Credit rating, post-earnings-announcement drift, and arbitrage from transient institutions

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Abstract: This study first establishes a robust link between credit rating and post-earnings-announcement drift (PEAD). I find strong evidence that PEAD is more salient for firms with low credit ratings. This finding is consistent with the notion that investors are prone to underreact to earnings news from low-credit-rating firms that are characterized by high uncertainty of asset fundamentals. The association between credit rating and PEAD is not driven by traditional information uncertainty proxies such as earnings volatility, cash flow volatility, accruals quality, firm age, idiosyncratic volatility, and analyst forecast dispersion. I further investigate whether transient institutions exploit the differential of PEAD among different rated firms in their arbitrage trades. The results reveal that transient institutions tend to focus their arbitrage on low-credit-rating firms. However, the existence and concentration of PEAD in low-credit-rating firms suggest that transient institutions fail to arbitrage away PEAD among low-rated firms and that the arbitrage strategy is riskier than expected by the transient institutions. This in turn implies that estimation risk associated with pricing the earnings news of low-rated firms plays a substantive role in forming the strong PEAD of these firms.

Keywords**:** credit rating; post-earnings-announcement drift; uncertainty; estimation risk; transient institutional investors; arbitrage

JEL Classifications**:** M41 G24 G14

1. INTRODUCTION

One robust, long-standing market anomaly well documented in the asset pricing literature is post-earnings-announcement drift (hereafter, PEAD). PEAD refers to the tendency of stocks to continue to earn positive (negative) abnormal returns after positive (negative) earnings surprises. Beginning with the early work by Ball and Brown (1968), the finance and accounting literature (e.g., Bernard & Thomas, 1989, 1990; Ball & Bartov, 1996; Brown & Pope, 1996; Jegadeesh & Livnat, 2006; Chordia, Goyal, Sadka, Sadka, & Shivakumar, 2008) documents that investors tend to underreact to earnings information at earnings announcements, followed by continuous return drifts going in the same direction as earnings surprises. As such, firms that report high standardized unexpected earnings (hereafter, *SUE*) subsequently outperform firms that report low *SUE*. This phenomenon is known as PEAD anomaly.

Prior studies (e.g., Bernard & Thomas, 1989; Chan, Jegadeesh & Lakonishok, 1996; Ke & Ramalingegowda, 2005; Chung & Hrazdil, 2011) document that the anomalous PEAD returns remain significant after adjusting/controlling for systematic risk and transaction costs, suggesting that the anomaly is likely to be caused by investors' under-reactions to earning news. There are two main explanations for the investors' under-reactions. First, investors do *not* pay sufficient attention to earnings news (e.g., Dellavigna & Pollet, 2009; Hirshleifer, Lim, & Teoh, 2011). Even they do so, constrained in the ability to process information, they fail to correctly infer the implication of earnings news for future earnings (e.g., Barberis, Shleifer, & Vishny, 1998; Battalio & Mendenhall, 2005). As such, mispricing emerges, but it can be subsequently corrected by sophisticated investors (e.g., McLean & Pontiff, 2016). Second, investors face high estimation risk in pricing firms that have high uncertainty of asset fundamentals. It thus takes time for investors to learn about the earnings formation process over time to form their beliefs about future firm prospect, thereby leading to their delayed reactions to earnings news. If PEAD is attributed to the estimation risk and associated investor learning, the anomaly will persist and not be exploitable by sophisticated investors (e.g., Cochrane, 1999; McLean & Pontiff, 2016). Whether PEAD is due to the mispricing or estimation risk is unclear.

The first aim of this study is to explore the link between credit rating and PEAD, and provide insights into how this link is attributed to the aforementioned explanations for PEAD. The existing literature (Avramov, Chordia, Jostova, and Philipov, 2007, 2009a) finds that market anomalies such as price momentum and analyst forecast dispersion anomaly are concentrated in stocks with high credit risk, which is measured by credit rating. However, this literature does not give a reason for why such market inefficiencies and associated anomalies are evident mainly among low-credit-rating firms. PEAD provides a powerful setting to probe the underlying reason, because unlike other anomalies (e.g., price momentum, low-volatility anomaly, analyst forecast dispersion anomaly), PEAD anomaly involves explicitly a highly price-relevant event, i.e., earnings announcement. In the earnings announcements by higher-credit-risk firms, information about not only earnings but also higher uncertainty of future profitability is likely to be revealed. This thus facilitates us to shed light on the role the estimation risk *vis-à-vis* mispricing would play in the formation of PEAD among lower-credit-rating firms.

Given that PEAD, if attributed to the mispricing (estimation risk), is likely (unlikely) to be exploitable by sophisticated investors (McLean & Pontiff, 2016), the second aim of this study is to examine whether transient institutional investors exploit PEAD among different rated firms. Transient institutions are arguably more sophisticated in acquiring and processing information than general investors, and hence may be better in understanding the earnings news, and associated PEAD, of low-credit-rating firms (Bartov, Radhakrishnan, & Krinsky, 2000; Ke &

Ramalingegowda, 2005; Campbell, Hilscher, & Szilagyi, 2008). If transient institutions make the arbitrage trades but fail to arbitrage away the PEAD, it should be at least partially attributed to the foregoing estimation risk.

I argue for a negative association between PEAD and credit rating in two ways. First, low-credit-rating firms are likely to have more unanticipated changes in firm fundamentals for the current and/or previous years. Consistent with this notion, I find evidence that lower credit ratings of firms are associated with higher earnings variability, higher cash flow volatility, higher accruals volatility, higher analyst forecast dispersion, higher idiosyncratic volatility, a higher frequency of large increases/decreases in quarterly earnings, and a higher incidence of large losses. Credit rating captures not only the historical changes and/or variability of firm fundamentals but also uncertainty about a firm's future earnings, growth rates, and cost of equity capital --- the ingredients used in asset valuation (e.g., Merton, 1974; Avramov, Chordia, Jostova, & Philipov, 2009a). Standard & Poor's (2009) states that "*credit rating is meant to be forward-looking and their time horizon extends as far as is analytically foreseeable*." This suggests that credit rating is forward-looking in discriminating long-term risk and uncertainty about a firm's asset fundamentals in future years, which might largely not be captured by the historical measures of risk and uncertainty.[1] As such, current earnings released by a low-credit-rating firm have weaker implications for long-term streams of future earnings. It is thus more difficult for investors to comprehend the firm's current earnings news and form expectations about future earnings in a timely manner (to be empirically tested further in Section 3.1); investors may have to spend time in learning the updated earnings process (e.g., Markov & Tamayo, 2006). As a

[1] Altman and Rijken (2004) quantify the impact of the long-term default horizon and show that, in contrast to one-year default prediction models, credit rating agencies place less weight on short-term indicators of credit risk and focus on the long-term ones in assigning credit ratings to firms.

result, they delay their reactions to earnings news released by firms with low credit ratings. This leads to stronger PEAD for these firms.

Second, investors might be less attentive to earnings news of low-credit-rating firms, or be more limited in the ability to process information for correctly updating expectations about these firms' future earnings. The mispricing of low-rated stocks that arises in this regard may also explain their stronger PEAD, which, on the other hand, can be arbitraged away by sophisticated investors (McLean & Pontiff, 2016).

Using a large sample of U.S. listed companies, I find strong and robust evidence that PEAD is more salient for firms with low credit ratings. In particular, a univariate portfolio analysis reveals that a zero-investment portfolio that longs the highest *SUE* stocks and shorts the lowest *SUE* stocks yields larger payoffs (hereafter, PEAD payoffs or earnings momentum payoffs) among the lower-credit-rating group. This payoff differential across different credit-rating groups is not driven by a host of traditional information uncertainty proxies such as firm age, earnings volatility, accruals quality, cash flow volatility, idiosyncratic volatility, or analyst forecast dispersion, as evidenced by the results obtained from independent double sorts by credit rating and each of the information uncertainty variables.[2] After using a Carhart-based (1997) calendar-time portfolio approach to risk-adjust PEAD payoffs, the PEAD profitability disappears among high-credit-rating firms and is concentrated in the worse-rated firms.

My multivariate regression analysis also reveals that the credit rating effect on PEAD exists, and is both independent of, and stronger than, the effect of the aforementioned information uncertainty proxies. In particular, when controlling for the historical measures of information uncertainty, most of them lose their predictive power for PEAD whereas the effect of credit

[2] Following Zhang (2006), I define information uncertainty as ambiguity with respect to the implications of new information for a firm's intrinsic value.

rating remains highly significant. On the other hand, without the control of the information uncertainty variables, the credit-rating-predicted PEAD returns appear higher. Together, these suggest that PEAD being concentrated among low-rated firms are due to either mispricing or risks that are not captured by the information-uncertainty variables but are incorporated in credit rating. My regression results hold for PEAD associated with both seasonal random-walk-based earnings surprises (hereafters, RW-based PEAD) and analyst-forecast-based earnings surprises (hereafter, AF-based PEAD) over different drift windows and are robust to controlling for an array of other PEAD determinants (e.g., transaction costs) documented in the literature.

I next examine whether transient institutions tend to exploit the significance of earnings momentum payoffs among low-credit-rating firms and to engage in the arbitrages accordingly. Transient institutions are defined as institutions that exhibit high turnover and high investment portfolio diversification (Bushee, 2001; Ke & Petroni, 2004). I focus on the transient institutions' arbitrages for two reasons. First, transient institutions make a considerable amount of stock trades in the U.S. stock market (e.g., Porter, 1992; Ke & Ramalingegowda, 2005). Unlike dedicated or quasi-indexing institutions (e.g., pension funds), transient institutions are generally not subject to regulatory restrictions on investments in low-rated firms. Second, transient institutions have short trading horizons and fragmented investments in a large number of firms, and feature high frequency of arbitrage activities (Bushee, 2001; Ke & Petroni, 2004). Prior research (e.g., Gompers & Metrick, 2001; Yan & Zhang, 2009) shows that transient institutions are sophisticated, informed investors who trade actively to exploit their information advantages. They aim at maximizing short-term profits and tend to arbitrage anomalies in financial markets (Ke & Ramalingegowda, 2005). Hence, by showing how capable transient institutions are in exploiting the PEAD payoff differential among different rated firms, we can determine the implications for investors in their understanding of how feasible it is for them to profit from arbitrage trades on high-credit-risk stocks; also, and importantly, we can thereby draw an inference about whether the stronger PEAD of low-rated firms is due to mispricing or estimation risk; in the former (latter) case, the PEAD is largely exploitable (unexploitable) by transient institutions.

To the extent that credit rating is a robust determinant of PEAD payoffs, transient institutions who wish to pursue high arbitrage profits should be particularly sensitive to a firm's credit rating information. If transient institutions are sophisticated in collecting and processing information, they would be able to identify the significance of PEAD payoffs among low-rated firms. Given the high PEAD payoffs, high idiosyncratic risk from low-credit-rating firms would not disincentivize a transient institution from exploiting PEAD, provided that the transient institution believes herself or himself to be capable to diversify away the idiosyncratic risk. In this scenario, I expect that transient institutions tend to trade more aggressively to exploit PEAD among low-credit-rating firms. Results confirm this. Specifically, transient institutions focus their arbitrage trades on PEAD among low-rated firms, and that this arbitrage strategy applies not only to RW-based PEAD but also to AF-based PEAD.

