Online Appendix

Psychological Barrier and Cross-Firm Return Predictability

Content:

OA1. Descriptive statistics on key variables

Panel A of Table OA1 reports the basic statistics of the key variables in different cross-firm return predictability settings. Panel B of Table OA1 shows the distribution of *PRC* in customer momentum setting.

OA2. Additional results on portfolio sorting and return decomposition

This section reports additional results on portfolio sorting and return decomposition analysis: 1). we conduct the portfolio analysis in subperiods following high and low market returns; 2). we conduct two robustness checks for the return decomposition. First, we exclude Januaries and re-conduct return decomposition. Second, we replace *PRC* by the past 12-month returns and conduct a placebo return decomposition by customer returns and the supplier's past 12-month returns; 3). we conduct return decompositions in subsamples of supplier firms classified by their *PRC*; 4). we split all months into two subperiods by the number of stocks in the top (bottom) *PRC* quintile that are close to (far from) the 52-week high, and we re-conduct return decomposition in the two subperiods separately.

OA2.1. Portfolios returns following periods of high and low market return

In Table OA2.1, we split all months into two periods based on the past one-month market return and follow Table 2 to conduct the double-sorting portfolio analysis in each period. Within the top *CR* quintile, we find the *PRC5−PRC1* return spread to be larger in months following high market return periods. In contrast, within the bottom *CR* quintile, we find the *PRC5−PRC1* return spread to be larger in months following low market return periods. This finding suggests that the 52-week high effect induces stronger underreaction to good (bad) news about customer firms when more stocks are close to (far away from) the 52-week high following a period of high (low) market returns.

OA2.2. Return decomposition: excluding Januaries

To rule out the potential January effect in returns, we exclude all observations in Januaries and re-conduct the return decomposition following Table 4. Table OA2.2 shows that the results are robust.

OA2.3. Return decomposition: placebo test using past 12-month returns

Since the nearness to the 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*. Table OA2.3 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 52-week high effect) are significantly positive.

OA2.4. Return decomposition: subsample by suppliers' *PRC*

Our main results establish that the 52-week high effect induces investors' underreaction to good (bad) news about customer firms. Naturally, such underreaction to good (bad) news would be stronger when the suppliers' stock prices are closer to (farther from) the 52-week high. To test this conjecture, we split supplier firms into two groups such that the average *PRC* in the top (bottom) *PRC* group is higher (lower) in the first group than that in the second group. We expect to find a stronger interaction effect between *PRC* and *CR* for the first group of suppliers.

We form subsamples as follows. In each month, we first sort suppliers into terciles by their *PRC* at the previous month-end. We denote the bottom, middle, and top *PRC* groups by *PRC1*, *PRC2*, and *PRC3*, respectively. Within the *PRC3* group, we further sort the suppliers into two even groups based on their *PRC* at the previous month-end. We denote the sub-group with lower (higher) *PRC* by *PRC3-1* (*PRC3-2*). Similarly, we can further split *PRC1* into two sub-groups: sub-group *PRC1-1* with lower average *PRC* and sub-group *PRC1-2* with higher average *PRC*. Finally, we form the first subsample by combing suppliers in *PRC1-1*, *PRC2*, and *PRC3-2* groups in each month, and we form the second subsample by combing suppliers in *PRC1-2*, *PRC2*, *PRC3-1* groups in each month. By construction, the top *PRC* group in the first subsample (i.e., *PRC3-2* group) have stock prices on average closer to 52-week high than the top *PRC* group in the second subsample (i.e., *PRC3-1* group), and the bottom *PRC* group in the first subsample have stock prices on average farther from 52-week high than that in the second subsample. In each month, we further sort the supplier firms into terciles by their *CR* in the previous month. For each subsample, the interaction between the *CR* and *PRC* groups produces 3×3 double-sorted portfolios. Within each subsample, we then conduct the return decomposition based on the double-sorted portfolios.

Panel A of Table OA2.4 reports the results. While interaction effect generates an average monthly FFC4 alpha of 1.15% (*t*-statistic = 2.82) for the first subsample, it is only 0.1% (*t*-statistic = 0.30) in the second subsample. This finding supports our conjecture that the 52-week high effect induces a stronger underreaction to good (bad) news when stock prices are closer to (farther from) the 52-week high. In Panel B of Table OA2.4, we use the full-sample 15^{th}/85^{th} percentile values of *PRC* to split the *PRC1*/*PRC3* groups into sub-groups and form subsamples in a similar manner. The pattern is similar to Panel A.

