 ***	1.948 ***
	(3.10)	(3.16)	(3.12)	(3.18)	(5.27)	(6.32)	(5.20)	(6.12)
$r_{i,t-1}$	–0.047 ***	–0.046 ***	–0.048 ***	–0.047 ***	–0.062 ***	–0.056 ***	–0.063 ***	–0.057 ***
	(–8.59)	(–8.71)	(–8.75)	(–8.80)	(–10.73)	(–11.51)	(–10.82)	(–11.51)
ln(*Size*)	–0.122 *	–0.109 *	–0.112 *	–0.096	–0.329 ***	–0.250 ***	–0.335 ***	–0.248 ***
	(–1.87)	(–1.84)	(–1.73)	(–1.60)	(–4.47)	(–4.92)	(–4.42)	(–4.78)
PRW	0.157	0.310 ***	–0.081	0.077	0.173	0.182 *	0.069	0.068
	(1.09)	(3.00)	(–0.64)	(0.89)	(1.43)	(1.75)	(0.71)	(0.84)
PRL	–0.452 ***	–0.386 ***	–0.317 **	–0.271 ***	0.249	0.035	0.281 *	0.069
	(–3.19)	(–3.45)	(–2.46)	(–2.81)	(1.41)	(0.28)	(1.83)	(0.66)
SRW(*S*,*B*)	0.055	0.138	0.029	0.078	0.013	0.043	0.069	0.094
	(0.55)	(1.56)	(0.36)	(1.06)	(0.15)	(0.62)	(0.91)	(1.53)
SRL(*S*,*B*)	–0.328 ***	–0.208 ***	–0.379 ***	–0.255 ***	–0.165 **	–0.148 **	–0.201 ***	–0.170 ***
	(–3.39)	(–2.89)	(–4.18)	(–3.94)	(–2.47)	(–2.51)	(–2.99)	–3.10)
SRW(*A*,*S*)	0.185 *	0.241 ***	0.131 *	0.178 ***	0.132 *	0.112 *	0.083	0.076
	(1.96)	(3.09)	(1.78)	(2.82)	(1.84)	(1.75)	(1.28)	(1.25)
SRL(*A*,*S*)	–0.429 ***	–0.342 ***	–0.433 ***	–0.354 ***	–0.186 ***	–0.162 ***	–0.226 ***	–0.193 ***
	(–4.68)	(–5.70)	(–5.10)	(–6.07)	(–3.21)	(–2.79)	(–4.43)	(–3.89)
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)