Psychological Barrier and Cross-firm Return Predictability

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This paper provides a psychological explanation for the delayed price response to news about economically linked firms. We show that the return predictability of economically linked firms depends on the nearness to the 52-week high. The interaction between news about economically linked firms and the nearness to 52-week high can at least partially explain the underreaction to news about customers, geographic neighbors, industry peers, standalone firms, or foreign industries. We further examine how anchoring on the 52-week high affects belief updating regarding analyst recommendation revisions. We find that analysts react to news about economically linked firms but that anchoring on the 52-week high reduces such reactions.

JEL Classification: G10, G11, G14, G24, G41
Keywords: Cross-firm return predictability, Psychological barrier, 52-week high, Customer momentum.

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Abstract

This paper provides a psychological explanation for the delayed price response to news about economically linked firms. We show that the return predictability of economically linked firms depends on the nearness to the 52-week high. The interaction between news about economically linked firms and the nearness to 52-week high can at least partially explain the underreaction to news about customers, geographic neighbors, industry peers, standalone firms, or foreign industries. We further examine how anchoring on the 52-week high affects belief updating regarding analyst recommendation revisions. We find that analysts react to news about economically linked firms but that anchoring on the 52-week high reduces such reactions.

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1. Introduction

Firms are economically linked to each other in various forms, such as customers and suppliers, geographic neighbors, and industry peers. A growing body of literature documents that firms' stock prices respond slowly to value-relevant news about their economically linked firms (e.g., Cohen and Frazzini, 2008; Cohen and Lou, 2012; Parsons, Sabbatucci, and Titman, 2018). This delayed price response provides suggestive evidence of market inefficiency.[1] Hence, understanding why stock prices slowly adjust to news about economically linked firms sheds light on the potential underlying mechanism of this market inefficiency. Most existing studies argue that investor inattention could be one of the main reasons for this market underreaction.[2] We propose a new psychological explanation in which anchoring on the 52-week high price (hereafter referred to as *nearness to 52-week hig*h) induces delayed price responses to news about economically linked firms.

The intuition is that without psychological bias, investors can promptly update their beliefs about a firm's fundamental in response to news about economically linked firms. However, with bias, anchoring on the 52-week high distorts the belief-updating process, which, in turn, leads to an underreaction to public information about economically linked firms. For example, for stocks with prices near the 52-week high, upward price movements are bounded above by the 52-week high in the minds of anchoring investors. Consequently, when good news about economically linked firms arrives, these investors do not fully adjust their beliefs, and they respond slowly to the good news. Similarly, for stocks with prices far from the 52-week high, investors respond slowly to bad news from economically linked firms.

[1] In the literature, news about economically linked firms is usually stock returns, earnings announcements, and other easily accessible information for investors. Information on firm relationships such as firms' material customers, locations, and industries are also publicly available.

[2] For example, Cohen and Frazzini (2008) argue that if investors ignore publicly available information from firms' customers, lagged customer stock returns can predict suppliers' future stock returns. Cohen and Lou (2012) and Huang (2015) also explain cross-firm return predictability in their papers but pay limited attention to this issue.

This intuition is in line with the argument of George and Hwang (2004), who show that the nearness to 52-week high predicts a firm's future stock returns. They argue that anchoring investors do not fully incorporate the firm's own information into their beliefs due to anchoring bias. In a similar spirit, we argue that anchoring on the 52-week high generates a market underreaction to public information about economically linked firms. Accordingly, we propose the following testable hypothesis: *When a firm's economically linked firms have good (bad) news and its own stock price is near (far from) the 52-week high, it has higher (lower) future returns*. We test our hypothesis by focusing on the empirical setting of the customer-supplier link (Cohen and Frazzini, 2008), with other settings (e.g., geographic momentum and industry momentum) as extensions.[3]

To provide more direct evidence of how anchoring on the 52-week high biases the belief-updating process, we further examine how analyst recommendation revisions respond to news about economically linked firms. The advantage of using recommendation revisions is that we have a clean and direct measure of the belief-updating process. As analysts are important information intermediaries in the financial market, showing how the 52-week high affects their responses to news about economically linked firms also helps directly pin down the economic mechanism. Hence, we propose our second hypothesis: *For stocks with prices near (far from) the 52-week high, analysts underreact to good (bad) news about economically linked firms, leading to a lower likelihood that the stocks will be upgraded (downgraded).*

We test our first hypothesis by both portfolio sorting and Fama-MacBeth regressions. First, we double sort supplier firms by their customer returns and their own nearness to 52-week high into

[3] For the main analysis, we focus on the customer momentum setting (Cohen and Frazzini, 2008). In the customer momentum setting, a supplier firm's returns can be predicted by the lagged returns of its customer firms. We also analyze the geographic momentum (Parsons, Sabbatucci, and Titman, 2018), industry momentum (Moskowitz and Grinblatt, 1999), complicated firm (Cohen and Lou, 2012), and foreign information (Huang, 2015) settings as extensions. We focus on the customer momentum setting for two reasons: First, the customer-supplier relationship is perhaps the most direct economic link among firms since customer firms are stakeholders in supplier firms' business. Second, the customer-supplier link setting has been broadly applied in various empirical studies.

portfolios. Specifically, in each month, we independently sort supplier firms into quintile portfolios based on their customer returns in the previous month and their own nearness to 52-week high at the previous month-end. The portfolios are held for one month and rebalanced monthly. When adopting the double sorting method, a natural concern is that two sorting variables are potentially correlated. Our setting is largely immune from this issue, as the correlation between two sorting variables is only 0.05.[4]

Consistent with Cohen and Frazzini (2008), we find that the portfolio return of suppliers increases with the customer return ranking. More importantly, within the top quintile of customer returns, only stocks in the top quintile of nearness to 52-week high earn positive and significant returns. For example, within the top quintile of customer returns, stocks in the top quintile of nearness to 52-week high earn an average Fama-French-Carhart (1997) four-factor alpha (FFC4 alpha) of 0.82% per month (t-statistic = 4.38), while stocks in the bottom quintile of nearness to 52-week high earn an average nonsignificant FFC4 alpha of 0.02% per month (t-statistic = 0.08). The return spread, an FFC4 alpha of 0.79% per month, is also significant (t-statistic = 2.45).

Similarly, within the bottom quintile of customer returns, stocks in the bottom quintile of nearness to 52-week high earn an FFC4 alpha of -0.91% per month (t-statistic of -3.85), while stocks in the top quintile of nearness to 52-week high earn an FFC4 alpha of 0.01% per month (t-statistic of 0.01). The return spread, an FFC4 alpha of 0.92%, is also significant (t-statistic = 3.06). These results are consistent with our first hypothesis that investors underreact to good (bad) news about customer firms only when stock prices are already near (far from) the 52-week high, which leads to cross-firm return predictability in the form of customer momentum.

[4] In addition, Table 2 shows that within each quintile of customer returns, there is little variation of customer returns across quintiles of nearness to 52-week high. Within each quintile of nearness to 52-week high, there is also little variation of nearness to 52-week high across customer return quintiles.

Given the documented return spread between the top and bottom quintiles of nearness to 52-week high (George and Hwang, 2004), one may be concerned that the two previous return spreads within the top and bottom quintiles of customer returns are driven purely by the effect of the 52-week high. To address this concern, we examine 52-week high return spreads across all five customer return quintiles and find a U-shaped relationship between 52-week high return spreads and the customer return quintile ranking. That is, while the 52-week high return spread within the top and bottom customer return quintiles is large, the return spreads for the middle customer return quintiles are lower. This finding suggests that the 52-week high return spreads in the high and low customer return quintiles are not driven solely by investors' underreaction to information captured by the nearness to 52-week high itself. Otherwise, we should also observe an equally large 52-week high return spread for the middle customer return quintiles.

The portfolio analysis provides evidence of the interaction effect between customer news and nearness to 52-week high regarding cross-firm return predictability. To better shed light on the economic significance of this interaction effect, we follow George, Hwang, and Li (2017) and run Fama-MacBeth cross-sectional regressions to decompose returns in the double-sorted portfolios into the pure effect of customer momentum, the pure effect of anchoring, and the interaction effect between customer momentum and anchoring. We term this method *return decomposition*.

We find that the interaction effect is indeed significantly positive, with an FFC4 alpha of 1.58% per month (t-statistic = 2.32). In addition, after including the interaction effect, the pure customer momentum effect becomes insignificant, with an FFC4 alpha of 0.01% per month (t-statistic = 0.03); in contrast, without the interaction effect, the customer momentum effect is significant, with an FFC4 alpha of 0.52% (t-statistic = 3.65). This return decomposition result indicates that anchoring bias can largely explain investors' underreaction to news about customer firms.[5]

Regarding our second hypothesis, we find that analysts do indeed pay attention to recent news about customer firms, as reflected by a higher likelihood of upgrading the supplier firm when there is good news about its customers. However, when the supplier firm's own stock price is near the 52-week high, the likelihood of upgrading the supplier firm due to the good news about its customers is reduced. This finding provides direct evidence for our hypothesis that anchoring on the 52-week high biases analysts' belief updating regarding information about economically linked firms.

An alternative explanation for our findings is that when stock prices are approaching the 52-week high, investors or analysts pay less attention to these firms, which, in turn, generates an underreaction to good news about economically linked firms. Although to the best of our knowledge there is no prior study on the nearness to 52-week high and limited attention, we examine the relationship between investor attention and the nearness to 52-week high to address this potential alternative explanation. We use two proxies to measure investor attention: abnormal trading volume (Barber and Odean, 2008) and the Bloomberg search score (Ben-Rephael, Da, and Israelsen, 2017). We find that investor attention increases rather than decreases when a stock price is near the 52-week high, which contradicts the limited attention explanation.

We conduct several robustness checks to corroborate our findings. First, the results are robust to using Daniel-Grinblatt-Titman-Wermers (1997) characteristic-adjusted returns, adjusting for risk exposures based on the five factors of Fama-French (2015) or the Q factors of Hou-Xue-Zhang (2015), and excluding Januaries. Second, the interaction effect is stronger among firms with a smaller size, lower institutional ownership, lower analyst coverage, and higher idiosyncratic volatility, which is

[5] Since nearness to 52-week high is potentially correlated with past 12-month returns, one natural concern is that our findings may be driven by past 12-month returns. To address this concern, we carry out a placebo return decomposition based on past 12-month returns and find no significant interaction effect between customer returns and past 12-month returns; however, the pure customer momentum effect and the pure momentum effect themselves remain significant.

consistent with the effect of limits to arbitrage. Finally, as an extension, we find that there is also a positive significant interaction effect in other cross-firm return predictability settings, including the geographic momentum (Parsons, Sabbatucci, and Titman, 2018), industry momentum (Moskowitz and Grinblatt, 1999), complicated firm (Cohen and Lou, 2012), and foreign industry (Huang, 2015) settings.

Our major contribution to the literature is that we provide a new psychological explanation for the market underreaction to news about economically linked firms. A plethora of studies document the return predictability of economically related firms;[6] these studies mainly use investor inattention as the economic mechanism to explain the market underreaction. We add to this literature by providing evidence that anchoring on the 52-week high induces both investor and analyst underreactions to news about economically linked firms. Proposed by George and Hwang (2004), this anchoring bias, which contributes to a stock's own return momentum, also at least partially explains various kinds of cross-firm return predictability.

Our paper also complements Ali and Hirshleifer (2019), who argue that analysts tend to cover economically linked firms and that, therefore, the shared analyst coverage can capture the economic linkage among firms better than the relationships in the existing literature, such as customers and suppliers or geographic neighbors. Our paper differs from theirs because they identify a unified measure of economic linkages, whereas we provide a unified and novel psychological explanation for the market underreaction to news about economically linked firms.

We further contribute to the literature regarding the effect of anchoring on the 52-week high on option exercises (Heath, Huddart, and Lang, 1999; Poteshman and Serbin, 2003), cross-sections of stock returns (George and Hwang, 2004; George, Hwang, and Li, 2018), trading decisions (Grinblatt

[6] Also, see Menzly and Ozbas (2010), who show that firms in economically linked upstream and downstream industries can cross-predict each other's returns. Hou (2007) finds that the returns of large firms in an industry can predict the future returns of small firms in the same industry. Lee, Sun, Wang, and Zhang (2019) find that returns of technology-linked firms have strong predictive power for focal firm returns.

and Keloharju, 2001; Huddart, Lang, and Yetman, 2009), option implied volatility (Driessen, Lin, and Van Hemert, 2013), offer prices and valuation in mergers and acquisitions (M&As) (Baker, Pan, and Wurgler, 2012; Ma, Whidbee, and Zhang, 2019), time series of market returns (Li and Yu, 2012), and analyst recommendation revisions (Li, Lin, and Lin, 2018). We expand this line of research by showing that the 52-week high serves as a psychological anchor when investors and analysts are evaluating the impact of news about economically linked firms.

Our paper is also related to George, Hwang, and Li (2017) and Birru (2015). Both papers find that the interaction between anchoring on the 52-week high and firms' earnings news can generate a market underreaction to firms' own earnings announcements (e.g., postearnings announcement drift). Our paper differs from theirs because they mainly examine the investor underreaction to firms' own earnings news, whereas we are interested in the underreaction to the news of economically linked firms and its explanatory power with regard to cross-firm return predictability.