In an ideal setting where arbitrages are riskless, the residual variance of returns to a hedge portfolio should be equal to zero. If transient institutions exploit PEAD among low-credit-rating stocks, they would have to bear substantive arbitrage risk, and the residual variance of returns in their hedge portfolios would be high. In the case that the fundamental values of the high-credit-risk stocks would change unexpectedly, the arbitrageurs may hedge these unexpected changes by using close substitute stocks whose returns are highly correlated with the returns of the stocks that are subject to the PEAD anomaly. Nonetheless, finding such substitute stocks is often a difficult task for the arbitrageurs in practice (e.g., Pontiff, 1996; Wurgler & Zhuravskaya, 2002). When failing to identify such substitute stocks, the arbitrageurs have to take volatile arbitrage positions against the idiosyncratic risk, but they might not have the required capital at hand to cover their volatile arbitrage positions on a timely basis (Shleifer & Vishny, 1997; Gromb & Vayanos, 2002; Mitchell, Pulvino, & Stafford, 2002; Brunnermeier & Pedersen, 2009). If the arbitrageurs fail to hedge away the idiosyncratic risk, the anomalous returns of the stocks would persist and may even worsen in the short run (Liu & Longstaff, 2003; Lam & Wei, 2011).

The result as to PEAD existing and being concentrated in low-credit-rating firms suggests that the transient institutions still fail to arbitrage away PEAD among low-rated firms, and that such an arbitrage opportunity is not as exploitable as expected. This is thus consistent with the estimation-risk explanation, but inconsistent with the mispricing explanation, for the PEAD, given that it is largely unexploitable if investors' under-reactions to the earnings news of low-rated firms is due to the high estimation risk associated with pricing these firms that tend to have high idiosyncratic risk. That said, overall, my study does not provide conclusive evidence of the extent to which the strong PEAD of low-credit-rating firms is attributed to estimation risk *vis-à-vis* mispricing. This remains a limitation of the paper.

This study adds to the extant literature in several ways. First, I contribute to the PEAD literature by exploring the association between credit rating and PEAD anomaly. I give insights and support for the notion that earnings news of low-credit-rating firms, which are featured as having high long-term uncertainty of future fundamentals, is difficult to interpret with respect to its value implications. Investors may thus have to spend time and effort in re-learning the earnings formation process and inferring the implications of earnings news for future earnings (Lewellen & Shanken, 2002; Markov & Tamayo, 2006). From this, I expect that investors are likely to rationally delay reactions to earnings news released by low-credit-rating firms, thus leading to stronger PEAD for these firms. My overall results are consistent with this expectation, suggesting that investors' under-reactions to earnings news might be the outcome of investors' rational behavior. In this way, my study complements the rationality explanation for market anomalies (Morris, 1996; Lewellen & Shanken, 2002; Dontoh, Ronen, & Sarath, 2003), which has received relatively little attention in the PEAD literature (Francis, LaFond, Olsson, & Schipper, 2007).

Second, this study adds to the literature which examines the link of market anomalies with credit rating. Prior studies (Avramov, Chordia, Jostova, & Philipov, 2007; Avramov, Chordia, Jostova, & Philipov, 2009a) find that the price momentum and analyst forecast dispersion anomaly are concentrated among low-credit-rating firms, but do not give a reason behind such findings. To the best of my knowledge, this paper is the first to shed light on reasons for why a market anomaly, particularly, PEAD, is related to credit rating.

Furthermore, Chordia and Shivakumar (2006) find that price momentum is entirely subsumed by earnings momentum (i.e., PEAD) but that price momentum does not in turn capture earnings momentum. Hence, a significant, robust association between credit rating and price momentum, as documented in Avramov, Chordia, Jostova, and Philipov (2007), does not necessarily imply that earnings momentum is also significantly, robustly related to credit rating. I establish a strong, predictable link between credit rating and earnings momentum, and therein contribute to more understanding of the profitability of momentum strategies. By showing that the link between credit rating and PEAD is unexplained by varied proxies for information uncertainty and by other drift-related variables, I corroborate that credit rating is a robust predictor of PEAD anomaly.

Third, Bartov, Radhakrishnan, & Krinsky (2000) and Campbell, Ramadorai, & Schwartz (2009) find that changes in institutional stock holdings predict earnings surprises and RW-based PEAD, suggesting that institutional investors exploit the PEAD. Ke and Ramalingegowda (2005) provide further evidence that transient institutions trade actively to exploit RW-based PEAD. However, there is no prior research evidence on how these institutions exploit PEAD to enlarge arbitrage profits. This study fills this gap in the literature, and provides direct evidence that transient institutions tend to focus their arbitrages on PEAD among low-rated firms which are featured as abundant in arbitrage gain, and that this arbitrage strategy applies to not only RW-based PEAD but also AF-based PEAD.

Given that PEAD returns are concentrated among low-credit-rating firms, and that institutional arbitrageurs would profit from exploiting PEAD (Campbell, Hilscher, & Szilagyi, 2008; Ke & Ramalingegowda, 2005), it might not necessarily follow that transient institutions would trade more intensively to arbitrage PEAD among lower-credit-rating stocks that feature potentially higher arbitrage gain, because higher arbitrage risk from lower-credit-rating stocks might dis-incentivize these institutions from making arbitrage trades. Therefore, it is unclear whether transient institutions tend to more intensively exploit PEAD of lower-credit-rating stocks. This study addresses this empirical question, thereby complementing the related literature (Bartov, Radhakrishnan, & Krinsky, 2000; Ke & Ramalingegowda, 2005; Campbell, Hilscher, & Szilagyi, 2008). My analysis suggests that even transient institutions, arguably the most capable arbitrageurs in capital markets, could not arbitrage away the PEAD among low-credit-rating stocks, let alone other investors who have only a limited knowledge and information of the stock markets and often do not have sufficient funds to cover risky arbitrage positions. My study thus holds implications for investors who seek to exploit and profit from the seeming arbitrage opportunities associated with PEAD. Its un-exploitability by sophisticated transient institutions also lends supports to the foregoing estimation-risk explanation for PEAD.

The rest of the paper proceeds as follows. Section 2 describes the data and sample selection procedures. Section 3 presents the research methodologies and discusses the results. Section 4 concludes.

2. DATA

2.1. Data sources

The empirical analysis is conducted based on data gathered primarily from the following sources: Institutional Brokers Estimate System (I/B/E/S), Center for Research in Security Prices (CRSP), Compustat, Factset, and Thomson Reuters Institutional Holdings (13F) database (formerly known as CDA Spectrum). Stock returns are obtained from CRSP for stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and Nasdaq stock market. Firm credit ratings are taken from the Standard and Poor's Long-Term Domestic Issuer credit ratings reported by Compustat from 1985. Thus, my sample period for testing the link between credit rating and PEAD begins in that year; it ends in 2019, the year before the Covid-19 pandemic. I obtain qualitatively the same results for all the related empirical tests, should the recession periods (i.e., 1990-1991, 2001, and 2007-2009) be excluded from my sample period.

Table 1 shows the full sample distribution of credit ratings at the firm-quarter level. The majority of the observations in the rated sample firms fall within the range of credit ratings spanning from B+ to BBB+, with the BBB-level observations accounting for the highest percentage (11.47%). I collect institutional stock ownership data on the Factset and Thomson Reuters Institutional Holdings (13F) databases, whereas the institutions' trading classification (transient, dedicated, and quasi-indexing) is obtained from Brian Bushee.[3] I focus on transient institutions' trading on PEAD, since prior studies (e.g., Ke & Ramalingegowda, 2005) provide evidence that transient institutions exploit PEAD whereas dedicated or quasi-indexing institutions do not. I require that firms have necessary data available to construct variables of interest in all my empirical analyses.

2.2. Measures of earnings surprises

Whereas the majority of prior studies focus on the drift associated with seasonal random-walk-based earnings surprises, some prior studies (e.g., Livnat & Mendenhall, 2006; Doyle, Lundholm, & Soliman, 2006) document a drift associated with analyst-forecast-based earnings surprises that appears not only distinct from, but even larger than, the drift associated with random-walk-based earnings surprises. Therefore, I focus on PEAD associated with both seasonal random-walk-based and analyst-forecast-based earnings surprises, namely, RW-based and AF-based PEAD, respectively. Following Bernard & Thomas (1989) and Chordia & Shivakumar (2006), I define a seasonal random-walk-based earnings surprise as current quarter's earnings less earnings four quarters ago, standardized by the standard deviation of earnings changes in the prior ten quarters (namely, RW-based *SUE*); the earnings are before extraordinary items and discontinued operations. To compute the random-walk-based earnings surprise, I require firms to have the earnings for the same quarter in the prior year. Following Livnat and Mendenhall (2006), I define an analyst-forecast-based earnings surprise as the actual earnings

[3] To obtain the institutional investor classification data from Brian Bushee, one must merge the classification codes into the Thomson Reuters Institutional Holdings (13F) database to compute the transient institutional stock holdings for each firm. To this end, I collected the institutional stock ownership data for the sample period 1985-2013 from the Institutional Holdings database in year 2014, when I was affiliated with the University of Warwick and it subscribed the database. However, the Durham University with which I am currently affiliated does not subscribe it. Therefore, my sample period for testing the transient institutions' arbitrages on PEAD starts in 1985 and ends in 2013.

per share (hereafters, EPS) minus the mean consensus analyst forecast of EPS in the 90 days before the earnings announcement date, standardized by the standard deviation of the earnings surprises in the prior ten quarters (namely, AF-based *SUE*). Accordingly, I require firms to have both analyst forecasts and actual earnings for a fiscal quarter in the I/B/E/S database.

3. RESEARCH DESIGN AND EMPIRICAL RESULTS

3.1. Is earnings news of lower-credit-rating firms more difficult to interpret?

Before investigating whether PEAD is related to credit ratings, I conduct an analysis of whether earnings news of lower-credit-rating firms is more difficult to interpret. To this end, I first test whether low-credit-rating firms tend to have high variability in asset fundamentals. Table 2 shows that low-credit-rating firms tend to have higher earnings variability (*EarnVol*), higher accruals volatility (*AccrualsVol*), higher cash flow volatility (*CfoVol*), higher analyst forecast dispersion (*Dispersion*), higher stock return volatility (*ReturnVol*), higher idiosyncratic volatility (*IdioVol*), a higher frequency of large increases/decreases in quarterly earnings (*LargeEarningsSur*), and a higher incidence of large losses (*Largeloss*). The differences in these variables between different credit rating groups are statistically significant at conventional levels. These results suggest that lower-credit-rating firms tend to have more unanticipated changes in asset fundamentals and higher uncertainty of earnings process. As such, it takes time for investors to learn the changing earnings process of low-credit-rating firms, thus investors delay their reactions to these firms' earnings news.

Given the results in Table 2, it follows that earnings may be more strongly correlated in time-series for higher-credit-rating firms. So, I next test whether the autocorrelation between *SUE* in quarter *t* and *SUE* in quarter *t*-1 is more pronounced for firms with higher credit ratings. I use a higher value of $Rating_t$ to represent a higher credit rating for a firm in the fiscal quarter *t*. It is shown in Panel A of Table 3 that the coefficients for $SUE_{t-1}*Rating_t$ are positive and statistically significant. This suggests that SUE_{t-1} is more predictive of SUE_t for high-credit-rating firms than for low-credit-rating firms. Put differently, the implications of current earnings news for future earnings are weaker for firms that have lower credit ratings.

In line with previous research (e.g., Bernard & Thomas, 1990), I further examine whether investors are efficient in inferring the value implications of earning news released by high-credit-rating firms *vis-à-vis* low-credit-rating firms. Specifically, I test whether the association between the market reaction to SUE_t (namely, CAR_t) and SUE_{t-1} is more evident for lower-credit-rating firms. Consistent with prior literature (e.g., Narayanamoorthy, 2006; Zhang, 2008; Zhang, 2012; Hung, Li, & Wang, 2015), the decile ranks of *SUE* (namely, *DSUE*) are used in the regression to reduce the potential problem of nonlinearity in the earnings-return relationship. If investors are efficient in processing earnings news, earnings news should not predict future stock returns, thus $DSUE_{t-1}$ should not have an association with CAR_t. However, if investors are inefficient and underreact to the earnings news at *t*-1, then $DSUE_{t-1}$ would be positively correlated with CAR_t. As reported in Panel B of Table 3, the coefficients on $DSUE_{t-1}$ are positive and statistically significant, consistent with the notion that investors are likely to underreact to earnings news of low-credit-rating firms. $DSUE_{t-1}*Rating_t$ takes on a significantly negative coefficient; this suggests that the investors' underreactions to earnings news are less salient for high-credit-rating firms than for low-credit-rating firms.