OA2.5. Return decomposition: effects in subperiods (I)

The return decomposition in our main results is based on grouping stocks by the relative ranking of nearness to the 52-week high. However, regarding absolute distance to the 52-week high, there could be months when a large fraction of stocks in the top *PRC* group are not close to the 52-week high and a large fraction of stocks in the bottom *PRC* group are not far away from the 52-week high. In these periods, we would expect the interaction effect to be weaker.

To test this conjecture, we first follow our main analysis in Table 4 to form 5×5 portfolios double-sorted by *CR* and *PRC*. Among stock-month observations in the full sample period, we find the median value of *PRC* for observations in the top *PRC* quintile and bottom *PRC* quintile, respectively. Then in each month, we count the fraction of stocks in the top *PRC* quintile with *PRC* above the group-median *PRC*, and we count the fraction of stocks in the bottom *PRC* quintile with *PRC* below the group-median *PRC*. In each month, we take the average of the two fractions as the "fraction of extreme *PRC*" in the month. We then split all months equally into two groups by the fraction of extreme *PRC* in the month. In months with a larger fraction of extreme *PRC*, the average *PRC* in the top and bottom *PRC* quintiles are 0.97 and 0.49; while in months with a smaller fraction of extreme *PRC*, the average *PRC* in the top and bottom *PRC* quintiles are 0.96 and 0.56. We then conduct return decomposition in the two periods separately. Table OA2.5 shows that the interaction effect between the 52-week high effect and customer returns is stronger in the months when there are more stocks with extreme *PRC*.

OA2.6. Return decomposition: effects in subperiods (II)

Similar to OA2.5, we split the sample period into two subperiods and conduct return decomposition within each subperiod separately. Specifically, in each month among the 5×5 supplier portfolios sorted by *CR* and *PRC*, we count the number of stocks with *PRC* greater than 0.95 in the *CR5~PRC5* portfolio. Then we split all months into two sub-periods based on whether there are more than 10 stocks or 15 stocks with *PRC* greater than 0.95 in the *CR5~PRC5* portfolio. Table OA2.6 reports the return decomposition results in the two sub-periods. For instance, Panel B shows that the interaction effect is 1.28% FFC4 alpha per month when more than 15 stocks in the *CR5~PRC5* portfolio have *PRC* greater than 0.95, while it is 0.53% FFC4 alpha per month when no more than 15 stocks have *PRC* greater than 0.95.

OA3. Additional results on analyst recommendation and investor attention

This section performs following robustness checks: 1) in analyst recommendation revision analysis, we compute abnormal customer returns as the Fama-French-Carhart four-factor (FFC4) adjusted returns of customer firms and re-conduct the regression analysis in Table 8; 2) we generate a variable, nearness to the 52-week low, as the ratio of stock price to 52-week low and investigate how it affects analyst downgrades in response to customer returns; 3) we examine the abnormal institutional investor attention when stock prices are near the 52-week high or far away from the 52-week high.

OA3.1. Analyst recommendation revision: alternative definition of abnormal customer returns

In Table OA3.1, we re-conduct the regression analysis in Table 8 using FFC4-adjusted returns to measure abnormal customer returns. We estimate customer firms' loading on FFC4 factors in a 12-month rolling window and compute FFC4-adjusted returns as raw returns minus expected returns based on the estimated factor loadings and realized factor returns. Under the alternative measure of abnormal customer returns, all results are consistent with Table 8.

OA3.2. Nearness to the 52-week low and recommendation downgrade

In the main results, we focus on nearness to the 52-week high and examine its effect on analyst recommendation revision. As a robustness check, we generate a variable, nearness to the 52-week low, as the ratio of stock price to the 52-week low price and examine its effect on analyst recommendation downgrade. Table OA3.2 reports the results. We find that, while analysts are more likely downgrade a supplier firm when its customer firms have bad news, such sensitivity would be reduced when supplier stock prices are close to the 52-week low.

OA3.3. Analyst recommendation revision: placebo test with pseudo-supplier-customer links

We form pseudo-supplier-customer links by assigning a pseudo customer firm to replace the real customer firm, and we re-perform the regression analysis in Table 8 with the pseudo links. To form pseudo links, for each customer firm linked to a supplier in a month, we find a pseudo customer firm in the same Fama-French 48-industry and with the closest market capitalization to replace the real customer firm. Table OA3.3 reports the placebo test results. We find the pseudo abnormal customer returns have no predictive effect on analyst recommendation revision of supplier firms, and the interaction term between pseudo abnormal customer returns and suppliers' nearness to the 52-week high is also insignificant.