2. Data

In the customer momentum setting, our sample consists of supplier firms traded on the NYSE, AMEX, and NASDAQ over the January 1981-June 2011 period. To construct a customer-supplier link, we extract firms' principal customers from the Compustat customer segment file and identify publicly traded customer firms following the method described in Cohen and Frazzini (2008). We retain supplier firms that can match with at least one customer firm listed in the Center for Research in Securities Prices (CRSP) database. In addition, we impose a six-month gap between the starting date of a customer-supplier link and stock returns to ensure that each firm's customer firms are public information.[7] Finally, we exclude stocks with a share price below $5 at the portfolio formation date.

[7] The six-month gap between the firm link and stock returns is also imposed in the complicated firm and foreign information settings.

Stock returns and prices are from the CRSP database; accounting data are from Compustat.

To measure the extent of investors' anchoring bias at the stock level, we compute *nearness to 52-week high* at each month-end as the ratio of the month-end close price to the maximum price over the previous 12-month period ending in that month; prices are adjusted for splits and stock dividends. For each supplier firm in each month, we compute its *customer returns* as the equal-weighted returns of its customer firms in that month.

We also test our anchoring hypothesis in four other settings of cross-firm return predictability. The first is the geographic momentum setting, where a firm's stock returns can be predicted by its geographic neighbors (Parsons, Sabbatucci and Titman, 2018). We identify firms' locations based on the zip code of their headquarters, recorded in the Compustat database; headquarters locations are then grouped by economic areas, defined by the Bureau of Economic Analysis (BEA).[8] Firms in a common economic area are defined as geographic neighbors. We compute the *area returns* for each firm in each month as the equal-weighted returns of other firms headquartered in the same economic area in that month. The sample period of this setting is January 1970 to December 2016.

The second setting is the industry momentum setting, where a firm's stock returns can be predicted by its industry peers (Moskowitz and Grinblatt, 1999). We classify firms into 48 industries according to the Fama-French 48-industry classification. For each firm, we compute its *industry returns* as the equal-weighted 12-month cumulative returns (skipping the most recent month) of its industry peers. The sample period in this setting is July 1963 to December 2016.

The third setting is the complicated firm setting, where a conglomerate firm's stock returns can be predicted by a portfolio of standalone firms that compose its industry segments (Cohen and Lou, 2012). We extract firms' segment information from Compustat segment files. The industry classification of

[8] The BEA classification aims to capture relevant regional markets surrounding metropolitan or micropolitan statistical areas. The definition can be found at the following website: https://www.bea.gov/newsreleases/regional/rea/rea1104.htm.

firm segments is based on the two-digit Standard Industrial Classification (SIC) code. Standalone firms are those operating in one industry with segment sales that account for more than 80% of total sales. Conglomerate firms are those operating in more than one industry and with total segment sales that account for more than 80% of total sales of the firms. For each conglomerate firm, we form a portfolio of its industry segments (pseudo-conglomerate) using standalone firms in the corresponding industries.[9] For each conglomerate firm, we compute *pseudo-conglomerate returns* as the equal-weighted returns of its pseudo-conglomerate portfolio in that month. The sample period in this setting is July 1977 to December 2016.

The fourth setting is the foreign information setting, where a U.S. multinational firm's stock returns can be predicted by corresponding industry returns in the foreign countries where the multinational firm operates. We obtain firms' geographic segment information from Compustat segment files and foreign industry returns from Datastream Global Equity Sector Indices. We compute *foreign information* for each U.S. multinational firm as a sales-weighted sum of the corresponding industry returns in foreign countries.[10] The sample period in this setting is January 1978 to December 2015.

Finally, to study analyst recommendation revisions, we obtain analyst recommendation data from the Institutional Brokers Estimate System (I/B/E/S) detailed recommendation file from November 1993 to December 2016. We compute recommendation revisions as the current recommendation level minus the most recent active recommendation issued by the same analyst for the same firm.[11] A recommendation is assumed to be active in the 12-month period after its issuance. *Upgrade* (*downgrade*) is defined as a positive change in the recommendation level; *reiteration* is defined as a

[9] For more details, see Cohen and Lou (2012).
[10] For more details, see Huang (2015).
[11] We reverse the recommendation level code from I/B/E/S so that 1 represents the least favorable recommendation and 5 represents the most favorable recommendation.

change of zero in the recommendation level. Table 1 shows that 37.6% of recommendation revisions in our sample are upgrades, which is in line with the summary statistics in existing studies.[12]

3. Portfolio analysis

In the analysis, we focus on customer momentum (Cohen and Frazzini, 2008) as the main empirical setting. We double sort supplier firms by customer returns and own nearness to 52-week high. There are two steps in this section. First, we show that our two sorting variables are largely uncorrelated, which ensures that our two-way sorting approach is valid. Second, we examine the cross-sectional return patterns among two-way sorted portfolios and study how the return predictability of customer returns depends on nearness to 52-week high.

4.1. Portfolio characteristics

We form two-way sorted portfolios as follows. In each month, we independently sort supplier firms into quintile portfolios based on their customer returns (*CR*) in the previous month or own nearness to 52-week high (*PRC*) at the previous month-end. We ultimately form 25 doubled sorted portfolios. The portfolios are held for one month and rebalanced monthly.

Table 2 reports the average *CR* and average *PRC* for each portfolio. *PRC1* (*CR1*) denotes the lowest *PRC* (*CR*) quintile, while *PRC5* (*CR5*) denotes the highest *PRC* (*CR*) quintile. An important pattern to note from Panel A is that within each *CR* quintile (column), the average *CR* varies little across different *PRC* quintiles (row). For example, within the *CR5* quintile, the average monthly *CR* is 12.26% per month for stocks in the *PRC1* portfolio, while the average monthly *CR* is 11.84% for stocks in the *PRC5* portfolio. Similarly, Panel B shows that within each *PRC* quintile (row), the average *PRC* varies little across different *CR* quintiles (column). Panel C shows that the correlation between

[12] For example, in their sample covering 1993-2013, Li, Lin, and Lin (2018) show that 37.9% of analyst recommendation revisions are upgrades.

the two sorting variables, *CR* and *PRC*, in our sample period is only 0.05.[13]

In summary, the portfolio characteristics presented in Table 2 ensure that sorting based on *PRC* is not just a further sort based on *CR*, which is a major concern in the double sorting approach.

3.2. Portfolio returns

In this section, we analyze the cross-sectional return patterns across the 25 supplier firm portfolios sorted by *CR* and *PRC*. For each portfolio in each month, we calculate the equal-weighted returns. Table 3 reports the performance of these portfolios. Panels A, B, and C report the average monthly CAPM alpha, the Fama-French (1993) three-factor alpha (FFC3 alpha), and the Fama-French-Carhart (1997) four-factor alpha, respectively.

In the following discussion, we focus on the FFC4 alpha (Panel C). The first pattern to note is that portfolio returns increase with the *CR* rankings within each *PRC* quintile. This result is consistent with the main finding in Cohen and Frazzini (2008) that a higher *CR* value predicts a higher supplier firm return in the subsequent month.

More importantly, within each *CR* quintile, portfolio returns increase with the *PRC* ranking, especially for portfolios in the *CR1* and *CR5* quintiles. For example, in the *CR5* quintile, the *CR5~PRC5* portfolio (the portfolio with the *CR5* ranking and the *PRC5* ranking) earns a positive and significant FFC4 alpha of 0.82% (*t*-statistic = 4.38) per month, while the *CR5~PRC1* portfolio earns monthly FFC4 alphas of only 0.02% (*t*-statistic = 0.08). Within the *CR5* quintile, the return spread between the *PRC5* and *PRC1* portfolio (represented by *PRC5-PRC1* in the table) is significant (*t*-statistic = 2.45), with an FFC4 alpha of 0.79% per month. These patterns suggest that high customer returns predict high supplier firm returns only when the supplier firms' stock prices are near the 52-week high.

[13] Appendix Table A2 shows that in other settings, variations in area returns, industry returns, pseudoconglomerate returns, and foreign information are also uncorrelated with variations in *PRC* across double-sorted portfolios.

Similarly, in the *CR1* quintile, the *CR1~PRC1* portfolio earns a negative and significant FFC4 alpha of -0.91% (*t*-statistic = -3.85) per month, while the *CR1~PRC5* portfolio earns a monthly FFC4 alpha of 0.01% (*t*-statistic = 0.03). Within the *CR1* quintile, the return spread between the *PRC5* and *PRC1* portfolio is significant (*t*-statistic = 3.06), with an FFC4 alpha of 0.92% per month. These patterns mean that low customer returns predict low supplier firm returns only when supplier firms' stock prices are far from the 52-week high.

Taken together, these results are consistent with our hypothesis that investors underreact to good (bad) news about customer firms only when stock prices are already near (far from) the 52-week high, which, in turn, generates customer momentum.

A potential concern is that the above return patterns are driven by the return predictabilities of nearness to 52-week high themselves (George and Hwang, 2004). It is likely that nearness to 52-week high captures some information that is not related to customer returns. When investors underact the information proxied by nearness to 52-week high, we can also observe return spreads between high and low *PRC* portfolios. To address this concern, we compare the *PRC5-PRC1* return spread across different *CR* quintiles. Strikingly, we observe a clear U-shaped relationship between the *PRC5-PRC1* return spread and *CR* ranking. In contrast to the *CR5* and *CR1* quintiles, within the *CR3* quintile, we find that *PRC5-PRC1* generates a nonsignificant FFC4 alpha of 0.29% (*t*-statistic = 0.86) per month, which suggests that the *PRC5-PRC1* return spread in the *CR5* and *CR1* quintiles is not driven purely by investors' underreaction to information captured by the nearness to 52-week high.[14]

Based on the above finding that the return predictability of *CR* depends on *PRC*, we can largely improve the customer momentum strategy, which longs suppliers with high customer returns and shorts suppliers with low customer returns, by further conditioning on suppliers' own nearness to 52-week

[14] We also find that the returns in the *PRC5~CR5* and *PRC1~CR1* portfolios do not revert over the long horizon (Figure 1), which suggests that the return patterns are not driven by investor overaction.

high. Specifically, the improved customer momentum strategy is to long suppliers in the *CR5~PRC5* portfolio and to short suppliers in the *CR1~PRC1* portfolio. Such an improved customer momentum strategy yields a monthly FFC4 alpha of 1.73% (*t*-statistic = 5.46), which outperforms the original customer momentum strategy by an FFC4 alpha of 0.83% per month (*t*-statistic = 3.15).[15]

4. Return decomposition

The above return patterns in double-sorted portfolios suggest that *CR*, *PRC*, and their interaction may each play a role in determining the average stock returns in a portfolio. The ultimate question that we want to address is whether the nearness to 52-week high can partially explain customer momentum. To address this question, we follow George, Hwang, and Li (2017) and decompose returns in the two-way sorted portfolios into the pure effect of customer momentum, the pure effect of anchoring, and the interaction effect between customer momentum and anchoring. We deem this method *return decomposition*.

Section 4.1 describes the methodology of return decomposition. Additionally, Section 4.2 presents our main results from return decomposition in the customer momentum setting. Finally, Sections 4.3 and 4.4 provide the subsample analysis and robustness checks of our main results, respectively.

4.1. Return decomposition method

We follow George, Hwang, and Li (2017) to decompose the returns of the two-way sorted portfolios. Section 3 shows that the cross-sectional return patterns among the 25 portfolios are largely determined by the *CR* quintile ranking, the *PRC* quintile ranking, and the coincidence of having both high *CR* and high *PRC* or both low *CR* and low *PRC*. This motivates us to decompose the returns of the stocks in the 25 portfolios into four types of components: first, a benchmark component that is

[15] See Appendix Table A4 for the detailed description and replication of original customer momentum strategy in our sample.

unrelated to either the *CR* ranking or the *PRC* ranking; second, pure customer momentum components that are solely related to the CR ranking; third, pure anchoring components that are purely associated with the PRC ranking; and, fourth, interaction components that are attributable to the coincidence of having both high *CR* and high *PRC* or both low *CR* and low *PRC*.

Panel A of Table 4 presents the components of the stock returns in each of the 5×5 portfolios sorted by *CR* and *PRC*. *PRC1* (*CR1*) denotes the lowest *PRC* (*CR*) quintile, while *PRC5* (*CR5*) denotes the highest *PRC* (*CR*) quintile. Since anchoring effects are assumed to exist only in the two extreme PRC quintiles, we combine the portfolios with a *PRC2*/*PRC3*/*PRC4* quintile ranking into one group (denoted by *PRC2~4* in Table 4). In this table, the sum of all components in a particular portfolio should equal the average stock returns of that portfolio. The portfolios located in the center of the table (with a *CR3* ranking and a *PRC2~4* ranking) are neutral to customer momentum and the anchoring effect. In this sense, the average stock returns in the benchmark portfolios represent the benchmark component, which is denoted by μ. Any portfolio outside the benchmark portfolios would have additional components.

