Insider Herding and Crashes: Evidence from the Korean Stock Market

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Abstract

This study examines the informational value of insider herding in comparison to those of non-herding. Contrary to conventional views, recent studies suggest that not all insider trading is informative which raises the question on the informational value of insider trading. To investigate the informational content of insider trading, we document whether the patterns of insider sell-herding (or buy-herding) can predict the likelihood of a crash (or a jump). We find that insider sell-herding which occurred in the immediate past of a crash is strongly related to the information flowed over a short period of time. However, we find that insider buy-herding is not associated with the likelihood of a jump. Our findings provide empirical evidence that insider herding contains more private information and especially insider sell-herding is useful in predicting crashes.

JEL classification: G14, G18

Keywords: Corporate Insider; Herding; Crash Risk; Largest Shareholders; Private Information

1. Introduction

There is extensive evidence in the literature that corporate insiders have superior information about their firms. Numerous studies investigate the informativeness of insider trading from a variety of aspects. At the market-level, aggregate insider trading is related to future market movement which makes a useful component of predicting changes in business conditions or fundamental values (Seyhun, 1988; Seyhun, 1992; Lakonishok and Lee, 2001; Jiang and Zaman, 2010). At the corporate-level, insider trading is associated with future operating performance and generates short- and long-term abnormal stock returns, which suggests the most likely explanations for insider trading contains private information (Lorie, 1968; Seyhun, 1986; Damodaran, Liu, 1993; Friederich, Gregory, Matatko and Tonks, 2002; Jeng, Metrick and Zeckhauser, 2003; Ke, Huddart and Petroni, 2003; Piotroski and Roulstone, 2005; Fidrmuc, Goergen and Renneboog, 2006; Gregory, tharyan and Tonks, 2013; Ketselas, 2018)[1].

However, recent studies cast doubt on informational value of insider trading and yield new insights into the field. First, several studies suggest that not all insider trades have the informational content. Cohen, Malloy and Pomorski (2012) posit insider trading that is likely to occur in the same month every year is not informative about firm value. They show that all routine trades should be eliminated to evaluate the informativeness of insider trading. Foley, Kwan, McInish and Phillip (2016) report discretionary trades by insiders are more informed than non-discretionary trades. They further demonstrate that discretionary purchases generate both short- and long-term higher abnormal returns. Cline, Gokkaya and Liu (2017) also find that persistently profitable (PP) insiders continue to generate higher abnormal returns than those of non-PP insiders. They also suggest that PP insiders provide a reliable signal about future performance[2].

Moreover, recent studies suggest that not all insiders have the same *access* to private information. Wang, Shin and Francs (2012) report that top-level officers such as chief executive officers (CEOs) and chief financial officers (CFOs) have superior information about firm performance than other insiders. The largest shareholders privately share information by tipping family, friends,

1 There are three plausible explanations for motivations for insider trading. Firstly, from information signal point of view, insider trading could send a positive (negative) signal to market participants. Secondly, insiders take advantage of abusing unrevealed corporate information for their own sake. Finally, insider trading is driven by liquidity needs or portfolio rebalancing for diversification.

2 Cohen et al. (2012) separate insider transaction into routine and opportunistic traders. They define routine traders as an insider who placed a trade in the same calendar month for at least three consecutive years. Foley et al. (2016) categorize insider transactions into twelve categories. Three of twelve categories are composed of discretionary trades and the remainder are non-discretionary trades. The lists of discretionary trades are as follows: purchases between related entities or transfers occurring due to the settlement of put/call options, simply on-market trade, and the director acquiring shares by choosing to become the underwriter of a rights issue. Cline et al. (2017) classify insiders as Persistently Profitable (PP), if more than 50% of the transacting insider’s buy and sell trades in the previous 36 months were profitable.

and other officers (Ahern, 2017). When insiders herd together, insider purchase (sale) herds obtain higher (lower) stock performance in the comparison to *normal* insider trading (Alldredge and Blank, 2017).