OA3.4. Nearness to the 52-week high and abnormal institutional attention

In the main results, we use abnormal trading volume as a proxy for investor attention and examine its relation with nearness to the 52-week high. As a robustness check, we follow Ben-Rephael, Da, and Israelsen (2017) to construct an alternative proxy, abnormal institutional attention (*AIA*), based on the Bloomberg search score. The Bloomberg search score takes values of 1, 2, 3, or 4. A higher score on a firm in a given day indicates a greater number of active searches or readings for news about the supplier firm in Bloomberg terminals, compared with that in the previous 30 days. *AIA* is a dummy variable that equals one when the score is 3 or 4 for a firm in a given day, and zero otherwise. With this measure, we examine the abnormal institutional attention when stock prices are near or far away from the 52-week high in the firm-by-day panel regressions.

Table OA3.4 shows that abnormal institutional attention increases when stock prices are either near the 52-week high or far from the 52-week high. This result is consistent with that in Table 8, and it confirms that the underreaction generated by the 52-week high effect cannot be explained by the lack of investor attention.

OA4. Portfolio characteristics and returns in other cross-firm return predictability settings

OA4.1. Portfolio characteristics in other cross-firm return predictability settings

Table OA4.1 reports the portfolio characteristics for the cross-firm return predictability settings in Table 11. For each setting, we conduct independent double-sort by the return predictor (e.g., area returns in geographic momentum setting) and PRC. In all settings, we find the variations of the return predictor are not sensitive to the variation of PRC across the double-sorted portfolios. This ensures that sorting by PRC is not further sorted by the return predictor.

OA4.2. Replication of cross-firm return predictabilities

Table OA4.2 reports replication results for each cross-firm return predictability studied in our paper. For each setting and in each month, we form quintile portfolios based on the return predictor and track the one-month ahead equal-weighted portfolio returns. For all settings, we find that the differences in FFC4 alpha between the top quintile and the bottom quintile are statistically significant and have a large economic magnitude.

Table OA1. Descriptive Statistics

Panel A reports summary statistics for the sample of firm-month observations. Summary statistics of firm size is based on the customer momentum sample from January 1981 to December 2018. Customer returns are average returns of a supplier firm's customers in a month. Area returns are equal-weighted returns of a firm's geographic neighbors that are headquartered in the same Economic Area defined by the Bureau of Economic Analysis in a month. Industry returns are average monthly returns of an equal-weighted portfolio of a firm’s industry peers in the past six months, where industries are defined following the Fama-French 48-industry classification. To compute Pseudo-conglomerate returns, for each conglomerate firm, we form a portfolio mimicking its industry segments using standalone firms in the corresponding industries. Pseudo-conglomerate return for a conglomerate-month is the sales-weighted average return of the segment portfolios in the previous month. Foreign information is sales-weighted industry returns in the foreign countries where the firm operates. Panel B reports the distribution of *PRC* in the customer momentum sample from January 1981 to December 2018.

Panel A: basic statistics for return predictors

	Min	Max	Mean	SD	Median
Firm Size (NYSE percentile)	0.000	0.999	0.316	0.274	0.230
Customer returns	−0.981	3.757	0.012	0.093	0.011
Area returns	−0.345	0.870	0.012	0.062	0.012
Industry returns	−0.355	0.618	0.013	0.032	0.013
Pseudo–conglomerates returns	−0.443	0.781	0.012	0.063	0.013
Foreign information	−0.368	0.670	0.004	0.026	0.004

Panel B: Distribution of *PRC* in Customer Momentum Setting

Min	10%	15%	20%	50%	80%	85%	90%	Max
0.033	0.518	0.584	0.636	0.830	0.951	0.967	0.983	1.000

Table OA2.1. Portfolio Returns Following Periods of High and Low Market Return

This table reports the performance of supplier firm portfolios sorted by customer returns (*CR*) and the nearness to the 52-week high (*PRC*) following periods of high and low market returns. We form double-sorted portfolios of supplier firms and compute equal-weighted portfolio returns in each month following Table 2. Then we sort all months from January 1981 to December 2018 into two periods based on CRSP value-weighted market return in the previous month. Panels A and B report the average monthly FFC4 alpha of portfolios in the months following low and high market returns, respectively.