The pure customer momentum components, denoted by *E*, are the components of stock returns associated solely with the *CR* ranking. All stocks in a particular *CR* quintile share a common customer momentum component that is independent of their *PRC* rankings. The pure customer momentum component captures the return predictability of lagged customer returns on supplier firms, regardless of the supplier firms' nearness of stock prices to the 52-week high. Since higher customer returns predict higher future stock returns, the pure customer momentum component increases from the *CR1* quintile to the *CR5* quintile. We use E_{bb} to denote the most negative pure customer momentum component (in the *CR1* quintile) and use E_{gg} to denote the most positive customer momentum component (in the *CR5* quintile). The subscripts *bb* (*gg*) represent extremely bad (good) economically related news, while the subscripts b (g) represent moderately bad (good) economically related news. Finally, we define a pure customer momentum effect as $E_{gg} - E_{bb}$, which is in line with a long-short strategy that exploits only the return predictability of lagged customer returns per se.

The pure anchoring components, denoted by A, are the components of stock returns associated solely with the *PRC* ranking. All stocks in a particular *PRC* quintile share the common pure anchoring component, which is independent of the *CR* ranking. The pure anchoring component is negative for stocks in the *PRC1* quintile and positive for stocks in the *PRC5* group. We use A_l to denote the negative pure anchoring component and use A_h to denote the positive pure anchoring component. We define the pure anchoring effect as $A_h - A_l$, which is in line with a long-short strategy that exploits only the return predictability of the nearness to 52-week high per se.

The interaction component, denoted by *I*, is the return associated with the coincidence of having good (bad) news about customer firms and having own stock prices near (far from) the 52-week high. In our specification, the coincidence of having moderate-level good news about customers (e.g., the *CR4* quintile) and high nearness to 52-week high can also generate interaction effects (e.g., $I_{g,h}$). However, the magnitude of this interaction component would be moderate since moderate-level good news itself has only a modest impact on stock returns. In this sense, we focus on the interaction effect in the extreme *CR* and *PRC* quintiles in the following analysis. We use $I_{gg,h}$ to denote the interaction component among the stocks at the intersection of the *CR5* quintile and *PRC5* quintile and use $I_{bb,l}$ to denote the interaction component among the stocks at the intersection of the *CR1* quintile and *PRC1* quintile; we define the interaction effect as $I_{gg,h}-I_{bb,l}$.

To interpret the pure customer momentum effect, the pure anchoring effect, and the interaction effect, consider a long-short strategy that buys the CR5-PRC5 portfolio and sells the short CR1-PRC1 portfolio.[16] We can decompose the long-short returns into the pure customer momentum effect ($E_{gg} - E_{bb}$), the pure anchoring effect ($A_h - A_l$), and the interaction effect ($I_{gg,h} - I_{bb,l}$). If there is no interaction effect between customer returns and the nearness to 52-week, then the interaction effect defined in our decomposition would be zero. In contrast, if the return predictability of high (low) customer returns relies on the coincidence of having stock prices near (or far) from the 52-week high, then the interaction effect would be significantly positive. Meanwhile, a positive interaction effect suggests that anchoring on the 52-week high could at least partially explain customer momentum.

To provide a benchmark for understanding the extent to which the nearness to 52-week high explains the return predictability of customer returns, we further conduct return decomposition by excluding the interaction components (see the detailed specification in Panel B of Table 4). In this return decomposition, the customer momentum effect is defined as $E_{gg} - E_{bb}$, and the anchoring effect is defined as $A_h - A_l$.

To estimate these effects, in each month, we run a cross-sectional stock-level regression of returns on a set of dummy variables that indicate the *PRC* and *CR* portfolio assignments of the stocks. We can then obtain the estimates of the pure customer momentum effect, the pure anchoring effect, and the interaction effect in each month based on the coefficient estimates in the cross-sectional regression. Finally, we compute the time series average of the pure customer momentum effect, the pure anchoring effect, and the interaction effect. Appendix Table A1 provides a detailed description of our estimation method.

4.2. Return decomposition results

Table 5 reports the return decomposition results in the customer momentum setting. Specifically, we report the average monthly CAPM alpha, FF3 alpha, and FFC4 alpha of the interaction effect, pure

[16] This is essentially a customer momentum strategy conditioning on supplier firms' nearness to 52-week high. In Section 4, we show that this strategy outperforms the original customer momentum strategy by an FFC4 alpha of 83 bps per month.

customer momentum effect, and pure anchoring effect.[17] Panel A reports the results in the benchmark excluding the interaction effect. Consistent with George and Hwang (2004) and Cohen and Frazzini (2008), we find that the customer momentum effect and anchoring effect are both positive and significant, with FFC4 alphas of 52 basis points (bps) (t-statistic = 3.65) and 68 bps (t-statistic = 2.92) per month, respectively.

Panel B reports the main results, including the interaction effect. The interaction effect generates an FFC4 alpha of 158 bps per month, with a t-statistic of 2.32; the CAPM alpha and FF3 alpha of the interaction effect are 178 bps (t-statistic = 2.72) and 173 bps (t-statistic = 2.61) per month, respectively.[18] A positive and significant interaction effect means that a nontrivial proportion of the return predictability of lagged customer returns comes from the coincidence of having stock prices near or far from the 52-week high when anchoring bias induces underreaction to news.

We also find that after including the interaction effect, the FFC4 alpha of the pure customer momentum effect is only 1 bp per month (t-statistic = 0.03). The FF3 alpha and CAPM alpha of the pure customer momentum effect are also close to zero. This result suggests that high (low) customer returns predict the high (low) future returns of suppliers only when supplier firms' stock prices are near (far from) the 52-week high. In other words, the nearness to 52-week high generates investor underreaction to news about customers. The comparison between Panels A and B suggests that anchoring bias can largely explain the customer momentum phenomenon.

We also use the return estimation in this section to plot the *PRC5-PRC1* return spreads across *CR* quintiles in Figure 2. Consistent with the return patterns in double-sorted portfolios, there is a clear U-shaped relation between the *PRC5-PRC1* return spreads and *CR* rankings. This result supports that our

[17] We first compute the monthly coefficient estimates of the pure customer momentum effect, pure anchoring effect, and interaction effect. Then, we estimate the average monthly risk-adjusted returns of the three effects from a time-series regression of the monthly coefficient estimates on market excess returns (CAPM alpha), the Fama-French (1993) three factors (FF3 alpha), and the Fama-French-Carhart (1997) four factors (FFC4 alpha).

[18] Appendix Table A3 shows similar results when we exclude January stock-month observations from the return decomposition.

return estimation methodology is valid.

Since the nearness to 52-week high is potentially highly correlated with past 12-month returns (*MOM*), one natural concern is that our findings may be driven by *MOM* rather than *PRC*. To address this concern, we carry out a placebo return decomposition based on *MOM*. Appendix Table A5 reports the placebo test results. The interaction effect between *CR* and *MOM* is not significantly different from zero, while both the pure customer momentum effect and the pure momentum effect (analogous to the previously defined pure anchoring effect) are significantly positive. This placebo test confirms that anchoring to 52-week high generates underreaction to news about economically linked firms.

4.3.Return decomposition in subsamples

To strengthen our argument, we carry out subsample analysis. If psychological bias is the driving factor for underreaction to news about economically linked firms, then the mispricing generated by psychological bias should be more prominent for firms that are more difficult to arbitrage. Therefore, we expect that the interaction effect will be stronger among firms that are smaller, that have lower institutional ownership, that have a lower level of analyst coverage, and that have higher idiosyncratic volatility.

To generate the subsamples, in each month, we sort supplier firms into two groups based on firm characteristics. For example, to generate size subsamples, in each month, we sort supplier firms into two even groups based on their market capitalization at the previous calendar year-end. Similarly, we split the sample into two groups based on supplier firms' institutional ownership at the previous quarter-end, analyst coverage in the previous year, or idiosyncratic volatility in the previous month.

Since the number of suppliers in each subsample is largely reduced compared to the full sample, each portfolio is thin in sample size if we further sort the suppliers into quintile-by-quintile portfolios and conduct return decomposition, as in Table 5. To deal with this thin portfolio problem in the subsample analysis, in each month within each subsample, we sort suppliers into tercile-by-tercile portfolios by their *CR* in the previous month and *PRC* at the previous month-end. The portfolios are held for one month and rebalanced monthly. We then conduct a similar return decomposition in the tercile-by-tercile portfolios. Panels C and D of Appendix Table A1 describe the specification and estimation of the return decomposition in the subsample analysis.

Table 6 reports the return decomposition results for the subsamples. Panel A reports the results for the small and large firm samples separately. The interaction effect is much larger for small firms than for large firms. For example, the FFC4 alpha of the interaction effect is 1.21% per month (*t*-statistic = 2.35) among small firms but 0.01% per month (*t*-statistic = 0.02) among large firms. Panels B, C, and D show that the interaction effect is larger for firms with lower institutional ownership, a lower level of analyst coverage and higher idiosyncratic volatility, respectively. For instance, in Panels B, C, and D, the FFC4 alphas of the interaction effect range between 0.99% and 1.32% per month for firms that are more difficult to arbitrage and between 0.03% and 0.15% per month for firms that are easier to arbitrage.

4.4. Other risk-adjustment methods

We also consider other factor models (e.g., Daniel-Grinblatt-Titman-Wermers (DGTW) or Q-factor) to compute risk-adjusted returns. Table 7 reports the decomposition results using other risk-adjustment methods for returns. In the first column, we replace raw stock returns with DGTW characteristic-adjusted stock returns (Daniel, Grinblatt, Titman, and Wermers, 1997) when performing Fama-MacBeth regressions in the return decomposition. The DGTW adjusted returns are computed as raw stock returns minus the returns on the corresponding benchmark portfolio of firms matched by size, market-to-book ratio, and momentum quintiles.

We also adjust for exposures based on three other factor models. In the second column, we use the

Fama-French (2015) five-factor (FF5) model, which expands the Fama-French three-factor model with a profitability factor and an investment factor. In the third column, we use the FF5 model augmented with the Carhart (1997) momentum factor (FF5+UMD). In the fourth column, we use the Q-factor model proposed by Hou, Xue, and Zhang (2015), which consists of a market factor, a size factor, an investment factor, and a profitability factor. We adjust the coefficient of the pure customer momentum effect, the pure anchoring effect, and the interaction effect for exposures based on the FF5, FF5+UMD, and Q-factor models by running a time series regression of monthly coefficient estimates on contemporaneous factor returns.

In summary, Table 7 shows that the interaction effect remains significant across different return adjustments. The magnitude of the interaction effect ranges from 1.65% to 2.15% per month, while the pure customer momentum effect after including the interaction effect is not significant.

5. A Test of the Economic Mechanism

In addition to the return patterns, we provide direct tests of how the nearness to 52-week high affects the belief-updating process. In Section 5.1, we examine how the nearness to 52-week high affects analysts' reaction to customer returns. In Section 5.2, we show that our results are not driven by limited attention.

5.1.Analysts' underreaction to news

In this section, we test the second hypothesis that anchoring on the 52-week high induces analysts' underreaction to news about economically linked firms in the recommendation revision context. We take two steps to investigate this hypothesis. First, we show that when analysts make recommendation revisions on a supplier firm, they do indeed pay attention to news about its customer firms. For example, analysts are more likely to upgrade a supplier firm when its customer firms have performed well in the recent past. Second, we show that when a supplier firm's stock prices are near the 52-week high, analysts are less likely to upgrade the supplier firm in response to good news about its customer firms.

We conduct regression analyses in an event sample of changes in analyst recommendations on supplier firms. Our main results are based on the following logit model:

$$Upgrade_{k,j} = f\left(\beta_1 ACR_{k,j} + \beta_2 PRC_{k,j} + \beta_3 ACR_{k,j} * PRC_{k,j} + \delta' X_{k,j} + \varepsilon_{k,j}\right),$$

where subscript k denotes firm k and subscript j denotes a recommendation revision event. The dependent variable is a dummy variable that equals one if recommendation revision j on a supplier firm is an upgrade and zero otherwise.[19] The key independent variable, *ACR*, is cumulative abnormal customer returns in the 21 trading days (approximately one calendar month) prior to the recommendation announcement day. We consider two ways to measure abnormal customer returns. First, we subtract contemporaneous CRSP value-weighted market returns from raw customer firm returns as market-adjusted customer returns. Second, we estimate customer firms' daily return loadings on the Fama-French-Carhart four factors (FFC4) in a 12-month rolling window and then compute the FFC4-adjusted customer returns. Compared with raw customer returns, abnormal customer returns should be a better proxy for the news content of customer firms. Another key independent variable, *PRC*, is the nearness to 52-week high at the end of the trading day prior to the recommendation announcement day. *ACR**PRC* is the interaction term between *ACR* and *PRC.* The control variables include supplier firm characteristics as of the previous month-end before recommendation revisions: earnings forecast revisions, analyst dispersion, analyst coverage, standardized unexpected earnings (*SUE*), firm size, the book-to-market ratio, cumulative returns in the past 12 months, idiosyncratic volatility, asset growth, and accruals. In addition, we include Fama-French 48-industry fixed effects and year fixed effects in the regressions. Standard errors are clustered by firm. We report the log odds

[19] In unreported results, we use a downgrade dummy as the dependent variable; this dummy equals one for downgrades and zero otherwise. The results are consistent with those reported in this section.

ratios from logit regressions, and *z*-statistics are in parentheses beneath the coefficients. To facilitate interpretation of the economic magnitudes, we also show the ordinary least squares (OLS) regression results where the dependent and independent variables follow the same definition as in the logit model.