As mentioned above, we should evaluate the informativeness of insider trading from a new point of view. Recent studies regarding insider trading suggest that not all insider trading is informative (Cohen et al., 2012; Foley et al., 2016; Cline et al., 2017). Hence, we need to control non-discretionary and routine trades to analyze informativeness of insider herding. As insiders share private information with special ties, they show better stock performance in the comparison to other insiders (Ahren, 2017; Alldredge and Blank, 2017). We infer that insider herding caused by information sharing is more informative compared to normal insider trading. We thus employ an in-depth study of the informational value of insider trading in the case of insider herding.

Our main question is whether herding behavior of firm insiders predicts crashes and jumps.[3] We extend Marin and Olivier (2008)'s work in which they provide empirical evidence of the patterns of insider trading preceding large variations in stock prices at the individual stock level − insiders' sales peak many months before a large drop in the stock price along with signaling theory. The motivation of their inquiry is the notion that crashes occur after insiders' holdings reach the point set by the constraint and is preceded by an immediate period of low insider trading activity. The main difference between our work and theirs is that Marin and Olivier (2008) consider all insider trades which include routine or non-discretionary insider trades. Alldredge and Blank (2017) also document that insider herding contains robust information. Considering the recent studies, we look at not only the impact of insider herding on a crash but also the impact of insider herding on a jump.

Our primary sample of Korean firms is comprised of listed companies on the Korea Stock Exchange (KSE) and the Korean Securities Dealers Automated Quotations (KOSDAQ) over the period from 2003 to 2015. The Korean environment offers an ideal setting to investigate the informativeness of insider herding. Firstly, family-controlled firms operate in various industries and have a substantial influence on the economy. This distinctive feature provides an exclusive environment in which member firms share resources and information. Another unique feature is that ownership in family-controlled firms is concentrated and the owner has complete control over all the firms in the group. In such a heavily concentrated environment, they operate like one entity (Chang and Hong, 2000; Classens, Djankov and Lang, 2000). As mentioned before, social connections based on trusting relationships are an important mechanism in the diffusion of incremental information

[3] Crashes (jumps) refer to a large movement in positive (negative) stock returns. Bad news and information asymmetry due to financial opaqueness are the main causes of crashes (Jin and Myers, 2006; Hutton, Marcus and Tehranian, 2009; Kim, Li and Zhang, 2011).

(Ahern, 2017). Therefore, a network of inside traders under these circumstances is more likely to share private information.

Secondly, the announcement of insider transactions triggers positive or negative stock price reactions (Fidrmuc et al., 2007). Thus, crashes (or jumps) may occur due to investor overreaction to the announcement rather than insiders' private information. The regulations on the announcement of insider transactions were completely reformed by the Korean Capital Market Act of 2009. Prior to the Capital Market Act, firms were mandatory to report on insider transactions within the maximum of 40 days. Put differently, it took a month for investors to actually acknowledge insider transactions by delay announcement. However, all listed companies are required under the Capital Market Act to promptly disclose information that may affect stock price in the public. If a crash (or a jump) following insider herding appears in the pre- and post- Korean Capital Market Act periods, it cannot be fully explained by investor overreaction. We can thus infer that insider herding contains robust private information. This is because investors are able to promptly recognize insider trading after the Capital Market Act, there should not be any crash or jump in the following month.

In this paper, we address the issues as follows. First, we explore the relation between insider herding and a crash (or a jump). To do so, we classify insider trades into insider buy-herding and insider sell-herding. We then evaluate the impact of insider sell-herding on a crash as well as the impact of insider buy-herding on a jump. Insider herding shows a significant difference between insider purchases (sales) and a jump (crash). We find that there is no relation between insider sell-herding in the far past (month t-2 to t-12) and a crash. However, insider sell-herding in the immediate past (month t-1) is associated with the high likelihood of a crash. Unlike insider sell-herding, insider buy-herding is not associated with the likelihood of a jump in both periods.