Panel A: Months following low market return period

	CR1	*CR2*	*CR3*	*CR4*	*CR5*
PRC1	−1.18	−0.36	−0.42	−0.34	−0.04
	(−3.61)	(−1.22)	(−1.16)	(−0.90)	(−0.12)
PRC2	−1.17	−0.41	−0.32	−0.56	0.11
	(−4.47)	(−1.79)	(−1.34)	(−2.18)	(0.44)
PRC3	−0.48	−0.12	−0.34	−0.46	0.31
	(−2.00)	(−0.55)	(−1.78)	(−2.20)	(1.35)
PRC4	−0.42	−0.04	−0.11	0.34	0.12
	(−1.85)	(−0.23)	(−0.56)	(1.56)	(0.48)
PRC5	0.05	−0.01	0.17	0.19	0.41
	(0.21)	(−0.05)	(0.74)	(0.96)	(1.78)
PRC5 –1	1.23	0.35	0.59	0.53	0.45
	(3.06)	(0.94)	(1.29)	(1.24)	(1.00)

Panel B: Months following high market return period

	CR1	*CR2*	*CR3*	*CR4*	*CR5*
PRC1	−0.72	−0.73	−0.03	−0.18	−0.22
	(−2.57)	(−2.61)	(−0.11)	(−0.64)	(−0.78)
PRC2	−0.54	0.05	−0.21	0.05	0.07
	(−2.46)	(0.23)	(−0.92)	(0.20)	(0.28)
PRC3	−0.17	0.21	0.15	−0.07	0.29
	(−0.72)	(1.08)	(0.76)	(−0.36)	(1.18)
PRC4	0.05	−0.03	0.42	0.59	0.83
	(0.21)	(−0.18)	(2.06)	(3.09)	(3.65)
PRC5	0.04	0.12	0.13	0.41	0.89
	(0.20)	(0.62)	(0.68)	(2.12)	(4.05)
PRC5 –1	0.76	0.85	0.16	0.59	1.12
	(2.10)	(2.40)	(0.45)	(1.69)	(3.29)

Table OA2.2. Return Decomposition: Excluding Januaries

This table reports a robustness check for return decomposition results in customer momentum setting, by excluding the January effect. Specifically, we exclude observations in January and conduct the same return decomposition as in Table 4. The return decomposition methodology is described in Appendix B. The pure customer momentum effect is computed as $E_{gg} - E_{bb}$, where $E_{gg}(E_{bb})$ is the return associated with having extremely good (bad) news about customer firms regardless of their price nearness to the 52-week high. The pure 52-week high 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) the 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	1.73	1.70	1.24
	(3.31)	(2.74)	(2.01)
Pure Customer Momentum	−0.01	−0.04	0.14
	(−0.04)	(−0.12)	(0.39)
Pure 52-week High	1.28	1.22	0.54
	(4.70)	(4.48)	(1.89)

Table OA2.3. Return Decomposition: Placebo Test Using Past 12-Month Returns

This table reports the placebo test for return decomposition results in the customer momentum setting. Specifically, we replace nearness to the 52-week high by the past 12-month cumulative returns and re-conduct the same return decomposition as in Table 4. The return decomposition methodology is described in Appendix B. The pure customer momentum effect is computed as $E_{gg} - E_{bb}$, where E_{gg} (E_{bb}) is the return associated with having extremely good (bad) news about customer firms regardless of past 12-month returns. The 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. 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 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	0.10	0.27	0.05
	(0.23)	(0.54)	(0.10)
Pure Customer Momentum	1.14	1.01	1.07
	(3.94)	(3.23)	(3.46)
Pure Momentum	1.38	1.49	0.53
	(4.80)	(4.81)	(2.53)