Panel A of Table 8 reports the regression results where *ACR* is measured by market-adjusted customer returns. Columns (1)-(3) present the results based on logit regressions; Columns (4)-(6) present the results based on OLS regressions. In a univariate regression of the *Upgrade* dummy on *ACR*, Column (1) shows that analysts are more likely to upgrade a supplier firm when its customer firms have had high abnormal returns in the recent past (*z*-statistic = 3.10). This result suggests that analysts do indeed pay attention to news about economically linked firms.

We further add *PRC* and *ACR*PRC* as regressors. Column (2) shows that while *ACR* remains positive and significant, the interaction between *ACR* and *PRC* is significantly negative, with a *z*-statistic of -3.43. In other words, when a supplier firm's stock prices are near the 52-week high, analysts are less likely to upgrade the supplier firm in response to good news about its customer firms. This result suggests that anchoring on the 52-week high induces analyst underreaction to news about economically linked firms. The effect is both economically and statistically significant. Given that the median *PRC* is 0.84, Column (5) suggests that analysts do not make favorable recommendation changes for half of supplier firms even if their customers have good news. We further control firm characteristics in Columns (3) and (6) and measure *ACR* by FFC4-adjusted customer returns in Panel B. The results are quantitively similar.

Taken together, Table 8 suggests that anchoring on the 52-week high induces analyst underreaction to news about economically linked firms. From another perspective, these results also shed light on how anchoring bias affects the belief-updating process (e.g., the recommendation revision decisions of analysts).

5.2.Nearness to 52-week high and investor attention

Previous analysis suggests that analysts do indeed pay attention to good news about a supplier firm's customers by upgrading their recommendation on the supplier firm; however, the nearness of supplier firm's stock prices to the 52-week high induces analyst anchoring bias and distorts analysts' belief-updating process. An alternative explanation is that when a supplier firm's stock prices are approaching the 52-week high, analysts pay less attention to the supplier firm, which, in turn, generates underreaction to good news about its customers. To distinguish this alternative explanation and our anchoring-based explanation, we examine the direct association between investor attention and the firm's nearness to 52-week high.

We use two proxies to measure investor attention. The first is abnormal trading volume. Barber and Odean (2008) argue that the high abnormal trading volume of a stock is an indicator of investor attention. In the spirit of Barber and Odean (2008), we compute abnormal trading volume as the dollar trading volume of a stock in a given week divided by its average dollar trading volume in the previous 52 weeks. The second proxy is the Bloomberg search score. Ben-Rephael, Da, and Israelsen (2017) propose a measure of institutional investor attention based on active news searches and news reading for a stock on Bloomberg terminals. Specifically, Bloomberg assigns a numerical score to a stock in a given day based on the number of times users actively search for news or read news about the stock, compared with the news searching or reading counts for the same stock in the previous 30 days.[20] In our test, we take the average daily Bloomberg search score in a given week as a proxy for institutional

[20] Bloomberg assigns a score of ten when a user actively searches for news about a stock and one when a user reads news about a stock. These scores are aggregated into hourly counts. Then, Bloomberg generates an attention score each hour by comparing the average hourly count during the previous 8 hours to all hourly counts over the previous 30 days for the same stock. A score of 0, 1, 2, 3 or 4 is assigned if the past 8-hour counts are below 80%, between 80% and 90%, between 90% and 94%, between 94% and 96%, or greater than 96% of the previous 30 days' hourly counts, respectively. The daily Bloomberg search score is the maximum hourly score on a calendar day. For a detailed description of Bloomberg search data, see Ben-Rephael, Da, and Israelsen (2017).

investor attention in that week.

To better measure investors' reaction to the nearness to 52-week high, we focus on weekly data.[21] Specifically, in a weekly panel of supplier firms, we regress investor attention on a firm in a given week on the nearness to 52-week high of that firm at the previous week-end. Table 9 reports the results. In Panel A, the dependent variable is the weekly abnormal trading volume. In the univariate regression shown in Column (1), we find a strong positive association between nearness to 52-week high and abnormal trading volume. In economic terms, a one standard deviation increase in nearness to 52-week high at the previous week-end leads to a 46.8% absolute increase in abnormal trading volume in a given week (*t*-statistic = 54.04). In Columns (2)-(5), we further control for firm fixed effects, year-by-week fixed effects and other control variables, including firm size, the book-to-market ratio, past 12-month returns, and return volatility. The coefficient estimates of nearness to 52-week high remain significant, and the magnitude is almost unchanged. These results are also consistent with Huddart, Lang, and Yetman (2009), who find that the abnormal trading volume spikes when stock prices break through the 52-week high.

Panel B shows that when a supplier firm's stock prices are approaching the 52-week high, the Bloomberg search score for the firm also increases. Based on the univariate regression result shown in Column (1), a one standard deviation increase in nearness to 52-week high leads to a 0.13 standard deviation increase in the weekly Bloomberg search score (*t*-statistic = 6.01). Columns (2)-(5) show that the results are robust to controlling for firm fixed effects, year-by-week fixed effects, and the set of control variables.

Overall, Table 9 suggests that investor attention increases when stock prices are approaching the

[21] If we focus on monthly data, then the dynamic of investor attention is not clear and may have alternative interpretations. For example, if there is a spike in investor attention only at the month-end, then it is consistent with investors' limited attention.

52-week high. Therefore, limited attention is unlikely to explain our previous empirical findings (e.g., return patterns and analysts' recommendation revisions), which further supports our anchoring-based explanation.

6. Extensions

In this section, we extend our return decomposition analysis to four other cross-firm return predictability settings studied in the previous literature. The first setting is the *geographic momentum* setting in Parsons, Sabbatucci, and Titman (2018). They find that a firm's stock returns can be predicted by the lagged returns of its neighboring firms, defined as firms in a common economic area classified by the BEA. The second setting is the *industry momentum* setting in Moskowitz and Grinblatt (1999). They document a strong momentum effect in industry components of stock returns; that is, a firm's stock returns can be predicted by lagged industry returns. The third setting is the *complicated firm* setting in Cohen and Lou (2012). They show that a conglomerate firm's stock returns can be predicted by a portfolio of standalone firms that compose the conglomerate firm's business segments. The fourth setting is the *foreign information* setting in Huang (2015). She finds that a U.S. multinational firm's stock returns can be predicted by corresponding industry returns in the foreign countries where the multinational firm operates.

The cross-firm return predictors (analogous to *CR* in the customer momentum setting) in the above four settings are defined in the Data section. We conduct similar return decompositions based on cross-firm return predictors and nearness to 52-week high in these settings. Regarding the number of conglomerate firms (complicated firm setting) and U.S. multinational firms (foreign information setting), each alone is not large enough for two-way portfolio sorting; therefore, we combine these two settings to conduct return decomposition.

Table 10 shows the return decomposition in these settings. The interaction effect and pure anchoring effect follow the same definition as in Table 5, and the pure cross-momentum effect is analogous to the pure customer momentum effect. Panel A reports the results for the geographic momentum setting. The interaction effect generates an FFC4 alpha of 0.39% per month (*t*-statistic = 2.15), while the pure cross-momentum effect generates an FFC4 alpha of 0.34% per month (*t*-statistic = 2.65). Unsurprisingly, the pure cross-momentum effect is persistent after controlling for the interaction effect since Parsons, Sabbatucci, and Titman (2018) find that geographic momentum is quite puzzling, in that it is invariant to several firm characteristics related to limits to arbitrage, including analyst coverage, size and trading volume. Our anchoring explanation can at least partially account for geographic momentum, as reflected in the positive and significant interaction effect.

Panel B reports the return decomposition results for the industry momentum setting. The interaction effect ranges between 0.46% and 0.60% per month and is significant under the CAPM, FF3, and FFC4 alphas. The pure cross-momentum effect generates a monthly FF3 alpha of 0.43% (*t*-statistic = 2.60); its monthly FFC4 alpha is -0.02% (*t*-statistic = -0.11).

Panel C reports the return decomposition results for the combined complicated firm and foreign information setting. Across all columns with different types of alphas, the interaction effect ranges between 0.90% and 1.04% per month, with *t*-statistics of approximately 2, while the pure cross-momentum effect is not significantly different from zero.

In summary, Table 10 provides evidence that our anchoring bias can at least partially account for the cross-firm return predictability documented in the previous literature.

7. Conclusion

Our paper provides a novel psychological explanation for the market underreaction to news about economically linked firms. That is, anchoring on the 52-week high induces investors to underreact to good news about economically linked firms when stock prices are near the 52-week high. Similarly, anchoring bias induces investors to underreact to bad news about economically related firms when stock prices are far from the 52-week high.

For our main analysis, we focus on customer momentum (Cohen and Frazzini, 2008). The return patterns of portfolios based on the double sorting approach are consistent with the psychological explanation. We then decompose stock return predictions into three components: the pure customer momentum effect, the pure anchoring effect, and the interaction effect between the customer momentum and anchoring effects. We find that the interaction effect is significant and that the customer momentum effect becomes nonsignificant after including the interaction effect.

Moreover, we use analyst recommendation revisions to examine how the nearness to 52-week high affect the belief-updating process. We find that analyst recommendation revisions are less sensitive to good (bad) news about economically linked firms when stock prices are near (far from) the 52-week high. Further analysis shows that this finding is not driven by limited investor attention.

We further extend our study to other settings of cross-firm return predictability, including the geographic momentum, industry momentum, complicated firm, and foreign information settings. We document that the nearness to 52-week high can at least partially explain the return predictability of economically linked firms in these settings.

In summary, our study suggests that the 52-week high serves as a psychological barrier that induces investors' underreaction to economically related news. While the previous literature mainly focuses on investor inattention as the mechanism for the market underreaction to economically related news, we provide strong evidence for a plausible psychological explanation.

References

Ali, Usman, and David Hirshleifer, 2019, Shared analyst coverage: Unifying momentum spillover effects, *Journal of Financial Economics,* Forthcoming.

Barberis, Nicholas, and Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Baker, Malcolm, and Xin Pan, and Jeffrey Wurgler, 2012, The effect of reference point prices on mergers and acquisitions, *Journal of Financial Economics* 106, 49-71.

Ben-Rephael, Azi, Zhi Da, and Ryan D. Israelsen, 2019, It depends on where you search: Institutional investor attention and underreaction to news, *Review of Financial Studies* 30, 3009-3047.

Birru, Justin, 2015, Psychological barriers, expectational errors, and underreaction to news, Working paper.

Brennan, Michael J., and Narasimhan Jegadeesh, and Bhaskaran Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information, *Review of Financial Studies* 6, 799-824.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chordia, Tarun, and Bhaskaran Swaminathan, 2000, Trading volume and cross-autocorrelations in stock returns, *Journal of Finance* 55, 913-935.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, *Journal of Finance* 63, 1977-2011.

Cohen, Lauren, and Dong Lou, 2012, Complicated firms, *Journal of Financial Economics* 104, 383-400.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance 52*, 1035-1058.

Daniel, Kent, and David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under-and overreactions, *Journal of Finance* 53, 1839-1885.

Driessen, Joost, and Tse-Chun Lin, and Otto Van Hemert, 2013, How the 52-week high and low affect option-implied volatilities and stock return moments, *Review of Finance* 17, 369-401.

Elton, Edwin J., and Martin J. Gruber, and Seth Grossman, 1986, Discrete expectational data and portfolio performance, *Journal of Finance* 41, 699-713.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1-22.

Frazzini, Andrea, 2006, The disposition effect and underreaction to news, *Journal of Finance* 61, 2017-2046.

George, Thomas J., and Chuan-Yang Hwang, 2004, The 52 - week high and momentum investing, *Journal of Finance* 59, 2145-2176.

George, Thomas J., and Chuan-Yang Hwang, and Yuan Li, 2017, Anchoring, the 52-week high and post earnings announcement drift, working paper.

George, Thomas J., Chuan-Yang Hwang, and Yuan Li, 2018, The 52-week high, q-theory, and the cross section of stock returns, *Journal of Financial Economics* 128, 148-163.

Grinblatt, Mark, and Matti Keloharju, 2001, What makes investors trade?, *Journal of Finance* 56, 589-616.

Heath, Chip, and Steven Huddart, and Mark Lang, 1999, Psychological factors and stock option exercise, *Quarterly Journal of Economics* 114, 601-627.

Hirshleifer, David, 2001, Investor psychology and asset pricing, *Journal of Finance* 56, 1533-1597.

Hou, Kewei, 2007, Industry information diffusion and the lead-lag effect in stock returns, *Review of Financial Studies* 20, 1113-1138.

Hou, Kewei, and Chen Xue, and Lu Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650-705.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Hong, Harrison, and Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265-295.

Huang, Xing, 2015, Thinking outside the borders: investors' underreaction to foreign operations information, *Review of Financial Studies* 28, 3109-3152.