Second, we divide insider herding into the cases where they include the largest shareholder and those do not to observe the relation with a jump and a crash. We observe that the movement of insider sell-herding in the presence of the largest shareholders shows similar results to those of the entire insider universe. A crash is higher for previous (month t-1) insider sell-herding in the presence of the largest shareholders. In contrast, insider buy-herding in the presence of the largest shareholders are not closely related to a jump.

Our final part of investigation is to identify the relative informativeness of corporate insiders. We split them up into three groups: the largest shareholders, major shareholders, and other officers. Then, we examine the relation between insider herding at each insider hierarchy level and a crash (jump). We look at the insider herding patterns of a three-level hierarchy of insiders. The strong association between insider sell-herding and a crash is only revealed at the largest shareholder level, and especially insider sell-herding led by the largest shareholders in the nearby past increases the probability of a crash.

Overall, we observe the patterns of insider sell-herding in the prior month of a crash. These results suggest that insiders potentially share information with insider peers just before a large drop in the stock price. By contrast, insider buy-herding which occurs before a large jump turns out to be irrelevant to the past trading patterns. Our findings contribute to the existing literature on informativeness of insider herding. First, we provide additional evidence on information content of insider herding. Alldredge and Blank (2017) investigate informativeness of insider herding by using stock price performance. The key difference between their study and our own is we present that stock return variation prior to insider herding contains short-term private information. Second, we empirically examine and find that insider herding mainly spreads negative information through insiders and access to information differs at the insider-hierarchy level.

We organize the remainder of this article as follows: Section 2 reviews the related literature. Section 3 explains our research design including model specifications, and data descriptions. Section 4 presents the empirical results. Section 5 discusses robustness checks of the empirical results. Finally, Section 6 concludes the paper.

2. Related research

Herding is defined as a group of investors following each other into (or out of) the same securities over some period of time (Sias, 2004). Such herding arises either from informational or non-informational attributes. The foundation of herding on the basis of informational attributes can be subdivided into two categories – informational cascades and investigative herding.[4] Investigative herding occurs when investors follow the same signals based on positively correlated information. Informational cascades especially result from trading with the herd when they infer information from each other's trades. Previous studies are mainly interested in herding behavior of institutional investors or fund managers. They find evidence that investors' herding is a result of inferring information (Lakonishok, Shleifer and Vishny, 1992; Wermers, 1999; Nofsinger and Sias, 1999; Sias, 2004; Kim and Nofsinger, 2005).

It comes as no surprise that not only institutional investors but also corporate insiders are able to herd together. It is highly likely that access to information determines informational advantage within the firm due to informational hierarchy. Wang et al. (2012) find insider trades following CFO purchases are greater returns than CEO purchases. Their findings indicate that CFO trades are more

4 Reputational herding and characteristic herding are two particular type of herding behavior from non-informational view, there are Reputational herding takes place when insiders are afraid of facing a reputational cost (as a result of failed investment) and mimic the action of others. Characteristic herding is said to occur as a result of their preference to shares with certain characteristics. In this paper, since we center on information traders, in other words informed insiders, there is a low chance of non-informational herding.

informative on future cash flow. Therefore, different amounts of information held by individual most likely makes the insiders herd together (Alldrege and Blank, 2017). Indjejikian, Lu and Yang (2014) and Ahern (2017) find rational explanations for insiders to share tradable information to jointly profit from private information. For examples, Ahren (2017) shows that inside traders are connected by strong social ties based on family, friends, and corporate officers. His results show that information about insider trading tends to originate from corporate insiders, especially the largest shareholders which lead to insider herding. The analysis on informational value of insider sales and insider purchases is well established in a variety of context, showing that insider trading contains private information on future corporate earnings. Thus, interpreting the existing literature is that insider purchases are highly likely to follow long-term positive abnormal returns. Moreover, insider purchases are more informative to corporate private information (Lakonishok and Lee, 2001; Ke et al., 2003; Piotroski and Roulstone, 2005). In contrast to insider purchases, stocks sold by insiders are not very significantly associated with future abnormal returns which strongly suggest that insider sales are driven by liquidity needs or portfolio rebalancing (Lakonishok and Lee, 2001; Jeng et al., 2003; Friederich et al., 2002; Fidrmuc et al., 2006).