Table OA2.4. Return Decomposition: Subsamples by *PRC*

This table reports the results of the return decomposition in subsamples classified by supplier firms' *PRC*. We form subsamples in Panel A as follows. In each month, we sort supplier firms into terciles by their *PRC* in the previous month. The bottom/middle/top *PRC* groups are denoted by *PRC1*/*PRC2*/*PRC3*, respectively. Within the *PRC3* group, we further sort stocks into two groups based on their relative *PRC* ranking in the month. Then, the sub-group with lower (higher) *PRC* is denoted by *PRC3-1* (*PRC3-2*). Similarly, the *PRC1* group is further split into a *PRC1-1* sub-group with a relatively lower average *PRC* and a *PRC1-2* sub-group with a relatively higher average *PRC*. We form a subsample with more extreme *PRC* by combining stocks in *PRC1-1*, *PRC2*, and *PRC3-2* groups each month (denoted by *Subsample 1* in Panel A), and we form a subsample with less extreme *PRC* by combing stocks in *PRC1-2*, *PRC2*, and *PRC3-1* groups each month (denoted by *Subsample 2* in Panel A). In each month, we further sort the supplier firms into terciles by their *CR* in the previous month. For each subsample, the interaction between the *CR* and *PRC* groups produces 3×3 double-sorted portfolios. Within each subsample, we then conduct the return decomposition based on the double-sorted portfolios (see Appendix B for details). In Panel B, we use a similar method to form subsamples, but we take a different approach to split the *PRC* groups into sub-groups. Specifically, in each month, we split the *PRC3* group into two sub-groups using the 85th percentile value of *PRC* in the full sample as a cut-off, and we split the *PRC1* group into two sub-groups using the 15th percentile value of *PRC* in the full sample as a cut-off. Similarly, in Panel B, *Subsample 1* consists of stocks with more extreme *PRC* in the top and bottom *PRC*, compared with *Subsample 2*. The average monthly FFC4 alpha of each effect is reported. *t*-statistics are in parentheses.

Panel A: Subsample by relative *PRC* ranking in each month				
	Subsample 1: More extreme *PRC* values in top and bottom *PRC* group		Subsample 2: Less extreme *PRC* values in top and bottom *PRC* group	
Interaction	1.15	(2.82)	0.10	(0.30)
Pure Customer Momentum	-0.05	(-0.22)	0.63	(2.77)
Pure 52-week High	0.31	(1.60)	0.61	(2.91)
Panel B: Subsample by full-sample 15th and 85th percentiles of *PRC*				
	Subsample 1: More extreme *PRC* values in top and bottom *PRC* group		Subsample 2: Less extreme *PRC* values in top and bottom *PRC* group	
Interaction	2.12	(3.64)	-0.08	(-0.19)
Pure Customer Momentum	-0.75	(-1.92)	0.69	(2.51)
Pure 52-week High	0.14	(0.54)	1.17	(5.92)

Table OA2.5. Return Decomposition: Effects in Subperiods (I)

In each month, we follow Table 4 to form the 5×5 portfolios double-sorted by *CR* and *PRC*. We further split all months into two periods based on the fraction of stocks with extreme *PRC* in the month, and we conduct return decomposition in each period separately. We generate the two sub-periods as follows. First, within the bottom *PRC* quintile or the top *PRC* quintile, we find the median of *PRC* of that quintile in the full sample period. Second, in each month, we calculate the fraction of stocks in the top *PRC* group with *PRC* above the full-sample group median, and we calculate the fraction of stocks in the bottom *PRC* group with *PRC* below the full-sample group median. In each month, we take the average of the two fractions as the fraction of stocks with extreme *PRC* in the month. Finally, we split all months into two periods based on the fraction of stocks with extreme *PRC* in the month, and we conduct the same return decomposition as in Table 4 but in the two subperiods separately. Panel A reports the return decomposition results in the months when fewer stocks have extreme *PRC*. Panel B reports the return decomposition results in the months when more stocks have extreme *PRC*. *t*-statistics are in parentheses.

Panel A: Months when fewer stocks are close to the 52-week high/low			
		FFC4 Alpha	*t*-statistic
CAPM	Interaction	0.98	(1.80)
	Pure Customer Momentum	0.15	(0.46)
	Pure 52-week High	1.56	(4.52)
FF3	Interaction	1.07	(1.85)
	Pure Customer Momentum	0.27	(0.76)
	Pure 52-week High	1.51	(3.87)
FFC4	Interaction	0.97	(1.59)
	Pure Customer Momentum	0.30	(0.73)
	Pure 52-week High	0.94	(3.03)
Panel B: Months when more stocks are close to the 52-week high/low			
		FFC4 Alpha	*t*-statistic
CAPM	Interaction	2.35	(3.03)
	Pure Customer Momentum	−0.11	(−0.26)
	Pure 52-week High	0.63	(1.64)
FF3	Interaction	2.15	(2.42)
	Pure Customer Momentum	−0.21	(−0.44)
	Pure 52-week High	0.36	(0.81)
FFC4	Interaction	2.00	(2.18)
	Pure Customer Momentum	−0.19	(−0.38)
	Pure 52-week High	−0.16	(−0.41)