Huddart, Steven, and Mark Lang, and Michelle H. Yetman, 2009, Volume and price patterns around a stock's 52-week highs and lows: Theory and evidence, *Management Science* 55, 16-31.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles Lee, 2004, Analyzing the analysts: When do recommendations add value?, *Journal of Finance* 59, 1083-1124.

Lee, Charles M.C., Stephen Teng Sun, Rongfei Wang, and Ran Zhang, 2019, Technological links and predictable returns, *Journal of Financial Economics 132*, 76-96.

Li, Fengfei, and Chen Lin, and Tse-Chun Lin, 2018, Salient anchor, limited attention, and analyst recommendation changes, Working paper.

Li, Jun, and Jianfeng Yu, 2012, Investor attention, psychological anchors, and stock return predictability, *Journal of Financial Economics* 104, 401-419.

Lo, Andrew W., and A. Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3, 175-205.

Ma, Qingzhong, David A. Whidbee, and Wei Zhang, 2019, Acquirer reference prices and acquisition performance, *Journal of Financial Economics* 132, 175-199.

Menzly, Lior, and Oguzhan Ozbas, 2010, Market segmentation and cross-predictability of returns, *Journal of Finance* 65, 1555-1580.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum? *Journal of Finance* 54, 1249-1290.

Parsons, Christopher A., and Riccardo Sabbatucci, and Sheridan Titman, 2018, Geographic lead-lag effects, Working paper. Available at SSRN: https://ssrn.com/abstract=2780139.

Poteshman, Allen M., and Vitaly Serbin, 2003, Clearly irrational financial market behavior: Evidence from the early exercise of exchange traded stock options, *Journal of Finance 58*, 37-70.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777-790.

Tversky, Amos, and Daniel Kahneman, 1974, Judgment under uncertainty: Heuristics and biases, *Science* 185, 1124-1131.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137-167.

Table 1. Descriptive Statistics

This table reports summary statistics for the sample of firm-month observations. Summary statistics of firm size and nearness to 52-week high are reported based on the pooled sample of five settings: customer momentum, geographic momentum, industry momentum, complicated firms, and foreign information, from July 1963 to December 2016. Customer returns are equally-weighted returns of a firm's customers. Area returns are equally-weighted returns of a firm's geographic peers that headquartered in the same Economic Area defined by Bureau of Economic Analysis. Industry returns are equally-weighted 12-month cumulative returns (skip the most recent month) of a firm's industry peers under Fama-French 48 industry classification. Pseudo-conglomerate returns are equally-weighted returns of a firm's pseudo-conglomerate portfolio that consists of a portfolio of the conglomerate firm's segments made up using standalone firms from the corresponding industries. Foreign information is sales-weighted industry returns in the foreign countries where the firm operates. Customer returns, area returns, industry returns, pseudo-conglomerates returns, and foreign information are shown in percentage points. Analyst recommendation upgrade is a dummy that equals one for an upgrade and zero for a downgrade or a reiteration.

	Min	Max	Mean	SD	Median
Firm Size (NYSE percentile)	0.000	1.000	0.375	0.298	0.316
Nearness to 52–week high	0.007	1.000	0.792	0.180	0.840
Customer returns %	–98.130	375.676	1.247	9.707	1.123
Area returns %	–34.460	86.985	1.200	6.257	1.205
Industry returns (12–month cumulative) %	–226.353	569.528	12.909	28.439	11.250
Pseudo–conglomerates returns %	–44.328	78.066	1.185	6.297	1.344
Foreign information %	–31.748	67.048	0.429	2.691	0.427

Table 2. Portfolio Characteristics

This table reports the characteristics of supplier firm portfolios sorted by their customer returns (*CR*) and own nearness to 52-week high (*PRC*). *CR* is computed as equally-weighted returns of a supplier firm's customers. *PRC* is nearness to 52-week high, computed as current month-end close price divided by the highest price during the previous 12 months. To form the double-sorting portfolios, in each month, supplier firms are independently sorted into 5 by 5 portfolios based on *CR* in the previous month and *PRC* at previous month-end. The portfolios are held for one month. Panel A and Panel B report average *CR* and *PRC* (sorting variables) for each portfolio, respectively. Mean *CR* in Panel A are shown in percentage points. Panel C reports the average correlation between two sorting variables PRC and CR in each month. The sample periods are from Jan 1981 to Apr 2011.

Panel A: Mean CR

	CR1	CR2	CR3	CR4	CR5
PRC1	–9.60	–2.40	0.90	4.40	12.26
PRC2	–9.20	–2.39	0.92	4.37	11.89
PRC3	–8.85	–2.41	0.89	4.38	11.86
PRC4	–8.63	–2.38	0.88	4.41	11.65
PRC5	–8.59	–2.36	0.93	4.42	11.84

Panel B: Mean PRC

	CR1	CR2	CR3	CR4	CR5
PRC1	0.51	0.51	0.51	0.51	0.51
PRC2	0.70	0.70	0.70	0.70	0.70
PRC3	0.80	0.80	0.80	0.80	0.80
PRC4	0.89	0.89	0.89	0.89	0.89
PRC5	0.96	0.96	0.96	0.96	0.97

Panel C: Correlation between CR and PRC

	PRC	CR
PRC	1.00	0.05
CR	0.05	1.00

Table 3. Portfolio Returns

This table reports the performance of supplier firm portfolios sorted by customer returns (CR) and nearness to 52-week high (PRC). To form the double-sorting portfolios, in each month, supplier firms are independently sorted into quintile by quintile portfolios based on *CR* in the previous month and *PRC* at previous month-end. The portfolios are held for one month. We then track the equal-weighted returns of each portfolio. This table reports the average monthly risk-adjusted returns of the portfolios. Risk-adjusted returns in Panels A, B, and C are the intercept estimates from time series regressions of the monthly excess returns on market excess return (CAPM), Fama-French (1993) three factors (FF3), and Fama-French-Carhart (1997) four factors (FFC4), respectively. We report the portfolio holding period returns during January 1981 – June 2011. We also show the difference in returns between corner portfolios, where *Port.55* refers to the portfolio with CR5 and PRC5 ranking and *Port.11* refers to the portfolio with CR1 and PRC1 ranking. In addition, we report the difference between Port.55 minus Port.11 and original customer momentum strategy returns. We compute original customer momentum returns as follows. In each month, we sort supplier firms into quintiles based on their customer returns in the previous month. We long the suppliers in the highest customer return quintile and short the suppliers in the lowest customer returns quintile, and we hold the portfolios for one month. We track the equal-weighted portfolio returns in the holding period, and original customer momentum strategy returns are the long-short returns. Appendix Table A4 reports the performance of the original customer momentum strategy in our sample. *t*-statistics are in parentheses.

Panel A: CAPM Alpha

	CR1	CR2	CR3	CR4	CR5
PRC1	–1.52	–1.18	–0.62	–0.50	–0.60
	(–4.65)	(–3.79)	(–1.79)	(–1.53)	(–1.72)
PRC2	–1.10	–0.40	–0.44	–0.25	–0.02
	(–4.46)	(–1.74)	(–1.87)	(–1.08)	(–0.08)
PRC3	–0.33	–0.09	–0.05	–0.17	0.50
	(–1.33)	(–0.41)	(–0.27)	(–0.80)	(2.03)
PRC4	0.00	0.12	0.47	0.74	0.89
	(–0.01)	(0.61)	(2.43)	(3.60)	(3.58)
PRC5	0.28	0.39	0.43	0.55	1.07
	(1.21)	(1.98)	(2.21)	(2.84)	(5.02)
PRC5 – PRC1	1.80	1.57	1.05	1.05	1.67
	(4.92)	(4.50)	(2.71)	(2.90)	(4.33)
Port.55 – Port.11		2.59	Port.55 – Port.11 – Original		1.60
		(6.89)	Customer Momentum		(4.92)

Panel B: FF3 Alpha

	CR1	CR2	CR3	CR4	CR5
PRC1	–1.47	–1.18	–0.69	–0.61	–0.56
	(–5.25)	(–4.38)	(–2.25)	(–2.05)	(–1.81)
PRC2	–1.15	–0.47	–0.54	–0.34	–0.08
	(–5.46)	(–2.58)	(–2.79)	(–1.66)	(–0.39)
PRC3	–0.37	–0.14	–0.13	–0.29	0.45
	(–2.00)	(–0.86)	(–0.85)	(–1.80)	(2.36)
PRC4	–0.04	0.04	0.38	0.61	0.81
	(–0.20)	(0.24)	(2.37)	(3.62)	(4.05)
PRC5	0.25	0.30	0.34	0.49	1.01
	(1.30)	(1.82)	(1.94)	(2.90)	(5.30)
PRC5 – PRC1	1.72	1.47	1.03	1.10	1.57
	(4.65)	(4.19)	(2.65)	(3.00)	(4.08)
Port.55 – Port.11		2.48	Port.55 – Port.11 – Original		1.51
		(6.62)	Customer Momentum		(4.70)

Panel C: FFC4 Alpha

	CR1	CR2	CR3	CR4	CR5
PRC1	–0.91	–0.69	–0.13	–0.15	0.02
	(–3.85)	(–2.92)	(–0.49)	(–0.57)	(0.08)
PRC2	–0.87	–0.25	–0.38	–0.24	0.09
	(–4.36)	(–1.41)	(–1.96)	(–1.19)	(0.48)
PRC3	–0.39	–0.10	–0.10	–0.31	0.43
	(–2.03)	(–0.59)	(–0.65)	(–1.87)	(2.20)
PRC4	–0.19	–0.05	0.28	0.48	0.64
	(–1.07)	(–0.33)	(1.73)	(2.88)	(3.23)
PRC5	0.01	0.06	0.16	0.29	0.82
	(0.03)	(0.42)	(0.93)	(1.77)	(4.38)
PRC5 – PRC1	0.92	0.75	0.29	0.44	0.79
	(3.06)	(2.56)	(0.86)	(1.37)	(2.45)
Port.55 – Port.11		1.73	Port.55 – Port.11 – Original		0.83
		(5.46)	Customer Momentum		(3.15)

Table 4. Specification of Return Decomposition

This table describes the specification of return decomposition for supplier firm portfolios double-sorted by customer returns (CR) and nearness to 52-week high (*PRC*). Each cell represents a group of stocks with a particular *PRC* and *CR* ranking. Portfolios with PRC ranked in PRC2, PRC3, and PRC4 quintiles are combined into one group in return decomposition. Each parameter in a cell reflects a component of average return of stocks in a group. The sum of all the effects in a cell by default equals the average monthly returns of stocks in the corresponding portfolio. μ is the benchmark return, reflecting average return of stocks in the portfolio with neither extreme economically related news nor extreme nearness to 52-week high. The *A* parameters are returns associated with high or low nearness to 52-week high, regardless of C*R* ranking. The *E* parameters are returns attributable to good or bad news about customer firms, regardless of *PRC* ranking. The *I* parameters capture returns associated with cthe oincidence of having good (bad) news about customer firms and having stock prices near (far from) the 52-week high. Subscript of a parameter indicates sign and magnitude of the effect on stock return. *g:* good news, *gg:* extreme good news, *b:* bad news, *bb:* extreme bad news, *l:* low, *m:* medium, *h:* high. Panel A shows the specification of return decomposition in which interaction effects are included (labeled *Interaction Included* in fthe ollowing tables). Panel B shows the specification of return decomposition in which interaction effects are assumed to be zero (labeled *Interaction Excluded* in fthe ollowing tables). Appendix Table A1 presents the methodology for estimating the effects.

Panel A: Return Decomposition including Interaction Effect

	CR1	CR2	CR3	CR4	CR5
PRC1	$\mu + A_l + E_{bb} + I_{bb,l}$	$\mu + A_l + E_b + I_{b,l}$	$\mu + A_l$	$\mu + A_l + E_g$	$\mu + A_l + E_{gg}$
PRC2~4	$\mu + E_{bb} + I_{bb,m}$	$\mu + E_b + I_{b,m}$	μ	$\mu + E_g + I_{g,m}$	$\mu + E_{gg} + I_{gg,m}$
PRC5	$\mu + A_h + E_{bb}$	$\mu + A_h + E_b$	$\mu + A_h$	$\mu + A_h + E_g + I_{g,h}$	$\mu + A_h + E_{gg} + I_{gg,h}$

Panel B: Return Decomposition excluding Interaction Effect

	CR1	CR2	CR3	CR4	CR5
PRC1	$\mu + A_l + E_{bb}$	$\mu + A_l + E_b$	$\mu + A_l$	$\mu + A_l + E_g$	$\mu + A_l + E_{gg}$
PRC2~4	$\mu + E_{bb}$	$\mu + E_b$	μ	$\mu + E_g$	$\mu + E_{gg}$
PRC5	$\mu + A_h + E_{bb}$	$\mu + A_h + E_b$	$\mu + A_h$	$\mu + A_h + E_g$	$\mu + A_h + E_{gg}$

Table 5. Return Decomposition Results

This table reports the estimates of average monthly pure customer momentum effect, pure anchoring effect, and interaction effect in the customer momentum setting. The return decomposition methodology is described in Appendix Table A1 and the specification of return decomposition is shown in Table 4. The pure customer momentum effect is computed as $E_{gg} - E_{bb}$, where $E_{gg}(E_{bb})$ is the return associated with having extreme good (bad) news about customer firms regardless of own nearness to 52-week high. The pure anchoring effect is computed as $A_h - A_l$, where A_h is the return attributable to having stock prices near (far from) 52-week high regardless of news about customer firms. The interaction effect is computed as $I_{gg,h} - I_{bb,l}$, where $I_{gg,h}$ $(I_{bb,l})$ is the return associated with the coincidence of having good (bad) news about customer firms and having stock prices near (far from) 52-week high. Panel A reports return decomposition in which interaction effects are excluded, and the return decomposition specification is shown in Panel B of Table 4. Panel B reports return decomposition in which interaction effects are included, and the return decomposition specification is shown in Panel A of Table 4. Average monthly CAPM Alpha, FF3 Alpha, and FFC4 Alpha are the intercepts from time series regressions of monthly estimates of each effect (e.g., pure customer momentum effect) on market excess return, Fama-French (1993) three factors, and Fama-French-Carhart (1997) four factors, respectively. The sample period is January 1981 – June 2011. *t*-statistics are in parentheses.