In sum, the results in Panel A of Table 3 reinforce the argument that it is more difficult for investors to interpret earnings news released by lower-credit-rating firms. It follows that investors are likely to underreact more to the earnings news of low-credit-rating firms than that of high-credit-rating firms, as suggested by the results in Panel B. On this basis, I predict that PEAD is stronger for firms with lower credit ratings. I go on to the next two sub-sections to test this prediction, using portfolio analysis and regression analysis, respectively.

3.2. Credit ratings and PEAD --- portfolio analysis

I rank firms into deciles based on *SUE* for each fiscal quarter.[4] The PEAD trading strategy involves a zero-investment hedge portfolio that takes the long (short) position in the decile portfolio of firms with the most positive (negative) *SUE*. Firms enter the portfolios on the second trading day following each earnings announcement, and the portfolios are held for 60 trading days thereafter. Because prior studies (e.g., Bernard & Thomas, 1990) show that a significant portion of PEAD is concentrated in a three-day window surrounding the announcements of the next three quarterly earnings, I also have the long (short) position held until one trading day after the earnings announcement date for quarter t+1, quarter t+2, and quarter t+3 (i.e., [2, E_{t+1}+1], [2, E_{t+2}+1], and [2, E_{t+3}+1] relative to the earnings announcement date for quarter t, respectively). Accordingly, I require firms to have stock returns data from the CRSP daily stock file during the corresponding drift windows. For ease of presentation, I only report results for the PEAD over the 60-day drift window. I obtain similar results and insights from all the tests conducted for the PEAD over the other three drift windows.

Following prior research on earnings-related anomalies (e.g., Dechow, Richardson, & Sloan, 2008; Zhang, 2008; Zhang, 2012; Hung, Li, & Wang, 2015), I use size-adjusted buy-and-hold abnormal returns to measure a firm's drift return. The expected return for firm i on trading day t, which is used to adjust the raw return of firm i on day t, is defined as the value-weighted

[4] As with Collins and Hribar (2000), I also use the cut-off values, which define the deciles of *SUE* for period t-1, to sort the *SUE* for period t into deciles. The results are qualitatively the same.

returns for all firms in the firm *i*'s size-matched decile on day *t*, where size is measured by the market capitalization at the beginning of the most recent calendar quarter. The return to the most positive (negative) *SUE* decile portfolio is then calculated as an equally-weighted average of size-adjusted drift returns of the corresponding firms in that *SUE* decile portfolio. Accordingly, payoff to the PEAD trading strategy is based on the hedge portfolio return from the strategy implemented at the earnings announcements and held over the drift window.

To investigate whether the PEAD anomaly differs across different credit-rating firms, I implement the PEAD strategy by conditioning on both credit rating and *SUE*. I consider 10 *SUE* portfolios and 3 credit rating (*Rating*) groups. Specifically, the *Rating*-*SUE* portfolios are formed on a sequential basis, sorting first on *Rating* and then on *SUE*. The high- (low-) credit-rating group contains the A- to AAA rated (SD to CCC+ rated) firms. The middle credit rating group incorporates firms that have ratings from B- to BBB+. Table 4 reports the results for payoffs from trading on PEAD in different credit-rating groups. The payoff to the PEAD trading strategy becomes larger as we move from the high- to low-credit-rating group. Focusing on, for example, the RW-based PEAD over the window of [2, 61] relative to earnings announcement dates, the average payoffs to the D10-D1 trading strategy for the high- and medium-credit-rating groups are 1.67% and 2.57%, respectively. In contrast, the payoff is much greater and economically significant at 14.30% for the low-credit-rating group.[5] The AF-based earnings momentum payoff is also highest (lowest) for the low- (high-) credit-rating group. I re-perform the portfolio analysis by re-dividing stocks into two credit rating groups based on the investment-speculative grade distinction. It is shown that the RW-based (AF-based) PEAD payoff for the speculative-

[5] The PEAD payoffs reported in Table 4 are measured on a size-adjusted basis and are not yet adjusted for other risk factors such as book-to-market and price momentum factors. Hence, it is not surprising that the PEAD payoffs are all significantly greater than zero across all the credit rating groups. After adjusting for all the risk factors using a Carhart-based calendar-time portfolio approach, the PEAD payoff is significant only for the low-credit-rating group (to be covered in the rest of this section).

grade rating group is 0.0370 (0.0327), which is substantively higher than that (i.e., 0.0172 (0.0177)) for the investment-grade rating group. Overall, the results for the PEAD payoffs lend initial support to the notion that the profits gained from implementing the PEAD trading strategy stem primarily from firms with low credit ratings.

The earnings momentum payoff differential across different credit-rating groups might be explained by information uncertainty proxies such as return volatility, accruals quality, cash flow volatility, earnings volatility, firm age, idiosyncratic volatility, and analyst forecast dispersion. To address this possibility, I assess the robustness of earnings momentum profitability across different credit-rating dimensions based on 3*3 portfolios that are sorted independently by credit rating and each of the information uncertainty variables. The results (not tabulated for parsimony) indicate that earnings momentum payoff still increases monotonically with the decrease in credit rating across all the groups sorted by each of the information uncertainty variables. However, not all the credit rating groups exhibit a monotonic increase in PEAD payoffs with an increase in the magnitude of the information uncertainty variables. Therefore, it is credit rating, not those information uncertainty variables, that provides the divergent earnings momentum returns. The information uncertainty variables are constructed based on historical figures, and primarily capture the pre-earnings-announcement information uncertainty that might be resolved in a short run (Shivakumar, 2007). By contrast, credit ratings capture not only the historical information uncertainty but also the uncertainty that is of a forward-looking nature on a long horizon (Altman & Rijken, 2004; Standard & Poor’s, 2009; Hovakimian, Kayhan, & Titman, 2009; He, 2018), hence it is particularly risky to exploit PEAD among low-credit-rating stocks.

To ensure that the profits of implementing the PEAD trading strategy among low-credit-rating firms do not merely compensate for exposure to systematic risk, I further use a calendar-time portfolio approach, in which returns are adjusted for the four Carhart-based risk factors (i.e., excess market returns, firm size, book-to-market, and price momentum factors), to assess the magnitude and statistical significance of earnings momentum payoffs. The advantage of the calendar-time portfolio approach is that the cross-sectional correlations of the abnormal returns are automatically accounted for in the portfolio variance at each point in calendar time (Fama, 1998; Mitchell & Stafford, 2000). Consistent with prior research (e.g., Mitchell & Stafford, 2000; Francis, LaFond, Olsson, & Schipper, 2007), I use monthly returns to construct the hedge portfolio returns, which involves taking the long (short) position in the highest (lowest) *SUE* decile portfolio. Firms enter the portfolio on the first day of the month following the most recent earnings announcement, and are held for nine months which normally cover three subsequent quarterly earnings announcements.[6] Accordingly, the monthly return to the hedge portfolio is measured as the difference between the equally-weighted average monthly return of the highest *SUE* decile portfolio and that of the lowest *SUE* decile portfolio. The hedge portfolio monthly returns, net of risk-free rate, are then regressed on the Carhart's (1997) four factors for each credit rating group, whereby alpha from the regression would represent the average monthly earnings momentum payoffs that are adjusted for the systematic risk.

Panel A of Table 5 reports the results for alphas obtained from the Carhart-based calendar-time portfolio regressions for each credit rating group. The alphas for the monthly RW-based earnings momentum payoffs amount to 3.35%, 0.36%, and -0.23%, which translate to annualized, compounded returns of 48.50%, 4.407%, and -2.73%, for the low-, medium-, and high-credit-rating groups, respectively. After adjusting for the risk factors, the annualized profits from implementing the RW-based PEAD trading strategy are statistically and economically significant

[6] Inferences are unchanged if I choose a three-month (six-month) portfolio holding period that normally covers one (two) subsequent quarterly earnings announcement(s).

for the low-credit-rating group but not for the high- and medium-credit-rating groups. The alpha for the monthly AF-based earnings momentum payoffs is 4.69% for the low-credit-rating group but is not positive for the higher-credit-rating groups. When moving from the low- to high-credit-rating group, both the RW-based and AF-based alphas decline in magnitude. I re-run the calendar-time portfolio regression for the speculative-grade rating group and investment-grade rating group, respectively. The RW-based alpha for the speculative-grade rating group is 0.42% (equivalent to approximately a 5.158% annualized, compounded return), and is substantially higher than that for the investment-grade rating group, which is 0.03% (equivalent to around a 0.361% annualized, compounded return). Overall, these results suggest that higher earnings momentum payoffs for lower-credit-rating firms do not represent compensation for systematic risk.

Mclean and Pontiff (2006) find evidence to suggest that investors learn about various stock market anomalies from academic publications. If the anomalies are due to mispricing, the anomalous returns associated with return predictors would disappear or decay, as investors learn about and trade against the mispricing, after papers about the anomalies were published. But if the anomalies are attributed to estimation risk and reflect investors' rational expectations, the anomalous return would not decay over time (e.g., Cochrane, 1999; Mclean and Pontiff, 2006). To discriminate between estimation risk and mispricing in their explanations for the credit-rating-predicted PEAD, I re-run the calendar-time portfolio regressions for the subsample periods 1985-2006 and 2010-2019, respectively, to see how the alphas estimated from the regressions would change since the papers examining the link between credit rating and market anomalies (i.e., Avramov, Chordia, Jostova, & Philipov, 2007; 2009a) were published. Panel B (Panel C) of Table 5 reports the results of alphas for each credit rating group for the pre- (post-)

publication period 1985-2006 (2010-2019). Both the RW-based alphas and AF-based alphas in the low-credit-rating groups appear larger for the post-publication period than for the pre-publication period; a potential explanation is that investors rationally delay their reactions to the earnings news of low-credit-rating firms to a larger degree during the post-publication period than before. This reconciles with the foregoing estimation-risk explanation for PEAD of low-rated firms, and is also in line with Jegadeesh and Titman (2001) which find that price momentum is enlarged since it was uncovered by Jegadeesh and Titman (1993).

It is worth noting that the univariate portfolio analysis does not account for other determinants of PEAD. I turn to the multivariate analysis in the next section to control for as many such determinant variables as possible.

3.3. Credit ratings and PEAD --- regression analysis

I specify the following pooled OLS regression model to test the association between credit rating and PEAD:

$$Drift = \alpha_0 + \alpha_1 DSUE + \alpha_2 DSUE * Rating + \alpha_3 Rating + \alpha_4 Controls + \alpha_5 Controls * DSUE + \varepsilon \qquad (1)$$

Drift is the size-adjusted buy-and-hold returns over the drift window of [2, 61] relative to the earnings announcement date, and equals the compounded raw returns minus the compounded value-weighted returns of the same CRSP size decile and the same CRSP exchange index (NYSE/AMEX/NASDAQ) to which a firm belongs.[7] Following prior studies (e.g., Zhang, 2008; Hung, Li, & Wang, 2015), I rank RW-based *SUE* and AF-based *SUE* into ten deciles indexed from 0 to 9 by quarters, and divide the index by 9 to obtain *DSUE*, which ranges from 0 to 1. As such, the coefficient on *DSUE* can be readily interpreted as the excess returns one can earn over

[7] I follow the PEAD literature (e.g., Ball & Bartov, 1996; Zhang, 2008; Zhang, 2012; Hung, Li, & Wang, 2015) to run the standard regression analysis, which uses size-adjusted buy-and-hold returns to measure PEAD and includes firm size (*Size*), book-to-market ratio (*BM*), and price momentum (*RET* and *Price*) as controls.

the drift window under a zero-investment portfolio strategy that takes a long position in the highest *SUE* decile (*DSUE* = 1) and a short position in the lowest *SUE* decile (*DSUE* = 0). *Rating* is coded 0 for firms that have ratings ranging from SD/D to CCC+, 0.5 for firms with ratings from B- to BBB+, and 1 for firms with ratings from A- to AAA. I expect the coefficient on the interaction term between *DSUE* and *Rating*, α_2, to be negative and statistically significant at a conventional level to support the prediction that PEAD for low-rated firms is stronger and that their earnings momentum payoffs are larger.