Table OA2.6. Return Decomposition: Effects in Subperiods (II)

In this table, we split the sample period into two subperiods and conduct the same return decomposition as in Table 4 within each subperiod. To split the sample period, among the 5×5 supplier portfolios sorted by *CR* and *PRC* in each month, we count the number of stocks with *PRC* greater than 0.95 in the *CR5~PRC5* portfolio. Then we split all months into two sub-periods based on whether there are more than 10 stocks or 15 stocks with *PRC* greater than 0.95 in the *CR5~PRC5* portfolio. Average monthly FFC4 alpha of pure customer momentum effect, pure 52-week effect, and interaction effect are reported. *t*-statistics are in parentheses.

Panel A: whether more than 10 stocks in *CR5~PRC5* portfolio have *PRC* > 0.95 in a month					
		#stock > 10		#stock <= 10	
	Interaction	1.43	(2.36)	-0.54	(-0.52)
FFC4 Alpha	Pure Customer Momentum	−0.03	(−0.10)	1.15	(1.62)
	Pure 52-week High	0.26	(0.83)	0.73	(1.42)

Panel B: whether more than 15 stocks in *CR5~PRC5* portfolio have *PRC* > 0.95 in a month					
		#stock > 15		#stock <= 15	
	Interaction	1.28	(1.96)	0.53	(0.49)
FFC4 Alpha	Pure Customer Momentum	−0.00	(−0.00)	0.70	(1.25)
	Pure 52-week High	0.26	(0.80)	0.48	(1.00)

Table OA3.1. Analyst Recommendation Revision: Alternative Definition of Abnormal Customer Returns

In this table, we re-define abnormal customer returns as the Fama-French-Carhart four-factor (FFC4) adjusted returns of customer firms and re-perform the regression analysis in Table 8. Specifically, we estimate the 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. Then we compute *ACR* as the cumulative FFC4-adjusted customer returns in the 21 trading days before the recommendation announcement days. Definitions of other variables and regression specifications follow Table 8.

	(1)	(2)	(3)	(4)	(5)	(6)
Regression Model:	(Ordered) Logit			OLS		
Dependent Variable:	*Rec_Change*	*Upgrade*	*Downgrade*	*Rec_Change*	*Upgrade*	*Downgrade*
ACR	1.496**	1.593**	−1.402**	0.691**	0.349**	−0.342**
	(2.55)	(2.48)	(−2.30)	(2.56)	(2.47)	(−2.31)
PRC	1.021***	0.868***	−1.115***	0.471***	0.203***	−0.268***
	(13.26)	(10.93)	(−13.62)	(13.29)	(11.00)	(−13.82)
*ACR*PRC*	−2.022***	−2.116**	1.914**	−0.932***	−0.467**	0.465**
	(−2.60)	(−2.50)	(2.31)	(−2.58)	(−2.47)	(2.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	38,815	38,815	38,815	38,815	38,815	38,815
Pseudo/Adj. R^2	0.014	0.014	0.014	0.018	0.017	0.017

Table OA3.2. Nearness to the 52-week Low and Recommendation Downgrade

We define nearness to the 52-week low in a given day (*PRC_Low*) as the ratio of daily close price to the 52-week low price as of the day. Then, we replace *PRC* by *PRC_Low* and re-perform the regression analysis in Table 8 to examine the effect of nearness to the 52-week low on analysis recommendation downgrades. Definitions of other variables and regression specifications follow Table 8.

Regression Model:		Logit			OLS	
ACR	−0.534***	−1.448***	−2.062***	−0.130***	−0.333**	−0.496***
	(−3.39)	(−2.64)	(−3.47)	(−3.39)	(−2.58)	(−3.53)
PRC_Low		0.171***	0.155***		0.034***	0.034***
		(8.33)	(6.48)		(9.55)	(7.52)
ACR PRC_Low*		1.548**	2.493***		0.346*	0.596***
		(2.05)	(3.07)		(1.95)	(3.11)
Controls	No	No	Yes	No	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	44,941	44,941	38,815	44,941	44,941	38,815
Pseudo/Adj. R^2	0.003	0.010	0.012	0.003	0.011	0.014

Table OA3.3. Analyst Recommendation Revision: Placebo Test with Pseudo Customers

In Table OA3.3, we form pseudo-supplier-customer links by assigning a pseudo customer firm to replace the real customer firm, and we re-perform the regression analysis in Table 8 with the pseudo links. To form pseudo links, for each customer firm linked to a supplier in a month, we find a pseudo customer firm in the same Fama-French 48-industry and with the closest market capitalization to replace the real customer firm. In the regression sample of this table, the independent variable *ACR* is computed based on abnormal returns of pseudo customer firms, and other variables follow the same definition as in Table 8.