Panel A: Interaction Effect Excluded

	CAPM Alpha	FF3 Alpha	FFC4 Alpha
Customer Momentum	0.72	0.64	0.52
	(5.08)	(4.52)	(3.65)
Anchoring	1.54	1.43	0.68
	(5.16)	(4.87)	(2.92)

Panel B: Interaction Effect Included

	CAPM Alpha	FF3 Alpha	FFC4 Alpha
Interaction	1.78	1.73	1.58
	(2.72)	(2.61)	(2.32)
Pure Customer Momentum	0.02	0.01	0.01
	(0.04)	(0.02)	(0.03)
Pure Anchoring	1.03	0.93	0.19
	(2.56)	(2.32)	(0.53)

Table 6. Return Decomposition: Subsample Analysis

This table reports results of return decomposition in subsamples of supplier firms. The subsamples are generated as follows. In Panel A, in each month supplier firms are sorted into two halves based on sample median market capitalization at previous year-end. In Panel B, in each month supplier firms are sorted into two halves based on sample median institutional ownership at previous quarter-end. In Panel C, in each month supplier firms are sorted into two halves based on sample median analyst coverage in the previous year. Analyst coverage in a given year is the average monthly number of analysts who made earnings forecasts in that year. We assume firms not covered by I/B/E/S have zero analyst coverage. In Panel D, in each month supplier firms are sorted into two halves based on sample median idiosyncratic volatility in the previous month. We compute idiosyncratic volatility as the standard deviation of daily Fama-French 3-factor residuals in a month. We then conduct return decomposition in each subsample using the methodology described in Appendix Table A1. Return decomposition in subsample is based on 3 by 3 sorts on CR and PRC while in Table 5 (whole sample) the decomposition is based on 5 by 5 sorts. A more detailed discussion can be found in Appendix Table A1. *t*-statistics are in parentheses.

		Panel A: Size			
		Small		Large	
CAPM Alpha	Interaction	1.20	(2.35)	0.01	(0.02)
	Pure Customer Momentum	0.36	(1.20)	0.49	(1.63)
	Pure Anchoring	1.09	(3.76)	1.07	(3.44)
FF3 Alpha	Interaction	1.33	(2.55)	–0.11	(–0.23)
	Pure Customer Momentum	0.29	(0.94)	0.52	(1.69)
	Pure Anchoring	1.01	(3.44)	0.94	(3.00)
FFC4 Alpha	Interaction	1.21	(2.28)	–0.12	(–0.24)
	Pure Customer Momentum	0.35	(1.14)	0.46	(1.48)
	Pure Anchoring	0.58	(2.13)	0.33	(1.25)
		Panel B: Institutional Ownership			
		Low IO		High IO	
CAPM Alpha	Interaction	0.98	(1.89)	–0.20	(–0.42)
	Pure Customer Momentum	0.32	(1.02)	0.88	(3.15)
	Pure Anchoring	1.31	(4.18)	0.79	(2.82)
FF3 Alpha	Interaction	1.07	(2.03)	–0.03	(–0.06)
	Pure Customer Momentum	0.28	(0.88)	0.77	(2.73)
	Pure Anchoring	1.11	(3.56)	0.71	(2.49)
FFC4 Alpha	Interaction	0.99	(1.85)	0.03	(0.07)
	Pure Customer Momentum	0.29	(0.90)	0.73	(2.54)
	Pure Anchoring	0.61	(2.16)	0.13	(0.56)

Panel C: Analyst Coverage					
		Low Coverage		High Coverage	
CAPM Alpha	Interaction	1.05	(2.06)	0.02	(0.06)
	Pure Customer Momentum	0.40	(1.36)	0.61	(1.99)
	Pure Anchoring	1.22	(4.12)	0.83	(2.77)
FF3 Alpha	Interaction	1.11	(2.14)	0.10	(0.23)
	Pure Customer Momentum	0.33	(1.10)	0.55	(1.76)
	Pure Anchoring	1.09	(3.75)	0.74	(2.42)
FFC4 Alpha	Interaction	1.13	(2.13)	0.09	(0.20)
	Pure Customer Momentum	0.33	(1.09)	0.45	(1.41)
	Pure Anchoring	0.68	(2.49)	0.05	(0.21)
Panel D: Idiosyncratic Volatility					
		Low IVOL		High IVOL	
CAPM Alpha	Interaction	0.29	(0.74)	1.25	(2.20)
	Pure Customer Momentum	0.46	(2.00)	0.13	(0.37)
	Pure Anchoring	0.37	(1.81)	1.03	(3.01)
FF3 Alpha	Interaction	0.24	(0.61)	1.31	(2.25)
	Pure Customer Momentum	0.49	(2.09)	0.06	(0.17)
	Pure Anchoring	0.40	(1.91)	1.00	(2.87)
FFC4 Alpha	Interaction	0.15	(0.36)	1.32	(2.23)
	Pure Customer Momentum	0.54	(2.28)	0.00	(0.01)
	Pure Anchoring	0.04	(0.19)	0.34	(1.11)

Table 7. Return Decomposition: Other Risk-Adjustment Methods

This table reports return decomposition results in customer momentum setting under other risk-adjustment methods. In DGTW column, we replace raw supplier firm returns by their Daniel, Grinblatt, Titman, and Wermers (DGTW) (1997) characteristics-adjusted returns and re-conduct the return decomposition. In FF5 column, risk-adjusted returns are estimated from time-series regressions of monthly return components (effects) on Fama-French (2015) five factors. In FF5+UMD column, we add momentum factor in addition to FF5 factors in the time-series regression. In Q-factor columns, we use Hou-Xue-Zhang (2015) Q-factor model to estimate risk-adjusted returns in the time-series regression. *t*-statistics are in parentheses.

	DGTW	FF5	FF5+UMD	Q-factor
Interaction	2.15	1.65	1.84	1.73
	(3.37)	(2.62)	(2.64)	(2.45)
Pure Customer Momentum	–0.35	–0.05	–0.17	–0.01
	(–0.85)	(–0.12)	(–0.38)	(–0.02)
Pure Anchoring	0.16	0.33	–0.16	–0.00
	(0.44)	(0.91)	(–0.43)	(–0.00)

Table 8. Analyst Recommendation Revision

This table reports the predictive effects of abnormal customer returns, nearness to 52-week high, and their interaction on the direction of subsequent analyst recommendation revision. The analysis is conducted on an event sample of analyst recommendation revisions on supplier firms during 1994-2011. In Column (1) to (3), we estimate a logit regression model as follows:

$$Upgrade_{k,j} = f\left(\beta_1 ACR_{k,j} + \beta_2 PRC_{k,j} + \beta_3 ACR_{k,j} * PRC_{k,j} + \delta' X_{k,j} + \varepsilon_{k,j}\right),$$

where the dependent variable is a dummy variable that equals one when an analyst recommendation revision on a supplier firm is an upgrade, and it equals zero when the revision is a downgrade or a reiteration. The key independent variable ACR is the cumulative abnormal customer returns in the 21 trading days prior to the recommendation announcement date. In Panel A, the abnormal customer returns are computed as raw customer returns minus CRSP value-weighted market returns. In Panel B, the abnormal customer returns are the Fama-French-Carhart four-factor (FFC4) adjusted returns of customer firms. Specifically, we estimate customer firms' loading on FFC4 factors in a 12-month rolling window, and compute FFC4-adjusted returns as raw customer returns minus expected returns based on the estimated factor loadings and realized factor returns. PRC is the nearness to 52-week high of the supplier firm *i* on the trading day prior to the announcement date. ACR*PRC is the interaction term between ACR and RPC. The control variables are supplier firm characteristics, including earnings forecast revisions, analyst dispersion, analyst coverage, standardized unexpected earnings (SUE), market capitalization, book-to-market ratio, past 12-month cumulative returns, idiosyncratic volatility, asset growth, accruals of supplier firm *i* as of the month-end prior to the recommendation announcement date. Fama-French 48 industry and year fixed effects are included. *Z*-statistics in parentheses are computed based on standard errors clustered by firm. In Column (4) to (6), we estimate an OLS regression model where dependent variables and independent variables are the same to Column (1) to (3). *t*-statistics in parentheses are computed based on standard errors clustered by firm. All right-hand-side variables are winsorized at 5% and 95% level. ***, **, and * denote the significance levels of 1%, 5%, and 10% respectively.

Panel A: Market-Adjusted Customer Returns						
	(1)	(2)	(3)	(4)	(5)	(6)
Regression Model:		Logit			OLS	
ACR	0.521***	2.136***	1.754***	0.122***	0.450***	0.379***
	(3.10)	(3.89)	(2.76)	(3.10)	(3.83)	(2.72)
PRC		0.990***	1.101***		0.229***	0.255***
		(16.71)	(12.02)		(17.09)	(12.19)
ACR*PRC		–2.640***	–2.422***		–0.555***	–0.529***
		(–3.43)	(–2.76)		(–3.28)	(–2.69)
Earnings forecast revisions			–3.450***			–0.796***
			(–5.11)			(–5.11)
Analyst dispersion			9.744			2.333
			(1.38)			(1.42)
Analyst coverage			0.025***			0.006***
			(5.28)			(5.28)
SUE			20.316***			4.731***
			(5.13)			(5.17)
Size			–0.022			–0.005
			(–1.54)			(–1.56)
Book-to-market			0.127**			0.030**
			(2.36)			(2.39)
Past 12-month returns			0.065**			0.015*
			(1.97)			(1.94)
Idiosyncratic volatility			4.352***			1.030***
			(3.18)			(3.25)
Asset growth			0.076*			0.018*
			(1.87)			(1.87)
Accruals			–0.279**			–0.065**
			(–2.25)			(–2.25)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	36,993	36,993	30,121	36,993	36,993	30,121
Pseudo R^2	0.008	0.015	0.018	0.009	0.018	0.021

Panel B: FFC4-Adjusted Customer Returns						
	(1)	(2)	(3)	(4)	(5)	(6)
Regression Model:		Logit			OLS	
ACR	0.414**	1.736***	1.692**	0.096**	0.365***	0.364**
	(2.39)	(3.10)	(2.57)	(2.39)	(3.06)	(2.54)
PRC		0.985***	1.090***		0.228***	0.253***
		(16.63)	(11.95)		(17.01)	(12.12)
ACR*PRC		–2.079***	–2.198**		–0.435***	–0.477**
		(–2.71)	(–2.49)		(–2.59)	(–2.43)
Earnings forecast revisions			–3.457***			–0.797***
			(–5.12)			(–5.12)
Analyst dispersion			9.957			2.386
			(1.41)			(1.45)
Analyst coverage			0.025***			0.006***
			(5.26)			(5.25)
SUE			20.280***			4.724***
			(5.11)			(5.15)
Size			–0.021			–0.005
			(–1.51)			(–1.52)
Book-to-market			0.128**			0.030**
			(2.37)			(2.39)
Past 12-month returns			0.065**			0.015*
			(1.97)			(1.94)
Idiosyncratic volatility			4.377***			1.036***
			(3.19)			(3.27)
Asset growth			0.077*			0.018*
			(1.87)			(1.88)
Accruals			–0.280**			–0.065**
			(–2.26)			(–2.26)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	36,993	36,993	30,121	36,993	36,993	30,121
Pseudo R^2	0.008	0.015	0.018	0.009	0.018	0.021

Table 9. Nearness to 52-week high and Investor Attention

This table reports predictive effects of nearness to 52-week high on investor attention in the weekly sample of supplier firms. In Panel A, the dependent variable is abnormal trading volume of supplier firms in a given week. The abnormal trading volume is defined as dollar trading volume in the current week divided by average weekly dollar trading volume in the previous 52 weeks. The key independent variable PRC is the nearness to 52-week high on the previous week-end. Control variables include market capitalization and book-to-market ratio as of the previous year-end, cumulative returns in the previous 12 months, and standard deviation of weekly returns in the previous 52 weeks. Firm fixed effects and year-week fixed effects are included. The sample period is January 1981 – June 2011. In Panel B, we conduct a similar analysis based on weekly Bloomberg search of news about supplier firms. The dependent variable is the average daily Bloomberg search score of a supplier firm in a given week. A higher Bloomberg search score on a supplier firm in a given day indicates a greater amount of active searches for news about the supplier firm in Bloomberg terminals, compared with that in the previous 30 days. A detailed description of Bloomberg search score can be found in Ben-Rephael, Da, and Israelsen (2017). PRC is the nearness to 52-week high of supplier firm on the previous week-end. Control variables are the same as in Panel A. Firm fixed effects and year-week fixed effects are included. The sample period is February 2010 – June 2011. In both panels, *t*-statistics in parentheses are computed based on standard errors double-clustered by firm and year-week. ***, **, and * denote the significance levels of 1%, 5%, and 10% respectively.