Prior literature (e.g., Jiang, Lee, & Zhang, 2005; Zhang, 2006) provides evidence that momentum payoffs are higher in firms that have higher information uncertainty. Hence, I control for a battery of information uncertainty proxies used in previous studies: firm age (*Firmage*), return volatility (*Returnvol*), earnings volatility (*Earningsvol*), cash flow volatility (*Cashvol*), accruals quality (*AQ*), idiosyncratic volatility (*IdioVol*), and analyst forecast dispersion (*Dispersion*) (Jiang, Lee, & Zhang, 2005; Zhang, 2006; Francis, LaFond, Olsson, & Schipper, 2007, among others).[8] Appendix II reports correlations among the credit rating variable and information uncertainty variables. Stronger PEAD is expected for younger firms or firms with higher return volatility, higher earnings volatility, higher cash flow volatility, lower accruals quality, higher idiosyncratic volatility, or higher analyst forecast dispersion. Because the seven information-uncertainty measures are correlated with each other and are used to capture one common construct, I conduct a factor analysis to extract a composite measure (*IUfactor*) for the seven information uncertainty variables and use it in the multivariate test as well. A higher factor (*IUfactor*) indicates higher information uncertainty.

I also control for firm size (*Size*), book-to-market ratio (*BM*), stock returns (*RET*), trading

[8] Inferences on the relationship between credit rating and PEAD remain unchanged if I include only one of the information-uncertainty proxies as the control in the regression analysis.

volume (*Tradingvol*), share price (*Price*), institutional stock ownership (*Insti*), analyst following (*Coverage*), the nature of earnings news (*Badnews*), change in *SUE* (*changeSUE*), and the indicator for the fourth-quarter earnings announcement (*THQTR*). These variables are identified by prior literature as being correlated with the magnitude of PEAD (e.g., Foster, Olsen, & Shevlin, 1984; Cornell & Landsman, 1989; Bartov, Radhakrishnan, & Krinsky, 2000; Hong, Lim, & Stein, 2000; Merndenhall, 2002; Mendenhall, 2004; Zhang, 2008; Campbell, Ramadorai, & Schwartz, 2009). I further include an indicator variable for the post Regulation-Fair-Disclosure period (*FD*) to control for the effect of change in information environments caused by the enforcement of Regulation Fair Disclosure (e.g., He, Bai, & Ren, 2019). All the control variables are defined in Appendix I. Finally, I include the industry-, year-, and quarter-fixed effects in the regression.

Following prior studies (e.g., Bartov, Radhakrishnan, & Krinsky, 2000; Zhang, 2008; Zhang, 2012; Hung, Li, & Wang, 2015), I interact all the control variables with *DSUE*. The interactions allow the slope of the *SUE*-return relation to vary with each control variable and hence enable us to assess how these control variables affect the magnitude of the drift. Each continuous control variable is ranked into deciles within each fiscal quarter and coded from 0 to 1. The coding allows the coefficient on the interaction term to be interpreted as the additional spread in abnormal returns, between the highest- and lowest-*SUE* decile portfolios, for firms with the largest versus smallest decile rank of the control variables (Mendenhall, 2004). In addition, the decile ranking of the control variables addresses the potential problem of outliers and nonlinearity in the earnings-returns relation (e.g., Bernard & Thomas, 1990; Bartov, Radhakrishnan, & Krinsky, 2000).

Table 6 presents the regression results. The coefficients on the interaction terms, *DSUE* Rating*, are all negative and statistically significant at the 1% level, consistent with the prediction that PEAD is more pronounced for firms with lower credit ratings. In Columns (1-2) and (4-5), both the coefficients on *DSUE* (indicating PEAD for lower-rated firms) and the coefficients on *DSUE+DSUE*Rating* (indicating PEAD for higher-rated firms) appear larger without the controls of the historical information-uncertainty measures (i.e., firm age, analyst forecast dispersion, earnings volatility, accruals quality, return volatility, idiosyncratic volatility, cash flow volatility). This suggests that part of the anomalous returns is attributed to the information uncertainty captured by the historical variables. The coefficients on the interaction of *DSUE* with almost all the information-uncertainty variables are not statistically significant at conventional levels, whereas the coefficients on *DSUE*Rating* remain negative and statistically significant. The results hold qualitatively not only for RW-based PEAD but also for AF-based PEAD. The evidence suggests that the information uncertainty purged out of the credit rating effect does not distinguish between more and less profitable PEAD, and is also consistent with the notion that credit rating involves the future aspects of information uncertainty that are orthogonal to the historical information-uncertainty variables. Hence, credit rating is a more primitive and stronger variable than those information uncertainty proxies in predicting PEAD.[9]

The coefficients on *Rating* are positive and statistically significant at the 1% level, consistent with prior evidence indicating that stock returns are negatively related to credit risk (Dichev, 1998; Campbell, Hilscher, & Szilagyi, 2008; Avramov, Chordia, Jostova, & Philipov, 2009b; Aretz & Pope, 2013). The coefficients for most of the other control variables and of their interaction terms with *DSUE* are statistically significant in the predicted sign. As a robustness

[9] To account for the possibility that changes in credit ratings affect PEAD, I remove observations that have rating changes during the drift window of [2, 61] relative to the earnings announcement date, and obtain qualitatively the same results.

check, I use an alternative credit-rating variable (*ISRating*), which is based on the classification of credit ratings into investment-grade and speculative-grade categories, for the regression analysis. The results, which are reported in Panel B of Table 6, remain qualitatively the same.

By and large, the univariate and multivariate results are consistent with the view that the market underreacts more saliently to earnings news released by low-credit-rating firms that feature high uncertainty about corporate fundamentals in the long run.

3.4. Do transient institutions focus their arbitrages on PEAD of low-credit-rating firms?

To assess the effect of credit ratings on transient institutions' arbitrage intensity, I estimate the following firm-fixed-effects regression of the quarterly changes in transient institutional stock ownership for firm *i* in calendar quarter *t´*:

$$\begin{aligned}
&\Delta Transient_{i,t'} = \alpha_0 + \alpha_1 \sum_{q=0}^{3} \beta_q DSUE_{i,t-q} + \alpha_2 Rating_{i,t} + \alpha_3 \sum_{q=0}^{3} \gamma_q DSUE_{i,t-q} * Rating_{i,t} \\
&+\alpha_4 TranCost_{i,t} + \alpha_5 \sum_{q=0}^{3} \delta_q DSUE_{i,t-q} * TranCost_{i,t} + \alpha_6 BM_{i,t} + \alpha_7 Size_{i,t} + \alpha_8 PW_{i,t} + \\
&\alpha_9 FD_{i,t} + \alpha_{10} RET1_{i,t} + \alpha_{11} (RET2-3)_{i,t} + \alpha_{12} (RET4-6)_{i,t} + \varepsilon_{i,t}
\end{aligned} \tag{2}$$

Δ*Transient* is change in transient institutional stock ownership as a percentage of the outstanding shares. Institutional holdings are reported by the Thomson Reuters Institutional Holdings (13F) database only at the end of calendar quarters. Thus, $\Delta Transient_{i,t'}$ is measured for firm *i* over a calendar quarter from the end of calendar quarter *t´*-1 to the end of calendar quarter *t´*, within which the earnings announcement date for fiscal quarter *t* falls. $SUE_{i,t}$ is the standardized unexpected earnings surprise of firm *i* for fiscal quarter *t*. $DSUE_{i,t-q}$ represents the decile ranks of *SUE* for firm *i* at fiscal quarter *t-q*. $PW_{i,t}$ is the mean portfolio weight of firm *i* in the portfolio of transient institutions at the end of fiscal quarter *t*. *PW* measures the extent to which stock investments of transient institutions are allocated to a given firm. I include *PW* because transient institutions whose stock holdings are heavily weighted towards a given firm are more likely to sell shares in the subsequent quarter for portfolio diversification. I control for firm size (*Size*) and book-to-market effect (*BM*) because they are systematically related to institutional stock ownership (Gompers & Metrick, 2001). I include *RET*1, *RET*2-3, and *RET*4-6 to control for the price momentum effect because prior research (e.g., Griffin, Harris, & Topaloglu, 2003) finds that institutional investors tend to be momentum traders. If transient institutions follow a momentum (contrarian) trading strategy, the coefficients on *RET*1, *RET*2-3, and *RET*4-6 would be significantly positive (negative). I also include an indicator for the post Regulation-Fair-Disclosure period (*FD*) to control for the impact of Regulation Fair Disclosure on transient institutions' trading behaviors (Ke, Petroni, & Yu, 2008). All the control variables are defined in Appendix I. Finally, I include industry-, year-, and quarter-fixed effects in the regression, because there might be systematic variation in institutional stock ownership across industries, over years, and over the four calendar quarters.

Prior studies (e.g., Bernard & Thomas, 1990; Ball & Bartov, 1996) document that a disproportionately large number of abnormal returns from the zero-investment RW-based PEAD trading strategy, which are accumulated from the day after the earnings announcement for quarter *t* through the earnings announcement for quarter *t*+3, are realized before the earnings announcement date for quarter *t*+1. Therefore, if transient institutions exploit RW-based PEAD, they would initiate their arbitrage positions well before the earnings announcement for quarter *t*+1. Accordingly, transient institutional ownership changes around the earnings announcement in quarter *t´* should be positively related to the *SUE* for quarter *t*, that is, the coefficient on $DSUE_t$ should be significantly positive. Moreover, because the direction of abnormal returns associated with RW-based *SUE* reverses at the earnings announcement for quarter *t*+4, transient institutions should unwind their arbitrage positions no later than quarter t+3, and hence one or more of the coefficients on lagged *DSUE*s (i.e., $DSUE_{(t\text{-}1\ to\ t\text{-}3)}$) should be significantly negative. Consistent with Ke and Ramalingegowda (2005), I do not expect all the coefficients on lagged *DSUE*s to be significantly negative, because transient institutions could choose to liquidate their arbitrage positions in any one of the following three quarters. Rather, I expect that the sum of the coefficients on lagged *DSUE*s is significantly negative.