Panel A: *Rec_Change* as the Dependent Variable				
	(1)	(2)	(3)	(4)
Regression Model:	Ordered Logit		OLS	
ACR	−0.044	−0.046	−0.019	−0.027
	(−0.26)	(−0.07)	(−0.24)	(−0.09)
PRC		1.042***		0.482***
		(12.50)		(12.52)
*ACR*PRC*		−0.272		−0.122
		(−0.32)		(−0.31)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. Obs.	33,043	33,043	33,043	33,043
Pseudo R^2	0.007	0.010	0.012	0.018

Panel B: *Upgrade* as the Dependent Variable				
Regression Model:	Logit		OLS	
ACR	0.078	−0.323	−0.002	−0.074
	(0.46)	(−0.48)	(−0.04)	(−0.50)
PRC		0.898***		0.210***
		(10.23)		(10.30)
*ACR*PRC*		0.203		0.046
		(0.22)		(0.22)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. Obs.	33,043	33,043	33,043	33,043
Pseudo R^2	0.012	0.015	0.013	0.017

Panel C: *Downgrade* as the Dependent Variable				
	(1)	(2)	(3)	(4)
Regression Model:	Logit		OLS	
ACR	−0.044	−0.046	−0.019	−0.027
	(−0.26)	(−0.07)	(−0.24)	(−0.09)
PRC		1.042***		0.482***
		(12.50)		(12.52)
*ACR*PRC*		−0.272		−0.122
		(−0.32)		(−0.31)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
No. Obs.	33,043	33,043	33,043	33,043
Pseudo R^2	0.007	0.010	0.012	0.018

Table OA3.4. Nearness to the 52-week High and Abnormal Institutional Attention

This table reports predictive effects of nearness to the 52-week high on abnormal institutional attention in the daily sample of supplier firms. We follow Ben-Rephael, Da, and Israelsen (2017) to measure institutional investor attention based on the Bloomberg search score. Bloomberg search score takes values of 1, 2, 3, or 4, and a higher score on a firm in a given day indicates a greater number of active searches for news about the supplier firm in Bloomberg terminals, compared with that in the previous 30 days. The dependent variable, abnormal institutional attention (*AIA*), is a dummy variable that equals one when the score is 3 or 4 for a firm in a given day, and zero otherwise. The key independent variable *Dummy_HighPRC* (*Dummy_LowPRC*) is a dummy variable that equals one if a firm has *PRC* ranked in the top (bottom) quintile on the previous trading day, and it equals zero elsewhere. Control variables include market capitalization and book-to-market ratio as of the previous month-end, cumulative returns in the previous 12 months, and standard deviation of weekly returns in the previous 52 weeks. Firm fixed effects and date fixed effects are included. The sample period is from 2010 to 2015. *t*-statistics in parentheses are computed based on standard errors double-clustered by firm and date. ***, **, and * denote the significance levels of 1%, 5%, and 10% respectively.

	(1)	(2)	(3)
Dummy_HighPRC	0.01***	0.01***	0.01***
	(4.42)	(4.58)	(3.92)
Dummy_LowPRC	0.00**	0.00**	0.01***
	(2.42)	(2.30)	(3.65)
Size			0.02***
			(5.83)
Book-to-Market			0.01***
			(2.83)
Past Returns			0.00
			(1.03)
Return Volatility			0.20***
			(3.56)
Firm FE	Yes	Yes	Yes
Time FE	No	Yes	Yes
No. Obs.	684,105	684,105	684,105
Adj. R2	0.063	0.084	0.085