However, current study provides another view on insider trading. Cohen et al. (2012) posits that there is identifiable routine insider trading which is not informative about firms' futures. Thus, their essential claim is to only leave a set of trades by opportunistic traders. They refer those insiders who have traded in the same years as the routine insiders, but for whom their trades are not repetitive over the past timing of their trades. Focusing on the unpredictable opportunistic traders allows us to eliminate uninformative signals and identify a set of information-rich trades that are meaningful predictors of future firm returns. Alldredge and Blank (2017) observe that insider buy-herding obtain 4% abnormal returns over the subsequent three months compared to routine insider trading. Primarily, the empirical evidence confirms that insider herding has more private information than routine insider trading. Marin and Oliver (2008) provide further evidence on this issue by using stock price crash risk. They empirically show that insider sales in the past are significantly associated with crashes, which suggests that insider sales are informationally driven. However, the data sample of Marin and Olivier (2008) studies also include routine insider trades which are regarded as inadequate information value. In order to better assess a clear pattern between crashes and insider trades, it is necessary to take insider trades into consideration that have informational value.

3. Sample selection, variable measurement, and research design

3.1 Data

This study incorporates data from several sources. We collect a sample of Korean firms which contain insider herding trades listed on the Korea stock markets from 2003 through 2015.[5] We first exclude financial firms and common equity trading records which involve less than 100 shares. Firms that do not provide necessary financial statements are also removed. Taken as a whole, we analyze 91,444 firm-month observations of insider trading dataset.[6] Insider trading data is processed based on ownership data from Fnguide database. The data includes detailed information on insider trading such as trading volume, share price for each transaction, announcement date, transaction date, the name of shareholders (insiders), types of shareholders (the largest shareholders, major shareholders, and other officers), reasons for transactions, the level of insider ownership as well as the direction of the trade (buy or sell). Thus, the data allows us to classify insider trading into herding and non-herding groups at each hierarchy level and we are able to define insider trading as insider buy-herding or insider sell-herding. Financial data comes from Total Solution 2000 (TS2000), administered by Korea Listed Companies Association (KLCA). Finally, we extract stock price data from Fnguide database.

Table 1 presents the number of shares traded from January 2004 to December 2015 by a class of insiders in samples: the total number of traded shares (287,487 transactions), encompassing 91,444 firm-months. The number of crashes estimated using the three crash measures (i.e., RETCRASH, ERCRASH, and MMCRASH) is 2,066, 1,890, and 1,944 respectively. The highest occurrence is observed in the global financial crisis. We also see from the table that a jump occurs more frequently than a crash on the basis of all jump measures (i.e., RETJUMP, ERJUMP, and MMJUMP). This yield total sample of 91,444 firm-months observations inclusive, of which 3,286 are insider sell-herding and 4,654 are insider buy-herding. Insider buy-herding is more common than insider sell-herding.

3.2 Measuring insider herding

The following settings of insider herding is an extension of Sias (2004) methodology. We begin by calculating the ratio of monthly net purchases ratio (NPR) for each insider and firm. Specifically, we define *NPR* as:

$$NPR_{i,t,k} = \left(\frac{Buy\ Volume_{i,t,k} - Sell\ Volume_{i,t,k}}{Outstanding\ Shares_{i,t-1}} \right) \times 100 \quad (1)$$

[5] One limitation of our data is that Fnguide provides data on insider trading collected from 2003 onwards. Moreover, since we are using insider trading data occurred during the period t-12 to t-2 from the event month, we only look at crashes (jumps) from 2004. Therefore, the period covered offers the best extant data.