Prior literature (e.g., Livnat & Mendenhall, 2006; Doyle, Lundholm, & Soliman, 2006) documents that the pattern of AF-based drift is different from that of RW-based drift around the four subsequent quarterly earnings announcements. Regarding the AF-based PEAD, there exist positive autocorrelations of abnormal returns around the earnings announcements for quarters t, t+1, t+2, and t+3, but no reversal of abnormal returns around the earnings announcement for quarter t+4. This finding suggests that analysts do not rely on a seasonal random-walk model to form earnings expectations. Hence, their earnings forecasts are free of any bias associated with assuming that earnings follow a seasonal random-walk pattern. Furthermore, prior studies (e.g., Livnat & Mendenhall, 2006) show that AF-based drift is concentrated around two subsequent quarterly earnings announcements. In this respect, if transient institutions wish to exploit the AF-based PEAD, they should establish their arbitrage positions before quarter t+2. Accordingly, I expect that transient institutional ownership changes ($\Delta Transient_{i,t'}$) are positively correlated with $DSUE_t$ or $DSUE_{t-1}$ (i.e., *SUE* for quarter t or quarter t+1), or both. Moreover, transient institutions might find it optimal to unwind their arbitrage positions in quarter t+2 or quarter t+3 to shift their capital to more profitable investments. Hence, transient institutional ownership changes ($\Delta Transient_{i,t'}$) would be negatively associated with $DSUE_{t\text{-}2}$ or $DSUE_{t\text{-}3}$ (i.e., *SUE* for quarter t+2 or quarter t+3), or both.[10]

I first carry out a regression analysis on the main effect of *DSUE*s on transient institutions' trading, omitting the moderating effect of the interaction terms in Model (2). The results (not tabulated) indicate that the coefficients on $DSUE_{(t\ to\ t\text{-}3)}$ are all highly significant in the predicted sign, demonstrating that transient institutions trade actively to exploit RW-based and AF-based PEAD. In Model (2), I allow the regression coefficients on *DSUE*s to differ for different credit-rating (*Rating*) firms. If transient institutions trade more intensively to exploit PEAD among firms with low credit ratings, the coefficients on *Rating***DSUE*s are expected to be in the opposite sign to the coefficients on *DSUE*s and be statistically significant. In particular, in the case that transient institutions exploit RW-based PEAD more intensively for low-credit-rating firms, the coefficient for $Rating{*}DSUE_t$ would be negative and statistically significant, while one or more of the coefficients (or the sum of the coefficients) for $Rating{*}DSUE_{(t\text{-}1\ to\ t\text{-}3)}$ would be significantly positive. In the case that transient institutions exploit AF-based PEAD more aggressively for lower-rated firms, one or the sum of the coefficients on $Rating{*}DSUE_t$ and $Rating{*}DSUE_{t\text{-}1}$ (on $Rating{*}DSUE_{t\text{-}2}$ and $Rating{*}DSUE_{t\text{-}3}$) would be significantly negative (positive). Following Ke and Ramalingegowda (2005), I also control for transaction costs (*TranCost*) and its interaction term with *DSUE*s.[11] If transient institutions trade more intensively

[10] I use my sample period to replicate Bernard and Thomas's (1990) and Livnat and Mendenhall's (2006) key findings on the RW-based and AF-based PEAD, respectively, and obtain qualitatively the same results as these two studies do.

[11] Following prior studies (e.g., Stoll, 2000; Mendenhall, 2004), I use the average of daily dollar trading volume (i.e., the product of the CRSP daily closing price and the number of daily shares traded, averaged over days from the beginning of the fiscal quarter to date -21 relative to the earnings announcement date) as the proxy for the transaction costs for stock trading. High trading volume corresponds to low transaction costs (e.g., Mendenhall, 2004). I rank the trading volume into deciles and convert them to [0, 1], with 0 (1) denoting the lowest (highest) trading volume. I then use the converted scores as a measure of transaction costs, with 1 (0) representing the highest (lowest) transaction costs. I also employ bid-ask spread, which is estimated using relative effective spreads or relative quoted spreads equally weighted over three months prior to the earnings

to exploit PEAD among firms with low transaction costs, the coefficients for *TranCost***DSUE*s would also be in the opposite sign to the coefficients for *DSUE*s and statistically significant.

Column (1) of Table 7 shows the regression results for the impact of credit rating on the intensity of transient institutions' arbitrage on RW-based PEAD. As expected, $DSUE_t$**Rating* ($DSUE_{t-2}$**Rating*) has a significantly negative (positive) coefficient that is in the opposite sign to the coefficient on $DSUE_t$ ($DSUE_{t-2}$). The overall coefficient for $DSUE_{t-1}$**Rating*+$DSUE_{t-2}$**Rating* +$DSUE_{t-3}$**Rating* is also in the predicted, positive sign and statistically significant (F-stat.= 16.26). These results demonstrate that transient institutions trade less intensively to exploit RW-based PEAD for higher-rated firms. The coefficient on $DSUE_t$**TranCost* is significantly negative (t-stat.= -2.12), whereas the coefficients on $DSUE_{t-1}$**TranCost*, $DSUE_{t-2}$**TranCost*, and $DSUE_{t-3}$ **TranCost* are significantly positive (t-stat.= 2.48, 5.46, and 2.13, respectively). Hence, there is also evidence that transient institutions trade less aggressively to exploit RW-based PEAD when transaction costs are higher.

Column (2) reports the results for the impact of credit rating on transient institutions' arbitrages on AF-based PEAD. The coefficients on $DSUE_t$**Rating* and $DSUE_{t-1}$**Rating* are significantly negative (t-stat.= -6.40 and -1.80, respectively), whereas $DSUE_{t-2}$**Rating* and $DSUE_{t-3}$**Rating* have a significantly positive coefficient (t-stat.= 4.48 and 5.17, respectively). The overall coefficient for $DSUE_t$**Rating*+$DSUE_{t-1}$**Rating* ($DSUE_{t-2}$**Rating*+$DSUE_{t-3}$**Rating*) is negative (positive) and statistically significant (F-stat.= -41.82 (58.55)). Hence, transient institutions appear to exploit AF-based PEAD less aggressively in firms with higher credit ratings. There is also evidence to suggest that high transaction costs mitigate the intensity of the transient institutions' arbitrage on AF-based PEAD. In particular, the coefficient for $DSUE_t$* *TranCost* is significantly negative (t-stat.= -5.45), whereas $DSUE_{t-2}$**TranCost* and $DSUE_{t-3}$*

announcements, as the proxy for transaction costs, and obtain similar results.

TranCost take on a significantly positive coefficient (t-stat.= 3.76 and 5.77, respectively). Last, I check the robustness of my results by using an alternative credit rating variable (*ISRating*), which is based on the investment-speculative grade distinction, for the regression analysis. The results, which are presented in Panel B of Table 7, remain qualitatively similar and elicit the same inferences.

In sum, the results indicate that transient institutions trade more intensively to exploit PEAD among low-credit-rating firms which are characterized as abundant in arbitrage gain. On this basis, we can infer that transient institutions are sophisticated enough to identify PEAD being concentrated among high-credit-risk stocks. Also, their arbitrage trades imply that they might believe themselves to be able to diversify away the high idiosyncratic risk inherent in low-credit-rating stocks. However, PEAD still existing and being concentrated in low-credit-rating firms alludes to the fact that transient institutions are not as capable as they thought in diversifying the idiosyncratic risk from low-credit-rating stocks. The PEAD arbitrage strategy comes out to be riskier than could be managed by the transient institutions. This also implies that estimation risk accounts for some or all of the PEAD anomaly, which cannot be eliminated by arbitrage trades (McLean & Pontiff, 2016).

4. CONCLUTION REMARKS

The first objective of this paper is to explore how PEAD anomaly is related with credit rating. I first offer insights that earnings news of high-credit-risk firms is difficult to interpret in respect of its implications for future earnings, and that investors need to spend time in learning about these firms' earnings formation process and associated value implications. As such, investors should be prone to delay their reactions to earnings news released by low-credit-rating firms, thus resulting in stronger PEAD arising in these firms. On the other hand, I allow for the possibility that investors may misprice earnings news of lower-rated firms to a larger degree; this thereby leads to their stronger PEAD. As expected, I find that PEAD is more pronounced for firms with lower credit ratings. By further corroborating that the effect of credit rating on PEAD is not subsumed by the effect of the information-uncertainty proxies (i.e., earnings volatility, cash flow volatility, return volatility, accruals quality, firm age, idiosyncratic volatility, and analyst forecast dispersion), transaction costs as well as other drift determinants, this study demonstrates that credit rating is a robust, powerful predictor of PEAD anomaly.

Transient institutions are characterized by high turnover and high portfolio diversification with short trading horizons and fragmented investments in a large amount of companies. They are arguably the most able arbitrageurs in the financial marketplace, and may be better than general investors in understanding the earnings news, and associated PEAD, of low-credit-rating firms (Bartov, Radhakrishnan, & Krinsky, 2000; Ke & Ramalingegowda, 2005). Thus, I further investigate whether transient institutions exploit the differential of PEAD among different rated firms in their arbitrage trades. To the extent that PEAD caused by investors' mispricing of earnings news can be arbitraged away, but that PEAD caused by estimation risk cannot (e.g., McLean & Pontiff, 2016), the investigation of transient institutions' arbitrages on PEAD would help us obtain insights into whether the strong PEAD of low-rated firms is due to mispricing or estimation risk.

I find strong evidence that transient institutions trade more intensively to exploit both RW-based and AF-based PEAD for low-rated firms which feature high arbitrage gain. This evidence implies that transient institutions could identify the significance of PEAD among the low-rated firms. In an ideal setting in which PEAD is riskless to exploit, arbitrageurs can obtain significant average net payoffs from the trading positions they take to exploit PEAD. However, firms with low credit ratings tend to have higher fundamental idiosyncratic risk. The fundamental value of high-credit-risk stocks could change unexpectedly at any point in time, making the arbitrage risky. To hedge away the idiosyncratic risk, the arbitrageurs must have sufficient capital to cover their volatile arbitrage positions and to find close substitute stocks whose returns are highly correlated with the returns of the low-rated firms that are subject to the PEAD anomaly. These make it more difficult than thought for transient institutions to hedge away the idiosyncratic risk and to make a profitable arbitrage. My results are consistent with this reasoning. Specifically, despite the evidence that transient institutions exploit PEAD more intensively in firms with low credit ratings, the concentration of PEAD among low-credit-rating firms suggests that transient institutions fail to arbitrage away PEAD for low-rated firms. Their arbitrage strategies are not as implementable as they thought due to the unhedged idiosyncratic risk from the low-credit-rating firms. This in turn implies that the strong PEAD of low-credit-rating firms is at least partially attributed to the high estimation risk associated with investors pricing the earnings news of these firms which are in themselves subject to high idiosyncratic risk. That said, it should be noted that, overall, my study does not offer conclusive evidence of the extent to which the strong PEAD of low-credit-rating firms is attributable to estimation risk *vis-à-vis* mispricing.

This study also has important implications for investors who aim to arbitrage market anomalies. In particular, even if investors well understand the PEAD anomaly and its concentration in low-credit-rating firms, it is still advised that they exploit these firms with caution because the arbitrage is often riskier than perceived and is not as profitable as expected. This implication also applies to other market anomalies (e.g., price momentum), which, as prior studies suggest (e.g., Avramov, Chordia, Jostova, & Philipov, 2007, 2009a), are also concentrated among low-credit-rating firms.

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Table 1 Distribution of credit ratings

S&P Ratings	Frequency	Percentage (%)	Cumulative percentage (%)
AAA	5907	1.16	1.16
AA+	2871	0.56	1.72
AA	12062	2.36	4.08
AA-	15442	3.03	7.11
A+	26320	5.16	12.27
A	42058	8.24	20.51
A-	39233	7.69	28.19
BBB+	45883	8.99	37.18
BBB	58537	11.47	48.65
BBB-	47135	9.24	57.89
BB+	30135	5.90	63.79
BB	37629	7.37	71.17
BB-	46862	9.18	80.35
B+	46834	9.18	89.52
B	27350	5.36	94.88
B-	13890	2.72	97.60
CCC+	5005	0.98	98.59
CCC	2587	0.51	99.09
CCC-	1136	0.22	99.31
CC	892	0.17	99.49
C	18	0.00	99.49
D or SD	2587	0.51	100
Total	510373	100	100

Notes: This table shows the sample distribution of credit ratings at the firm-quarter level for the population of U.S listed companies, with a sample of 158,843 firm-quarter observations, from 1985 to 2019. The firm credit ratings are the long-term issuer credit ratings complied by Standard & Poor's (S&P) and reported in Compustat. The ratings range from AAA (the highest rating) to D (the lowest rating --- debt in payment default). These ratings reflect credit rating agencies' expectations of the creditworthiness of firms with respect to their long-term debt obligations.