	(1)	(2)	(3)	(4)	(5)
	Panel A: Abnormal Trading Volume				
PRC	2.34***	2.81***	2.19***	2.71***	2.38***
	(54.04)	(40.36)	(69.09)	(43.30)	(30.25)
Size					–0.22***
					(–4.54)
Book-to-Market					–0.08*
					(–1.73)
Past 12-Month Returns					0.11***
					(13.50)
Return Volatility					0.58
					(0.24)
Firm FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
No. Obs.	551,179	551,179	551,179	551,179	551,179
Adjusted R^2	0.005	0.007	0.021	0.021	0.022

Panel B: Bloomberg Search					
PRC	0.35***	0.20**	0.35***	0.19***	0.26***
	(6.01)	(1.98)	(9.45)	(3.31)	(4.73)
Size					0.18***
					(3.93)
Book–to–Market					0.01
					(0.15)
Past 12-Month Returns					–0.00
					(–0.15)
Return Volatility					1.25***
					(2.77)
Firm FE	No	Yes	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
No. Obs.	14,592	14,592	14,592	14,592	14,592
Adjusted R^2	0.007	0.320	0.081	0.392	0.394

Table 10. Return Decomposition: Other Settings

This table reports the return decomposition results in three additional cross-firm return predictability settings. Panel A reports the results in geographic momentum setting. The sample period is from January 1970 to December 2016. Panel B reports the results in the industry momentum settings. The decomposition method is similar to that in the customer momentum setting. The sample period covers from July 1963 to December 2016. Panel C reports the results in the pooled sample of complicated firms setting and foreign information setting. The sample period covers from July 1977 to December 2016. Average monthly CAPM Alpha, FF3 Alpha, and FFC4 Alpha are the intercepts from time series regressions of monthly estimates of each effect on market excess return, Fama-French (1993) three factors, and Fama-French-Carhart (1997) four factors, respectively. *t*-statistics are in parentheses.

Panel A: Geographic Momentum

	CAPM Alpha	FF3 Alpha	FFC4 Alpha
Interaction	0.50	0.48	0.39
	(2.85)	(2.69)	(2.15)
Pure Cross-Momentum	0.34	0.38	0.34
	(2.70)	(3.02)	(2.65)
Pure Anchoring	0.42	0.45	0.06
	(3.19)	(3.54)	(0.62)

Panel B: Industry Momentum

	CAPM Alpha	FF3 Alpha	FFC4 Alpha
Interaction	0.58	0.60	0.46
	(2.73)	(2.80)	(2.11)
Pure Cross-Momentum	0.41	0.43	–0.02
	(2.47)	(2.60)	(–0.11)
Pure Anchoring	0.39	0.45	–0.02
	(2.54)	(3.11)	(–0.16)

Panel C: Complicated Firms and Foreign Information

	CAPM Alpha	FF3 Alpha	FFC4 Alpha
Interaction	0.90	1.05	1.04
	(1.80)	(2.07)	(2.01)
Pure Cross-Momentum	0.44	0.34	0.24
	(1.45)	(1.09)	(0.77)
Pure Anchoring	0.09	0.14	–0.39
	(0.37)	(0.57)	(–1.83)

Figure 1. Cumulative FFC4 Alpha of Supplier Firm.

This figure plots the cumulative FFC4 alpha of supplier firm portfolios sorted by customer returns (CR) and nearness to 52-week high (PRC). In each month, we sort supplier firms into quintile by quintile portfolios based on their CR in the previous month and own nearness to 52-week high at previous month-end. These portfolios are then held in the next seven months. Month 1 denotes the first holding month. This figure plots the performance of CR5~PRC5 portfolio (portfolio with the highest CR ranking and highest PRC ranking) and CR1~PRC1 portfolio (portfolio with the lowest CR ranking and lowest PRC ranking). Cumulative FFC4 alpha is shown in percentage points.

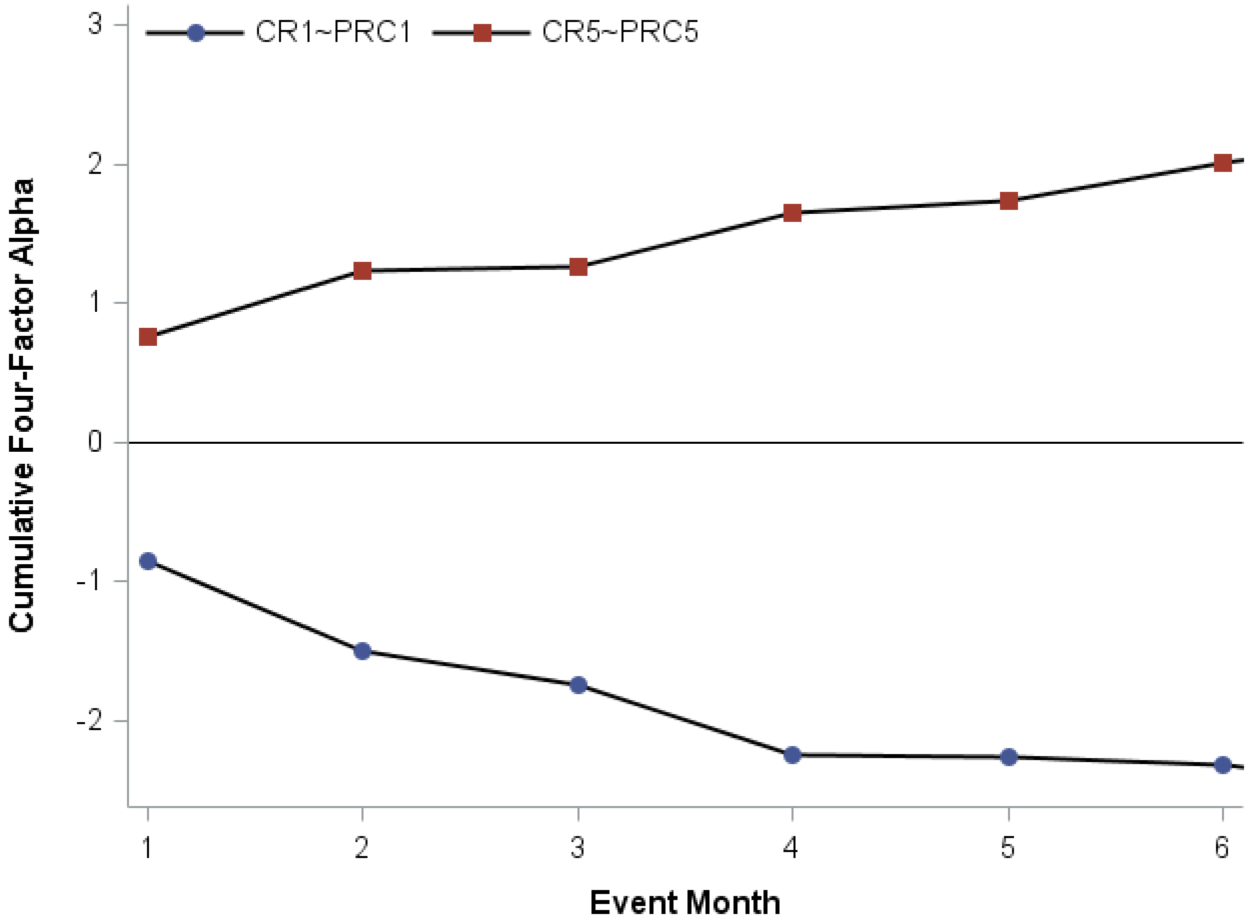
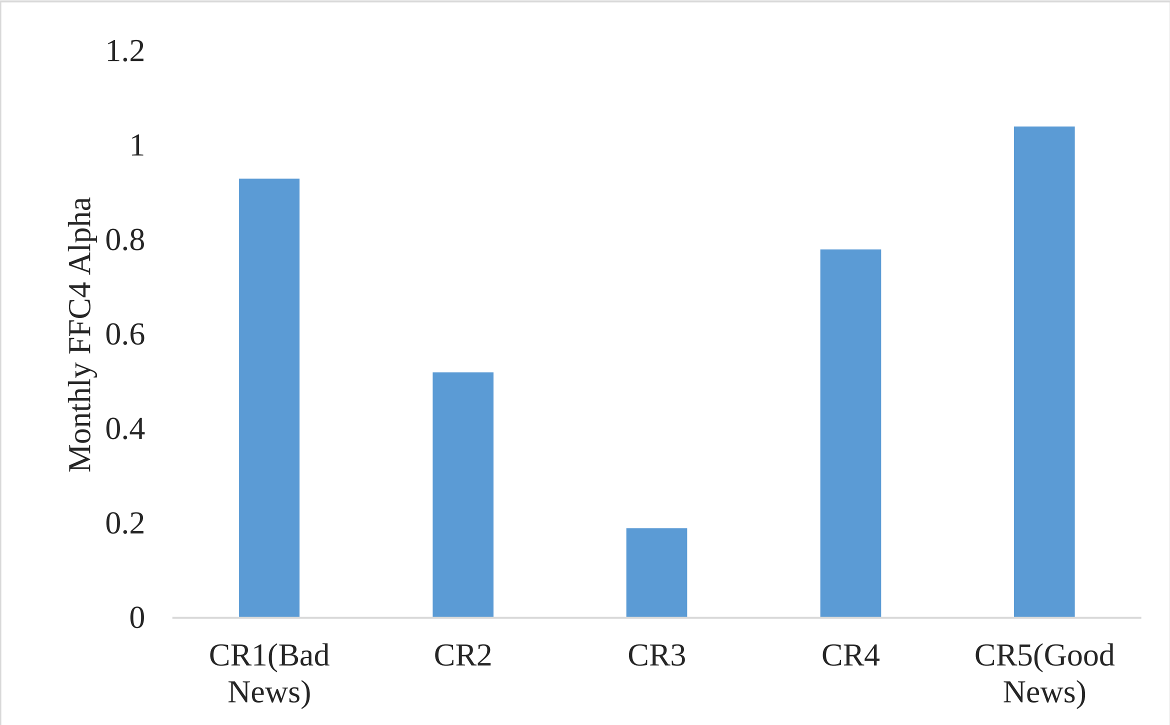


Figure 2. PRC5 – PRC1 in different CR Quintiles.

This figure plots average monthly FFC4 alpha of "PRC5 – PRC1" long-short portfolio within each CR quintile. We conduct the same return decomposition as in Table 5 to obtain the coefficient estimates of monthly FFC4 alpha of the effects specified in Panel A of Table 4. Following the specification in that Panel, we further compute the estimated PRC5 – PRC1 alpha within each CR quintile as follows. In CR1 quintile, PRC5-PRC1 = $A_h - A_l - I_{bb,l}$; In CR2 quintile, PRC5 – PRC1 = $A_h - A_l - I_{b,l}$; In CR3 quintile, PRC5 – PRC1 = $A_h - A_l$; In CR4 quintile, PRC5 – PRC1 = $A_h - A_l + I_{g,h}$; In CR5 quintile, PRC5 – PRC1 = $A_h - A_l + I_{gg,h}$. The estimates are shown in percentage points per month.



Appendix

Table A1. Return Decomposition Methodology

We illustrate the return decomposition method in customer momentum setting. In each month, we sort supplier firms into quintile by quintile portfolios based on their customer returns (*CR*) in previous month and own nearness to 52-week high (*PRC*) at previous month-end. The portfolios are held for one month and rebalanced monthly. Then we run a monthly stock-level Fama-Macbeth regression on supplier firms to estimate pure customer momentum effects, pure anchoring effects, and interaction effects from cross-sectional variation in stock returns across the 25 portfolios. The regression model is specified as:

$$R_{i,t} = b_0 + b_1 CR5_{i,t} + b_2 CR4_{i,t} + b_3 CR2_{i,t} + b_4 CR1_{i,t} + b_5 PRC5_{i,t} + b_6 PRC1_{i,t}$$

$$+b_7 CR5_{i,t} \times PRC5_{i,t} + b_8 CR4_{i,t} \times PRC5_{i,t}$$

$$+b_9 CR2_{i,t} \times PRC5_{i,t} + b_{10} CR1_{i,t} \times PRC5_{i,t}$$

$$+b_{11} CR5_{i,t} \times PRC1_{i,t} + b_{12} CR4_{i,t} \times PRC1_{i,t}$$

$$+b_{13} CR2_{i,t} \times PRC1_{i,t} + b_{14} CR1_{i,t} \times PRC1_{i,t},$$

where $R_{i,t}$ is return of supplier firm *i* in month *t*, and right-hand-side variables are dummies indicating CR and PRC quintile ranking of firm *i* in the month *t* (sorting variables are computed at month *t-1* end).