Table OA4.1. Portfolio Characteristics in Other Settings

This table reports the average nearness to the 52-week high and average economically linked firms' returns of double sorting portfolios in geographic momentum, industry momentum, complicated firms, and foreign information settings, respectively. At each month-end, stocks are independently double sorted by economically linked firms' returns (e.g., area returns in geographic momentum setting) and *PRC*. Definitions of area returns (*AR*), industry returns (*IR*), pseudo-conglomerate returns (*PCR*), and foreign information (*FI*) are described in the Data section. In industry momentum setting, stocks are independently double sorted into 5×5 portfolios based on the industry returns and nearness to the 52-week high. In other settings, stocks are sorted into quintiles based on *PRC (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	−2.84	−0.29	1.01	2.32	5.29	*PRC1*	0.66	0.66	0.66	0.66	0.66
PRC2	−2.73	−0.26	1.02	2.34	5.29	*PRC2*	0.84	0.84	0.84	0.84	0.84
PRC3	−2.70	−0.23	1.05	2.38	5.39	*PRC3*	0.94	0.94	0.94	0.94	0.94
Panel B: Industry Momentum											
	Mean Industry Returns (*IR*)						Mean *PRC*				
	IR1	*IR2*	*IR3*	*IR4*	*IR5*		*IR1*	*IR2*	*IR3*	*IR4*	*IR5*
PRC1	−0.98	0.37	1.14	1.90	3.23	*PRC1*	0.58	0.58	0.59	0.59	0.59
PRC2	−0.85	0.40	1.16	1.92	3.26	*PRC2*	0.76	0.76	0.76	0.76	0.76
PRC3	−0.77	0.44	1.18	1.94	3.30	*PRC3*	0.84	0.84	0.84	0.84	0.84
PRC4	−0.73	0.47	1.20	1.97	3.35	*PRC4*	0.91	0.91	0.91	0.91	0.91
PRC5	−0.70	0.49	1.22	2.00	3.44	*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	−4.28	−0.76	1.05	2.87	6.44	*PRC1*	0.69	0.70	0.70	0.70	0.70
PRC2	−3.96	−0.76	1.05	2.87	6.35	*PRC2*	0.86	0.86	0.86	0.86	0.86
PRC3	−3.82	−0.74	1.07	2.89	6.46	*PRC3*	0.94	0.94	0.94	0.94	0.95
Panel D: Foreign Industry Information											
	Mean Foreign Information (*FI*)						Mean *PRC*				
	FI1	*FI2*	*FI3*	*FI4*	*FI5*		*FI1*	*FI2*	*FI3*	*FI4*	*FI5*
PRC1	−2.06	−0.45	0.27	1.00	2.89	*PRC1*	0.63	0.64	0.64	0.64	0.63
PRC2	−1.96	−0.44	0.27	1.01	2.84	*PRC2*	0.83	0.83	0.83	0.83	0.83
PRC3	−1.92	−0.43	0.28	1.01	2.87	*PRC3*	0.93	0.93	0.93	0.94	0.94

Table OA4.2. Replication of Cross-Firm Return Predictabilities

This table reports replication results for each type of cross-firm return predictability studied in our paper. In each month, we sort all stocks into quintiles based on the return predictors. Stocks with the share price below $5 are excluded at the portfolio formation date. We hold the portfolios over the next month and compute equal-weighted portfolio returns. Average monthly FFC4 alpha (in percent) are reported. Panel A to E reports results on the cross-firm return predictability in customer momentum, geographic momentum, industry momentum, complicated firms, and foreign information setting, respectively. A detailed description of the return predictors and sample periods can be found in Section 2.

Panel A: Customer Momentum					
1 (Low CR)	2	3	4	5 (High CR)	5−1
-0.21	0.18	0.23	0.34	0.66	0.86
(-1.56)	(1.70)	(1.97)	(2.89)	(5.56)	(5.84)
Panel B: Geographic Momentum					
1 (Low AR)	2	3	4	5 (High AR)	5−1
0.00	0.22	0.32	0.49	0.64	0.65
(-0.05)	(2.98)	(4.74)	(7.10)	(8.97)	(6.49)
Panel C: Industry Momentum					
1 (Low IR)	2	3	4	5 (High IR)	5−1
0.07	0.50	0.61	0.69	0.79	0.72
(0.59)	(5.52)	(6.84)	(7.10)	(6.74)	(4.67)
Panel D: Complicated Firms					
1 (Low PCR)	2	3	4	5 (High PCR)	5−1
-0.12	0.25	0.52	0.71	0.80	0.92
(-1.21)	(2.84)	(6.66)	(8.32)	(7.27)	(6.41)
Panel E: Foreign Information					
1 (Low FI)	2	3	4	5 (High FI)	5−1
-0.18	0.24	0.34	0.60	0.48	0.66
(-0.95)	(1.60)	(2.37)	(2.98)	(2.72)	(2.52)