Table 2 Do low-credit-rating firms tend to have high variability in asset fundamentals?

Variables	AAA --- A- Mean	obs.	BBB+ --- B- Mean	obs.	Mean diff. (t-stat.)
EarnVol	0.0053	89359	0.0146	58351	-0.0093 (-57.09)***
AccrualsVol	0.1122	40151	0.1356	36820	-0.0234 (-10.42)***
CfoVol	0.0160	62805	0.0250	47070	-0.0090 (-53.80)***
ReturnVol	0.0190	85813	0.0319	62387	-0.0129 (-192.83)***
IdioVol	0.0326	92724	0.0580	64248	-0.0255 (-213.74)***
Dispersion	0.0081	92724	0.7018	64393	-0.6937 (-1.75)*
LargeEarningsSur	0.8399	94563	0.8961	67520	-0.0563 (-32.61)***
LargeLoss	0.0063	94563	0.0405	67520	-0.0342 (-48.20)***

Variables	BBB+ --- B- Mean	obs.	CCC+ --- C&D Mean	obs.	Mean diff. (t-stat.)
EarnVol	0.0146	58351	0.0405	3307	-0.0259 (-27.35)***
AccrualsVol	0.1356	36820	0.1505	1591	-0.0149 (-1.79)*
CfoVol	0.0250	47070	0.0463	2300	-0.0213 (-28.25)***
ReturnVol	0.0319	62387	0.0674	3283	-0.0355 (-106.67)***
IdioVol	0.0580	64248	0.1229	3486	-0.0649 (-111.36)***
Dispersion	0.7018	64393	5.3065	3505	-4.6047 (-2.14)**
LargeEarningsSur	0.8961	67520	0.9385	3580	-0.0424 (-8.19)***
LargeLoss	0.0405	67520	0.2316	3580	-0.1910 (-51.99)***

Notes: This table presents the results for the test as to whether lower-credit-rating firms tend to have higher variability in asset fundamentals, measured by earnings volatility (*EarnVol*), accruals volatility (*AccrualsVol*), cash flow volatility (*CfoVol*), stock return volatility (*ReturnVol*), idiosyncratic volatility (*IdioVol*), analyst earnings forecast dispersion (*Dispersion*), the frequency of large earnings surprises (*LargeEarningsSur*), and the incidence of large losses (*LargeLoss*), during the sample period 1985-2019. In particular, the mean values of the variables are presented for each credit rating group (namely, AAA --- A-, BBB+ --- B-, and CCC+ --- C&D). *EarnVol* equals the standard deviation of quarterly earnings over 12 quarters ending at the end of a fiscal quarter, divided by total assets at the fiscal quarter end. *AccrualsVol* equals the standard deviation of the residuals of a regression of working capital accruals on cash flows from operation in the current fiscal quarter, previous fiscal quarter, and future fiscal quarter; on current PPE; and on current revenue changes over 12 quarters ending at the end of a fiscal quarter. *CfoVol* equals the standard deviation of cash flows from operations over 12 quarters ending at the end of a fiscal quarter, divided by total assets at the fiscal quarter end. *ReturnVol* equals the standard deviation of daily market excess returns over a year ending on the earnings announcement date for the fiscal quarter. *IdioVol* equals the standard deviation of the residuals from the following regression model over the past 52 weeks as of the earnings announcement date for the fiscal quarter: $r_{i,t}=\alpha_i+\beta_{1i}r_{m,t}+\beta_{2i}r_{m,t+1}+\beta_{3i}r_{m,t+2}+\beta_{4i}r_{m,t-1}+\beta_{5i}r_{m,t-2}+\varepsilon_{i,t}$, where $r_{i,t}$ is the weekly return on stock i, and $r_{m,t}$ is the value-weighted CRSP index return. *Dispersion* equals the standard deviation of analyst earnings forecasts over the fiscal quarter, divided by stock price at the end of the fiscal quarter. *LargeEarningsSur* equals 1 if income before extraordinary items for the current fiscal quarter, minus that for the previous fiscal quarter, and divided by that for the previous fiscal quarter, is greater than 0.05, or less than -0.05, for a firm for fiscal quarter t, and 0 otherwise. *LargeLoss* equals 1 if a firm's ROA for a fiscal quarter is lower than -0.05, and 0 otherwise. The t-statistics are reported in parentheses. ***, **, and * denote the two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3 Is earnings news of lower-credit-rating firms more difficult for investors to interpret?

Panel A: Differences in the time-series properties of earnings surprises for low-credit-rating firms relative to high-credit-rating firms

Variables	RW-based PEAD (SUE_t)	AF-based PEAD (SUE_t)
Intercept	-0.2437 (-0.72)	-9.3467 (-0.51)
SUE_{t-1}*$Rating_t$	**0.0285** **(3.23)*****	**0.4099** **(25.21)*****
SUE_{t-1}	0.0433 (7.20)***	0.2069 (69.90)***
$Rating_t$	0.6332 (15.56)***	8.3328 (3.50)***
Observations	154479	122197
F-stat.	56.45	195.59

Panel B: Do investors understand the differential time-series properties of earnings surprises of low-credit-rating firms *vis-à-vis* high-credit-rating firms?

Variables	RW-based PEAD (CAR_t)	AF-based PEAD (CAR_t)
Intercept	-0.0089 (-1.27)	-0.0116 (-1.62)
$DSUE_{t-1}$*$Rating_t$	**-0.0143** **(-5.36)*****	**-0.0064** **(-2.27)****
$DSUE_{t-1}$	0.0104 (5.84)***	0.0047 (2.41)**
$Rating_t$	0.0095 (5.70)***	0.0045 (2.54)**
Observations	146348	117519
F-stat.	8.56	7.60

Notes: Panel A of this table presents the results for the test as to whether there is any difference in the time-series properties of earnings surprises for low-credit-rating firms *vis-à-vis* high-credit-rating firms; specifically, whether the association between earnings surprise in the fiscal quarter *t* (SUE_t) and earnings surprise in the fiscal quarter *t*-1 (SUE_{t-1}) is more pronounced for firms with higher credit ratings. Panel B reports the results for the test as to whether investors understand the differential time-series properties of earnings surprises of low-credit-rating firms *vis-à-vis* high-credit-rating firms; specifically, whether the association between the market reaction to earnings surprises at the fiscal quarter *t* (CAR_t) and earnings surprise at the fiscal quarter *t*-1 ($DSUE_{t-1}$) is more pronounced for firms that have lower credit ratings. CAR_t is the cumulative size-adjusted stock returns during the three-day window centered on the earnings announcement date. A pooled cross-sectional and time-series regression is used in the tests for the sample period 1985-2019. Year and quarter dummies are included in all the regressions but not reported for sake of brevity. The RW-based earnings surprise (*SUE*) is calculated as current quarter earnings less earnings four quarters ago, scaled by the standard deviation of the earnings changes in the prior ten quarters. The AF-based earnings surprise (*SUE*) is calculated as the actual EPS for a fiscal quarter minus the mean analyst consensus forecast of EPS in the 90 days preceding the earnings announcement date, standardized by the standard deviation of the earnings surprises in the prior ten quarters. *DSUE* corresponds to the decile rank of the earnings surprise and is coded from 0 to 1. *Rating* is coded 0 for firms with ratings ranging from SD/D to CCC, 0.5 for firms with ratings ranging from B- to BBB+, and 1 for firms rated with a grade from A- to AAA, for the fiscal quarter. *CAR* is the cumulative size-adjusted abnormal returns over the three-day window centered on the earnings announcement date for the fiscal quarter. The t-statistics are reported in parentheses. *** and ** denote statistical significance at the 1% and 5% levels (two-tailed), respectively.

Table 4 Portfolio analysis: PEAD across credit rating groups

Rating groups	Portfolios	(1) RW-based PEAD	(2) AF-based PEAD
CCC+ --- C&D	D10-D1	**0.1430**	**0.2109**
		(3.96)* **	**(2.12)** **
	D1	-0.1244	-0.1255
		(-5.50)***	(-4.67)***
	D10	0.0186	0.0854
		(0.69)	(0.89)
BBB+ --- B-	D10-D1	**0.0257**	**0.0218**
		(7.95)* **	**(6.59)*** **
	D1	-0.0143	-0.0077
		(-5.28)***	(-2.81)***
	D10	0.0114	0.0141
		(6.42)***	(7.62)***
AAA --- A-	D10-D1	**0.0167**	**0.0221**
		(5.94)* **	**(6.85)*** **
	D1	-0.0103	-0.0111
		(-4.28)***	(-4.04)***
	D10	0.0064	0.0110
		(4.41)***	(6.51)***
AAA --- C&D	D10-D1	**0.0264**	**0.0242**
		(10.31)* **	**(9.26)*** **
	D1	-0.0166	-0.0109
		(-7.53)***	(-4.92)***
	D10	0.0098	0.0133
		(7.50)***	(9.59)***
Alternative grouping of credit ratings			
Speculative grades	D10-D1	**0.0370**	**0.0327**
(BB+ --- C&D)		**(7.48)*** **	**(6.35)*** **
	D1	-0.0239	-0.0159
		(-5.99)***	(-3.88)***
	D10	0.0131	0.0168
		(4.47)***	(5.38)***
Investment grades	D10-D1	**0.0172**	**0.0177**
(AAA --- BBB-)		**(7.81)*** **	**(7.09)*** **
	D1	-0.0092	-0.0062
		(-4.97)***	(-2.95)***
	D10	0.0080	0.0115
		(6.70)***	(8.54)***

Notes: This table reports the size-adjusted PEAD for the drift window, [2, 61], where day zero is the earnings announcement date for a quarter. The sample period ranges from 1985 to 2019. Firm-quarter observations are grouped by credit ratings. Column (1) ((2)) presents the results for the RW-based (AF-based) PEAD across different credit-rating groups. For Column (1), within each credit rating group, observations are sorted into deciles based on current quarter earnings less earnings four quarters ago, scaled by the standard deviation of the earnings changes in the prior ten quarters. For Column (2), within each credit rating group, observations are sorted into deciles based on the actual EPS minus the mean consensus analyst forecast of EPS in the 90 days before the earnings announcement date, standardized by the standard deviation of the earnings surprises in the prior ten quarters. The buy-and-hold abnormal return of a firm equals the compounded raw returns minus the compounded benchmark returns of the same CRSP size deciles and the same CRSP exchange index to which the firm belongs. The buy-and-hold abnormal returns for the *SUE* decile portfolios are computed by equally weighting the buy-and-hold abnormal returns of all observations in that decile rank. The PEAD trading strategy involves buying (selling) the winner (loser) portfolio (D10 (D1)) and holding the positions over the drift window. D10-D1 corresponds to the average payoffs to the PEAD trading strategy during the holding period for both winner and loser portfolios. The sample used for the portfolio tests is confined to observations having necessary data required to construct the *SUE*s and drift returns. The t-statistics are reported in parentheses. *** and ** denote statistical significance at the 1% and 5% levels (two-tailed), respectively.