Panel A shows how the average stock returns of each portfolio can be decomposed into parameter estimates from above Fama-Macbeth regression. Based on the estimation of those *b* parameters, Panel B demonstrates how to decompose average return of each portfolio into the sum of different effects. We then calculate the estimates of pure customer momentum effects, pure anchoring effects, and interaction effects through equating sum of parameter estimates in Panel A to the corresponding sum of effects in Panel B.

Panel A					
	CR1	CR2	CR3	CR4	CR5
PRC1	$b0 + b4 + b6 + b14$	$b0 + b3 + b6 + b13$	$b0 + b6$	$b0 + b2 + b6 + b12$	$b0 + b1 + b6 + b11$
PRC2~4	$b0 + b4$	$b0 + b3$	$b0$	$b0 + b2$	$b0 + b1$
PRC5	$b0 + b4 + b5 + b10$	$b0 + b3 + b5 + b9$	b0 + b5	$b0 + b2 + b5 + b8$	$b0 + b1 + b5 + b7$

Panel B					
	CR1	CR2	CR3	CR4	CR5
PRC1	$\mu + A_l + E_{bb} + I_{bb,l}$	$\mu + A_l + E_b + I_{b,l}$	$\mu + A_l$	$\mu + A_l + E_g$	$\mu + A_l + E_{gg}$
PRC2~4	$\mu + E_{bb} + I_{bb,m}$	$\mu + E_b + I_{b,m}$	μ	$\mu + E_g + I_{g,m}$	$\mu + E_{gg} + I_{gg,m}$
PRC5	$\mu + A_h + E_{bb}$	$\mu + A_h + E_b$	$\mu + A_h$	$\mu + A_h + E_g + I_{g,h}$	$\mu + A_h + E_{gg} + I_{gg,h}$

The effects specified in Panel B can be calculated using parameter estimates from Panel A as follows:
$\mu = b0$,
$A_l = b6, \quad A_h = b5$
$E_{bb} = b4 + b10, \quad E_b = b3 + b9, \quad E_g = b2 + b12, \quad E_{gg} = b1 + b11,$
$I_{bb,l} = b14 - b10, \quad I_{b,l} = b13 - b9, \quad I_{bb,m} = -b10, \quad I_{b,m} = -b9, \quad I_{g,m} = -b12, \quad I_{gg,m} = -b11,$
$I_{g,h} = b8 - b12, \quad I_{gg,h} = b7 - b11.$

Finally, the pure customer momentum effect, pure anchoring effect, and interaction effect can be computed as follows:
Pure Customer Momentum Effect = $E_{gg} - E_{bb}$, Pure Anchoring Effect = $A_h - A_l$, Interaction Effect = $I_{gg,h} - I_{bb,l}$.

To do return decomposition in subsamples of suppliers (Table 6), we first cut the supplier-month sample into two halves based on firm characteristics. Then in each month within each subsample, we further sort suppliers into *tercile by tercile* portfolios based on their CR in the previous month and PRC at previous month-end.[22] We run a similar Fama-Macbeth regression as in the previous example:

$$R_{i,t} = b_0 + b_1 CR3_{i,t} + b_2 CR1_{i,t} + b_3 PRC3_{i,t} + b_4 PRC1_{i,t} + b_5 CR3_{i,t} \times PRC3_{i,t} + b_6 CR1_{i,t} \times PRC3_{i,t}$$

$$+ b_7 CR3_{i,t} \times PRC1_{i,t} + b_8 CR1_{i,t} \times PRC1_{i,t},$$

where $R_{i,t}$ is return of supplier firm *i* in month *t*, and right-hand-side variables are dummies indicating CR and PRC quintile ranking of firm *i* in the month *t*.

Panel C			
	CR1	CR2	CR3
PRC1	$b0 + b2 + b4$	$b0 + b4$	$b0 + b1 + b4 + b7$
PRC2	$b0 + b2$	$b0$	$b0 + b1$
PRC3	$b0 + b2 + b3 + b6$	$b0 + b3$	b0 + b1 + b3 + b5

Panel D			
	CR1	CR2	CR3
PRC1	$\mu + A_l + E_b + I_{b,l}$	$\mu + A_l$	$\mu + A_l + E_g$
PRC2	$\mu + E_b + I_{b,m}$	μ	$\mu + E_g + I_{g,m}$
PRC3	$\mu + A_h + E_b$	$\mu + A_h$	$\mu + A_h + E_g + I_{g,h}$

Similarly, The effects specified in Panel D can be calculated using parameter estimates from Panel C as follows:
$\mu = b0, \ A_l = b4, \ A_h = b3, \ E_b = b2 + b6, \ E_g = b1 + b7,$
$I_{b,l} = b6 - b6, \quad I_{g,h} = b5 - b7, \quad I_{b,m} = -b6, \ I_{g,m} = -b7.$

Pure customer momentum effect, pure anchoring effect, and interaction effect can be computed as follows:
Pure Customer Momentum Effect = $E_g - E_b$, Pure Anchoring Effect = $A_h - A_l$, Interaction Effect = $I_{g,h} - I_{b,l}$.

[22] Here we use 3 by 3 sort instead of 5 by 5 sort, since the number of supplier firms in each of the subsample is not large enough for 5 by 5 sort.

Table A2. Portfolio Characteristics in Other Settings

This table reports the average nearness to 52-week high and average economically related returns of double sorting portfolios in geographic momentum, industry momentum, complicated firms, and foreign information. At each month-end, stocks are independently double sorted by economically related returns and *PRC*. Definitions of area returns (AR), industry returns (IR), pseudo-conglomerate returns (PCR), and foreign information (FI) are described in Data Section. In industry momentum setting, stocks are independently double sorted into 5 by 5 portfolios based on industry returns and nearness to 52-week high. In other settings, stocks are sorted into quintiles based on *PR (FI)* and are independently sorted into three groups (bottom 40%, middle 20%, top 40%) based on *PRC.*

Panel A: Geographic Momentum											
	Mean Area Returns (AR)						Mean PRC				
	AR1	AR2	AR3	AR4	AR5		AR1	AR2	AR3	AR4	AR5
PRC1	–2.88	–0.30	1.01	2.34	5.36	PRC1	0.63	0.64	0.64	0.64	0.64
PRC2	–2.79	–0.28	1.02	2.36	5.34	PRC2	0.83	0.83	0.83	0.83	0.83
PRC3	–2.76	–0.24	1.05	2.40	5.47	PRC3	0.93	0.93	0.93	0.93	0.93
Panel B: Industry Momentum											
	Mean Industry Returns (IR)						Mean PRC				
	IR1	IR2	IR3	IR4	IR5		IR1	IR2	IR3	IR4	IR5
PRC1	–4.71	5.97	12.70	19.68	32.81	PRC1	0.54	0.54	0.55	0.55	0.55
PRC2	–3.92	6.31	12.84	19.68	32.90	PRC2	0.73	0.74	0.74	0.74	0.74
PRC3	–3.37	6.55	12.99	19.83	32.94	PRC3	0.83	0.83	0.83	0.83	0.83
PRC4	–2.97	6.79	13.12	20.01	33.01	PRC4	0.90	0.90	0.90	0.90	0.90
PRC5	–2.85	6.91	13.21	20.18	33.40	PRC5	0.97	0.97	0.97	0.97	0.97
Panel C: Complicated Firms											
	Mean Pseudo–Conglomerate Returns (PCR)						Mean PRC				
	PCR1	PCR2	PCR3	PCR4	PCR5		PCR1	PCR2	PCR3	PCR4	PCR5
PRC1	–4.24	–0.79	1.00	2.84	6.43	PRC1	0.62	0.62	0.62	0.62	0.63
PRC2	–4.11	–0.80	1.02	2.85	6.48	PRC2	0.81	0.81	0.81	0.81	0.81
PRC3	–4.10	–0.80	1.00	2.86	6.57	PRC3	0.92	0.92	0.92	0.92	0.92
Panel D: Foreign Information											
	Mean Foreign Information (FI)						Mean PRC				
	FI1	FI2	FI3	FI4	FI5		FI1	FI2	FI3	FI4	FI5
PRC1	–2.24	–0.51	0.31	1.13	3.18	PRC1	0.57	0.57	0.58	0.57	0.57
PRC2	–2.20	–0.50	0.33	1.15	3.18	PRC2	0.77	0.77	0.77	0.77	0.77
PRC3	–2.16	–0.51	0.31	1.14	3.26	PRC3	0.91	0.91	0.91	0.91	0.91

Table A3. Return Decomposition: Excluding January

This table reports return decomposition results of customer momentum setting, excluding the January effect. Specifically, we exclude observations in January and conduct the same return decomposition as in Table 5. The return decomposition methodology is described in Appendix Table A1 and the specification of return decomposition is shown in Table 4. Pure customer momentum effect is computed as $E_{gg} - E_{bb}$, where $E_{gg}(E_{bb})$ is the return associated with having extreme good (bad) news about customer firms regardless of own nearness to 52-week high. Pure anchoring effect is computed as $A_h - A_l$, where A_h is the return attributable to having stock prices near (far from) 52-week high regardless of news about customer firms. Interaction effect is computed as $I_{gg,h} - I_{bb,l}$, where $I_{gg,h}$ $(I_{bb,l})$ is the return associated with the coincidence of having good (bad) news about customer firms and having stock prices near (far from) 52-week high. Average monthly CAPM Alpha, FF3 Alpha, and FFC4 Alpha are the intercepts from time series regressions of monthly estimates of each effect on market excess return, Fama-French (1993) three factors, and Fama-French-Carhart (1997) four factors, respectively. *t*-statistics are in parentheses.

	CAPM Alpha	FF3 Alpha	FFC4 Alpha
Interaction	2.01	2.20	1.63
	(2.81)	(3.04)	(2.16)
Pure Customer Momentum	0.24	0.07	0.31
	(0.53)	(0.16)	(0.66)
Pure Anchoring	1.01	0.79	0.20
	(2.47)	(1.95)	(0.49)

Table A4. Replication of Customer Momentum Strategy

This table reports the performance of customer momentum strategy in our sample. In each month, supplier firms are sorted into quintiles based on customer returns (*CR*) in the previous month. We long the highest CR quintile and short the lowest CR quintile. The portfolios are held for one month. We then track the equal-weighted returns of each portfolio. This table reports the average monthly risk-adjusted returns of the portfolios. Risk-adjusted returns in Panels A, B, and C are the intercept estimates from time series regressions of the monthly excess returns on market excess return (CAPM), Fama-French (1993) three factors (FF3), and Fama-French-Carhart (1997) four factors (FFC4), respectively. We report the average monthly portfolio returns during the holding period of January 1981 to June 2011. *t*-statistics are in parentheses.

Portfolio	CAPM Alpha	*t*-statistic	FF3 Alpha	*t*-statistic	FFC4 Alpha	*t*-statistic
CR1	–0.67	(–3.27)	–0.68	(–5.27)	–0.55	(–4.26)
CR2	–0.24	(–1.45)	–0.29	(–3.06)	–0.21	(–2.23)
CR3	–0.07	(–0.42)	–0.16	(–1.58)	–0.06	(–0.67)
CR4	0.10	(0.62)	0.00	(0.01)	0.05	(0.48)
CR5	0.32	(1.81)	0.30	(2.75)	0.36	(3.15)
CR5–CR1	0.99	(5.95)	0.98	(5.79)	0.91	(5.00)

Table A5. Return Decomposition Placebo Test using Past 12-Month Returns

This table reports the placebo test for return decomposition results in customer momentum setting. Specifically, we replace nearness to 52-week high by past 12-month cumulative returns and re-conduct the same return decomposition as in Table 5. The return decomposition methodology is described in Appendix Table A1 and the specification of return decomposition is shown in Table 4. Pure customer momentum effect is computed as $E_{gg} - E_{bb}$, where $E_{gg}(E_{bb})$ is the return associated with having extreme good (bad) news about customer firms regardless of past 12-month returns. Pure momentum effect is computed as $A_h - A_l$, where A_h is the return attributable to having high (low) past 12-month returns regardless of news about customer firms. Interaction effect is computed as $I_{gg,h} - I_{bb,l}$, where $I_{gg,h}$ $(I_{bb,l})$ is the return associated with the coincidence of having good (bad) news about customer firms and having high (low) past 12-month returns. Average monthly CAPM Alpha, FF3 Alpha, and FFC4 Alpha are the intercepts from time series regressions of monthly estimates of each effect on market excess return, Fama-French (1993) three factors, and Fama-French-Carhart (1997) four factors, respectively. *t*-statistics are in parentheses.

	CAPM Alpha	FF3 Alpha	FFC4 Alpha
Interaction	0.49	0.41	0.13
	(0.70)	(0.58)	(0.18)
Pure Customer Momentum	1.02	0.99	1.10
	(2.32)	(2.23)	(2.42)
Pure Momentum	1.44	1.67	0.64
	(3.60)	(4.17)	(2.05)