Table 5 Risk-adjusted PEAD payoffs across credit rating groups

Panel A: Risk-adjusted PEAD payoffs across different rating groups for the sample period 1985-2019

Rating groups	Alphas from Carhart-based calendar-time portfolio regressions	
	RW-based PEAD payoffs (monthly)	AF-based PEAD payoffs (monthly)
CCC+ --- C&D	0.0335 (2.43)**	0.0469 (1.47)
BBB+ --- B-	0.0036 (2.34)**	-0.0018 (-0.90)
AAA --- A-	-0.0023 (-1.51)	-0.0013 (-0.87)
Alternative grouping of credit ratings: speculative grades vs. investment grades		
BB+ --- C&D	0.0042 (1.80)*	0.0001 (0.04)
AAA --- BBB-	0.0003 (0.29)	-0.0002 (-0.12)

Panel B: Risk-adjusted PEAD payoffs across different rating groups for the sample period 1985-2006

Rating groups	Alphas from Carhart-based calendar-time portfolio regressions	
	RW-based PEAD payoffs (monthly)	AF-based PEAD payoffs (monthly)
CCC+ --- C&D	0.0362 (2.10)**	0.0105 (0.25)
BBB+ --- B-	0.0044 (2.33)**	-0.0049 (-1.93)*
AAA --- A-	-0.0057 (-3.22)***	-0.0035 (-1.90)*
Alternative grouping of credit ratings: speculative grades vs. investment grades		
BB+ --- C&D	0.0051 (1.82)*	-0.0026 (-0.76)
AAA --- BBB-	-0.0009 (-0.57)	-0.0028 (-1.58)

Panel C: Risk-adjusted PEAD payoffs across different rating groups for the sample period 2010-2019

Rating groups	Alphas from Carhart-based calendar-time portfolio regressions	
	RW-based PEAD payoffs (monthly)	AF-based PEAD payoffs (monthly)
CCC+ --- C&D	0.0508 (1.96)**	0.1290 (1.14)
BBB+ --- B-	0.0048 (1.64)	0.0058 (1.66)*
AAA --- A-	-0.0005 (-0.27)	-0.00006 (-0.03)
Alternative grouping of credit ratings: speculative grades vs. investment grades		
BB+ --- C&D	0.0081 (1.69)*	0.0071 (1.52)
AAA --- BBB-	0.0021 (1.14)	0.0045 (2.30)**

Notes: This table reports the alphas from the calendar-time portfolio regressions that are based on the Carhart's (1997) four-factor model. The sample period for the results in Panel A covers the years 1985-2019. The sample period for the results in Panel B ranges from 1985 to 2006. The sample period for the results in Panel C covers the years 2010-2019. For each calendar quarter, firms are ranked into decile portfolios based on *SUE*. Firms enter the portfolio on the first day of the month following each earnings announcement and are held for nine months, which normally cover three subsequent quarterly earnings announcements. The PEAD trading strategy involves taking the long (short) position in the highest (lowest) *SUE* decile portfolio. Accordingly, the monthly returns to the hedge portfolios are calculated as the difference between the equally-weighted average monthly return of the highest *SUE* decile portfolio and that of the lowest *SUE* decile portfolio. The hedge portfolio monthly return net of the risk-free rate is then regressed on the four Carhart-based monthly risk factors (i.e., excess market returns, firm size, book-to-market, and price-momentum factors) for each credit rating group, whereby the alpha from the regression represents the average monthly earnings momentum payoffs that are adjusted for the systematic risk. The coefficients on the systematic risk factors are omitted for the sake of brevity. The t-statistics are in parentheses. ***, **, and * denotes the two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Multivariate tests of the association between credit rating and PEAD

Panel A: Regression of PEAD on credit rating

Variables	Pred. sign	Dependent variable = *drift*					
		RW-based PEAD			AF-based PEAD		
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept	?	-0.1624 (-5.41)***	-0.1640 (-5.40)***	-0.1673 (-5.48)***	-0.0784 (-2.70)***	-0.0749 (-2.58)***	-0.0777 (-2.59)***
DSUE	+	0.0755 (4.24)***	0.0692 (3.72)***	0.0766 (4.01)***	0.0919 (5.06)***	0.0854 (4.34)***	0.0894 (4.52)***
*DSUE*Rating*	-	-0.0414 (-3.40)***	-0.0437 (-3.47)***	-0.0417 (-3.33)***	-0.0409 (-3.32)***	-0.0398 (-3.16)***	-0.0401 (-3.19)***
Rating	+	0.0413 (5.08)***	0.0428 (5.08)***	0.0425 (5.10)***	0.0428 (5.00)***	0.0403 (4.53)***	0.0425 (4.73)***
[Information uncertainty variables]							
IUfactor	+			0.0006 (0.67)			-0.0001 (-0.09)
*DSUE*IUfactor*	+			-0.0002 (-0.15)			0.0003 (0.25)
EarningsVol	+		0.0100 (1.15)			0.0157 (1.93)*	
*DSUE*EarningsVol*	+		0.0003 (0.02)			-0.0093 (-0.77)	
CashVol	+		0.0041 (0.47)			0.0128 (1.53)	
*DSUE*CashVol*	+		0.0217 (1.61)			-0.0011 (-0.09)	
AQ	+		-0.0080 (-1.43)			-0.0177 (-3.21)***	
*DSUE*AQ*	+		0.0041 (0.49)			0.0255 (3.28)***	
ReturnVol	+		-0.0049 (-0.43)			-0.0062 (-0.55)	
*DSUE*ReturnVol*	+		0.0201 (1.14)			0.0163 (0.98)	
Dispersion	+		-0.0254 (-2.91)***			-0.0153 (-1.97)**	
*DSUE*Dispersion*	+		0.0125 (0.93)			-0.0148 (-1.26)	
Firmage	-		-0.0007 (-0.12)			0.0114 (2.00)**	
*DSUE*Firmage*	-		0.0066 (0.72)			-0.0087 (-1.03)	
IdioVol	+		0.0062 (0.60)			0.0062 (0.56)	
*DSUE*IdioVol*	+		-0.0118 (-0.72)			-0.0119 (-0.72)	
[Other control variables]		included	included	included	included	included	included
[Year, quarter & industry dummies]		included	included	included	included	included	included
Observations		76779	76779	76779	64588	64588	64588
Adj.R^2		0.018	0.019	0.018	0.018	0.019	0.018

Panel B: Use of an alternative credit-rating variable for the multivariate analysis

		Dependent variable = *drift*					
Variables	Pred. sign	RW-based PEAD			AF-based PEAD		
		(1)	(2)	(3)	(4)	(5)	(6)
Intercept	?	-0.1700	-0.1757	-0.1810	-0.0777	-0.0794	-0.0832
		(-5.72)***	(-5.77)***	(-5.91)***	(-2.65)***	(-2.68)***	(-2.73)***
DSUE	+	0.0704	0.0656	0.0751	0.0861	0.0831	0.0883
		(4.02)***	(3.48)***	(3.94)***	(4.71)***	(4.12)***	(4.41)***
*DSUE*ISRating*	-	-0.0362	-0.0352	-0.0384	-0.0385	-0.0363	-0.0394
		(-2.83)***	(-2.55)***	(-2.84)***	(-2.94)***	(-2.63)***	(-2.94)***
ISRating	+	0.0430	0.0454	0.0471	0.0467	0.0453	0.0488
		(5.08)***	(4.94)***	(5.25)***	(5.29)***	(4.85)***	(5.36)***
[Information uncertainty variables]							
IUfactor	+			0.0012			0.0006
				(1.44)			(0.80)
*DSUE*IUfactor*	+			-0.0006			-0.0002
				(-0.47)			(-0.20)
EarningsVol	+		0.0119			0.0168	
			(1.37)			(2.04)**	
*DSUE*EarningsVol*	+		-0.0015			-0.0102	
			(-0.10)			(-0.84)	
CashVol	+		0.0034			0.0126	
			(0.40)			(1.50)	
*DSUE*CashVol*	+		0.0228			-0.0007	
			(1.70)*			(-0.06)	
AQ	+		-0.0075			-0.0176	
			(-1.36)			(-3.19)***	
*DSUE*AQ*	+		0.0034			0.0254	
			(0.41)			(3.26)***	
ReturnVol	+		-0.0017			-0.0030	
			(-0.15)			(-0.27)	
*DSUE*ReturnVol*	+		0.0179			0.0137	
			(1.02)			(0.83)	
Dispersion	+		-0.0242			-0.0138	
			(-2.77)***			(-1.77)*	
*DSUE*Dispersion*	+		0.0110			-0.0169	
			(0.82)			(-1.44)	
Firmage	-		-0.0018			0.0101	
			(-0.30)			(1.78)*	
*DSUE*Firmage*	-		0.0066			-0.0082	
			(0.72)			(-0.98)	
IdioVol	+		0.0081			0.0085	
			(0.79)			(0.77)	
*DSUE*IdioVol*	+		-0.0124			-0.0135	
			(-0.75)			(-0.82)	
[Other control variables]		included	included	included		included	included
[Year, quarter & industry dummies]		included	included	included		included	included
Observations		76779	76779	76779	64588	64588	64588
Adj.R^2		0.018	0.019	0.018	0.016	0.017	0.016

Notes: This table reports the regression results for the tests of the association of credit rating with the RW-based or AF-based PEAD after controlling for information uncertainty and other PEAD determinants. The sample period ranges from 1985 to 2019. The dependent variable is the drift returns, which equal the compounded raw returns minus the compounded benchmark returns of the same CRSP size deciles and the same CRSP exchange index to which a firm belongs, over the window of [2, 61] relative to the earnings announcement date. *DSUE* corresponds to the decile rank of the standardized unexpected earnings (*SUE*) and is coded from 0 to 1. The RW-based earnings surprise is calculated as current quarter earnings less earnings four quarters ago, scaled by the standard deviation of the earnings changes in the prior ten quarters. The AF-based earnings surprise is calculated as the actual EPS for quarter *t* minus the mean analyst consensus forecast of EPS in the 90 days preceding the earnings announcement date, standardized by the standard deviation of the earnings surprises in the prior ten quarters. In panel A, *Rating* is coded 0 for firms with ratings ranging from SD/D to CCC, 0.5 for firms with ratings ranging from B- to BBB+, and 1 for firms rated with a grade from A- to AAA. In panel B, *ISRating* is coded 0 for firms with ratings of SD/D to CCC, 0.5 for firms with ratings ranging from B- to the upper limit point for a speculative grade, which is BB+, and 1 for firms rated with an investment grade (i.e., BBB- or above). All the control variables are defined in Appendix I. If the control variables are continuous, they are ranked into deciles within each fiscal quarter and coded from 0 to 1 as well. The results for some control variables in Panel B are not reported for the sake of brevity. The t-statistics in parentheses are based on the robust standard errors clustered by firm. Industry-, year-, and quarter-dummies are included in the regressions but are omitted from the table for the sake of brevity. The t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 7 Multivariate tests of transient institutions' arbitrage on PEAD of different rated firms

Panel A: Regression of transient institutions' stock ownership changes

Variables	Pred. Sign	dependent variable = $\Delta Transient_{i,t'}$ (1) RW-based PEAD	Pred. Sign	(2) AF-based PEAD
DSUE $_t$	+	0.0088 (4.70)***	+	0.0165 (8.77)***
DSUE $_{t-1}$	-	-0.0048 (-2.41)***	+	0.0058 (3.01)***
DSUE $_{t-2}$	-	-0.0125 (-6.26)***	-	-0.0135 (-7.00)***
DSUE $_{t-3}$	-	-0.0070 (-3.71)***	-	-0.0172 (-9.15)***
Rating	?	-0.0015 (-0.96)	?	-0.0007 (-0.48)
*DSUE $_t$*Rating*	-	-0.0078 (-3.85)***	-	-0.0126 (-6.40)***
*DSUE $_{t-1}$*Rating*	+	0.0029 (1.36)	-	-0.0036 (-1.80)*
*DSUE $_{t-2}$*Rating*	+	0.0058 (2.70)***	+	0.0090 (4.48)***
*DSUE $_{t-3}$*Rating*	+	0.0019 (0.95)	+	0.0102 (5.17)***
TranCost	?	-0.0131 (-9.55)***	?	0.0021 (1.68)*
*DSUE $_t$*TranCost*	-	-0.0033 (-2.12)**	-	-0.0081 (-5.45)***
*DSUE $_{t-1}$*TranCost*	+	0.0040 (2.48)**	-	0.0018 (1.16)
DSUE $_{t-2}$ TranCost*	+	0.0089 (5.46)***	+	0.0057 (3.76)***
*DSUE $_{t-3}$*TranCost*	+	0.0033 (2.13)**	+	0.0086 (5.77)***
Size	?	-0.0011 (-5.92)***	?	0.0008 (3.59)***
BM	?	-0.0000 (-0.66)	?	0.0000 (1.63)
PW	-	-0.0691 (-1.75)*	-	-0.2269 (-4.32)***
FD	-	-0.0038 (-2.62)***	-	-0.0068 (-4.28)***
RET1	+	0.0090 (7.70)***	+	0.0131 (10.02)***
RET2-3	+	0.0336 (42.06)***	+	0.0373 (43.23)***
RET4-6	+	0.0098 (31.38)***	+	0.0107 (31.82)***
F-test:				
H_{01}: *DSUE $_{t-1}$* Rating + DSUE $_{t-2}$* Rating + DSUE $_{t-3}$ * Rating* = 0	+	0.0106 (16.26)***		

H02: *DSUE $_{t}$* Rating +* *DSUE $_{t-1}$* Rating* = 0			-	-0.0162 (-41.82)***
H03: *DSUE $_{t-2}$* Rating +* *DSUE $_{t-3}$ * Rating* = 0			+	0.0192 (58.55)***
Observations		95732		75072
Adj. R^2		0.0411		0.0565

Panel B: Use of an alternative credit-rating variable for the multivariate analysis

Variables	Pred. Sign	dependent variable = $\Delta Transient_{i,t'}$ (1) RW-based PEAD	Pred. Sign	(2) AF-based PEAD
DSUE $_{t}$	+	0.0090 (4.28)***	+	0.0189 (8.71)***
DSUE $_{t-1}$	-	-0.0035 (-1.59)	+	0.0093 (4.21)***
DSUE $_{t-2}$	-	-0.0140 (-6.29)***	-	-0.0172 (-7.79)***
DSUE $_{t-3}$	-	-0.0052 (-2.48)**	-	-0.0185 (-8.65)***
ISRating	?	-0.0003 (-0.21)	?	-0.0001 (-0.04)
*DSUE $_{t}$*ISRating*	-	-0.0064 (-3.40)***	-	-0.0128 (-6.59)***
*DSUE $_{t-1}$*ISRating*	+	0.0010 (0.53)	-	-0.0065 (-3.28)***
*DSUE $_{t-2}$*ISRating*	+	0.0061 (3.09)***	+	0.0112 (5.64)***
*DSUE $_{t-3}$*ISRating*	+	-0.0002 (-0.13)	+	0.0098 (5.09)***
TranCost	?	-0.0128 (-9.29)***	?	0.0023 (1.86)**
*DSUE $_{t}$*TranCost*	-	-0.0033 (-2.11)**	-	-0.0082 (-5.51)***
*DSUE $_{t-1}$*TranCost*	+	0.0036 (2.17)**	-	0.0009 (0.59)
DSUE $_{t-2}$ TranCost*	+	0.0094 (5.65)***	+	0.0064 (4.20)***
*DSUE $_{t-3}$*TranCost*	+	0.0026 (1.67)*	+	0.0085 (5.68)***
Other control variables		included		included
F-test:				
H01: *DSUE $_{t-1}$* ISRating +* *DSUE $_{t-2}$* ISRating + DSUE $_{t-3}$* ** ISRating* = 0	+	0.0069 (7.97)***		
H02: *DSUE $_{t}$* ISRating +* *DSUE $_{t-1}$* ISRating* = 0			-	-0.0193 (-41.82)***
H03: *DSUE $_{t-2}$* ISRating +* *DSUE $_{t-3}$ * ISRating* = 0			+	0.0210 (58.55)***
Observations		95732		75072
Adj. R^2		0.0410		0.0565

Notes: This table reports the results for the tests of transient institutions' arbitrage on PEAD of different rated firms. The sample period covers the years 1985-2013. The firm-fixed-effects regression model is used for the tests. The dependent variable is the changes in transient institutional stock ownership as a percentage of outstanding shares of a firm over a calendar quarter t', within which the earnings announcement date for the fiscal quarter t falls. $DSUE_t$ corresponds to the decile rank of the *SUE* for fiscal quarter t and is converted to [0, 1]. For the RW-based PEAD, the earnings surprise is calculated as current quarter earnings less earnings four quarters ago, scaled by the standard deviation of the earnings changes in the prior ten quarters. For the AF-based PEAD, the earnings surprise is calculated as the actual EPS minus the mean consensus analyst forecast of EPS in the 90 days before the earnings announcement date, standardized by the standard deviation of the earnings surprises in the prior ten quarters. In panel A, *Rating* is coded 0 for firms with ratings ranging from SD/D to CCC, 0.5 for firms with ratings ranging from B- to BBB+, and 1 for firms rated with a grade from A- to AAA. In panel B, *ISRating* is coded 0 for firms with ratings of SD/D to CCC, 0.5 for firms with ratings ranging from B- to the upper limit point for a speculative grade, which is BB+, and 1 for firms rated with an investment grade (i.e., BBB- or above). *TranCost* is measured by the average of daily dollar trading volume (i.e., the CRSP daily closing price times the number of daily shares traded) over days from the beginning of the fiscal quarter to date -21 relative to the earnings announcement date, and is ranked into deciles and converted to [0, 1] with 0 (1) representing the lowest (highest) transaction costs. All the control variables are defined in Appendix I. The results for some control variables in Panel B are not reported for the sake of simplicity. Year-, quarter-, and industry-dummies are included in the regressions but are omitted from the table for the sake of simplicity. The t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Appendix I Summary of variable definitions

Control variables	Definitions
Rating	Credit rating levels from AAA to D/SD, which are transformed into conventional numerical scores that take a value of 0 for firms with ratings ranging from SD/D to CCC+, 0.5 for firms with ratings from B- to BBB+, and 1 for firms with ratings from A- to AAA.
ISRating	Credit rating levels from AAA to D/SD, which are transformed into conventional numerical scores that equal 0 for firms with ratings ranging from SD/D to CCC, 0.5 for firms with ratings ranging from B- to the upper limit point for a speculative grade (i.e., BB+), and 1 for firms rated with an investment grade (i.e., BBB- or above).
EarningsVol	The standard deviation of quarterly earnings over 12 quarters ending at the end of a fiscal quarter.
CashVol	The standard deviation of cash flows from operations over 12 quarters ending at the end of a fiscal quarter.
AQ/AccrualsVol	The standard deviation of the residuals of a regression of working capital accruals on cash flows from operations in the current fiscal quarter, prior fiscal quarter, and future fiscal quarter; on PPE; and on revenue changes (see Francis, LaFond, Olsson, & Schipper (2005)) over 12 quarters ending at the end of a fiscal quarter.
ReturnVol	The standard deviation of daily market excess returns over a year ending on the earnings announcement date for a fiscal quarter.
Dispersion	The standard deviation of analyst earnings forecasts over a fiscal quarter, divided by the stock price at the end of the fiscal quarter.
Firmage	The number of months since a firm's initial public offerings (IPO). If the IPO date is not available in Compustat, *Firmage* equals the number of months since CRSP first reported the return date for the firm.
IdioVol	The standard deviation of the residuals from the following regression model over the past 52 weeks as of the earnings announcement date for the fiscal quarter: $r_{i,t}=\alpha_i+\beta_{1i}r_{m,t}+\beta_{2i}r_{m,t+1}+\beta_{3i}r_{m,t+2}+\beta_{4i}r_{m,t-1}+\beta_{5i}r_{m,t-2}+\varepsilon_{i,t}$, where $r_{i,t}$ is the weekly return on stock i, and $r_{m,t}$ is the value-weighted CRSP index return.
IUfactor	A composite measure for *EarningsVol*, *CashVol*, *AQ*, *ReturnVol*, *Dispersion*, *Firmage*, and *IdioVol*, which is constructed using factor analysis.
Coverage	The natural logarithm of 1 plus the number of analysts following a firm over a fiscal quarter.
Insti	Institutional stock ownership as a percentage of outstanding shares of a firm at the end of a fiscal quarter.
TradingVol/TranCost	The average of daily dollar trading volume (i.e., the CRSP daily closing price times the number of daily shares traded) (in millions of U.S. dollars) over days from the beginning of a fiscal quarter to date -21 relative to the earnings announcement date of the fiscal quarter.
Size	The natural logarithm of 1 plus the market value of a firm's common equity at the beginning of a fiscal quarter.
BM	The book value of a firm's common equity divided by the market value of the firm's common equity at the beginning of a fiscal quarter.
RET	The size-adjusted buy-and-hold returns from 61 days to 1 day before the earnings announcement date of a fiscal quarter.
Price	The average daily closing price within one week before the earnings announcement date for a fiscal quarter.
THQTR	1 if the current quarter is the fourth quarter of a fiscal year for a firm, and 0 otherwise.
Badnews	1 if a firm reports a negative earnings surprise for a fiscal quarter, and 0 otherwise.
ChangeSUE	The *SUE* in the current fiscal quarter, minus the *SUE* in the previous quarter.

FD	1 for a firm is in a fiscal quarter that is after October 2000 in which the Regulation Fair Disclosure was implemented, and 0 otherwise.
PW	The mean portfolio weight (in percentage) of a stock in the portfolio of transient institutions during a fiscal quarter.
RET1	The size-adjusted buy-and-hold returns from thirty days to three days before the earnings announcement date of a fiscal quarter.
RET2-3	The size-adjusted buy-and-hold returns over a two-month period ending thirty days prior to the earnings announcement date of a fiscal quarter.
RET4-6	The size-adjusted buy-and-hold returns over a three-month period ending three months prior to the earnings announcement date of a fiscal quarter.
EarnVol	The standard deviation of quarterly earnings over 12 quarters ending at the end of a fiscal quarter, divided by total assets at the fiscal quarter end.
CfoVol	The standard deviation of cash flows from operations over 12 quarters ending at the end of a fiscal quarter, divided by total assets at the fiscal quarter end, divided by total assets.
LargeEarningsSur	1 if income before extraordinary items for the fiscal quarter *t*, minus that for quarter *t*-1, and divided by that for quarter *t*-1, is greater than 0.05, or less than -0.05, for a firm for the quarter *t*, and 0 otherwise.
LargeLoss	1 if a firm's return on assets for a fiscal quarter is lower than -0.05, and 0 otherwise.

Appendix II Pearson correlation matrix

	Rating	*EarningsVol*	*CashVol*	*AQ*	*ReturnVol*	*Dispersion*	*Firmage*	*IdioVol*
Rating	1							
EarningsVol	0.0870 (0.000)***	1						
CashVol	0.2571 (0.000)***	0.3915 (0.000)***	1					
AQ	-0.0467 (0.000)***	0.0135 (0.000)***	0.0231 (0.000)***	1				
ReturnVol	-0.5080 (0.000)***	-0.0248 (0.000)***	-0.0979 (0.000)***	0.0404 (0.000)***	1			
Dispersion	-0.0105 (0.004)***	0.0005 (0.888)	-0.0008 (0.819)	-0.0014 (0.699)	0.0212 (0.000)***	1		
Firmage	0.4162 (0.000)***	0.0798 (0.000)***	0.2105 (0.000)***	-0.0282 (0.000)***	-0.2520 (0.000)***	-0.0029 (0.418)	1	
IdioVol	-0.5459 (0.000)***	-0.0356 (0.000)***	-0.1216 (0.000)***	0.0303 (0.000)***	0.8773 (0.000)***	0.0272 (0.000)***	-0.2802 (0.000)***	1

Notes: This table presents the Pearson correlations among the credit rating and information uncertainty variables that are used in the regression of PEAD on credit rating. 76,779 firm-quarter observations are involved in the correlation test. All the variables are defined in Appendix I. The figures in parentheses are *p*-values for the Pearson correlations. *** denotes statistical significance at the 1% level (two-tailed).