[6] We exclude transactions less than 100 shares due to the fact that these transactions contain relatively less meaningful information (Seyhun, 1986, Lakonishok and Lee, 2001; Jategaonkar, 2013)

Where *Buy Volume*$_{i,t,k}$ is the number of shares purchased by firm *i*, insider *k* in month *t*. *Sell Volume*$_{i,t,k}$ is the number of shares sold by firm *i*, insider *k* in month *t* and *Outstanding Shares*$_{i,t-1}$ is the number of outstanding shares at the end of last fiscal year. We then measure the ratio of net purchases by insider *k* at firm *i* in month *t* based on Equation (1) and identify whether insider *k* belongs to the largest shareholder, major shareholders or other officers. Next, we compute the number of net purchasers and the number of net sellers at firm *i* in month *t*. By definition of net trades in Equation (1), we simply count the number of net traders in each insider group for each month.

Next, following Sias (2004), we compute insider herding. *RAW* is equal to the ratio of net purchasers at firm *i* as shown in Equation (2). Next, we determine whether trades are insider herding or not using *RAW* from Equation (2). If the number of net purchasers or net sellers exceeds two at firm *i* in month *t* then *RAW* takes a positive or negative value, respectively.

$$RAW_{i,t} = \left(\frac{Net\ Buyer_{i,t} - Net\ Seller_{i,t}}{Net\ Buyer_{i,t} + Net\ Seller_{i,t}} \right) \tag{2}$$

Where *Net Buyer*$_{i,t}$ is the number of net purchasers at firm *i* in month *t* and *Net Seller*$_{i,t}$ is the number of net sellers at firm *i* in month *t*. We categorize *RAW* as insider buy-herding, if the number of net purchasers exceeds the number of net sellers (i.e., RAW>0) and insider sell-herding, if the value of *RAW* is less than zero. As a result, values of *RAW* must lie between -1 and 1. If there is only one net purchaser or net seller in month *t*, then we adjust *RAW* to zero for non-herding.

Meanwhile, insider herding mutually occurs within insider groups or a specific insider group solely performs insider herding. Here, we postulate insider herding within insider groups which consist of simultaneous insiders trading performed by different classes of insiders. For instance, one from the largest shareholder group and one from major shareholders group conduct insider herding. We also define insider herding within a specific group as each insider group solely conduct insider herding. For example, more than two insiders from the largest shareholder group trade in the same direction. Collectively, we explore classified insider herding within mixed insider groups or the largest shareholder group alone that may, in turn, influence the likelihood of a crash.

3.3 Measuring stock price crash and jump risk

Following Marin and Oliver (2008), we evaluate a large drop or a jump of the stock price in a specified month. More specifically, we define:

$$RETCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t} - \bar{r}_{i,t} \le -2\sigma_{i,t}; \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

RETCRASH takes the value one when the raw return (r) in month t falls more than two standard deviations away in the past 60-months and takes the value zero otherwise. We compute the mean raw returns and the standard deviation of raw returns over a rolling window of 60-months.

Equation (4) and (5) are constructed in similar fashion except that we apply abnormal returns instead by following the steps outlined above. We define $r_{i,t}^{ER} = r_{i,t} - r_{m,t}$, where $r_{i,t}$ is equal to the abnormal return of firm *i* in month *t* and $r_{m,t}$ is the market returns. $r_{i,t}$ in Equation (5) is abnormal returns estimated from the market model. Lastly, we formally define $r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t}))$, where $\beta_{i,t}$ is estimated over a 60-month window and $r_{f,t}$ is a proxy for risk-free rate using 3-year Korea treasury bond measured at the monthly level. *ERCRASH* and *MMCRASH* take the value one when the abnormal returns in month *t* is more than two standard deviations away in the past 60-months and take the value zero otherwise.

$$ERCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{ER} - \overline{r}_{i,t}^{ER} \le -2\sigma_{i,t}; \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$MMCRASH_{i,t} = \begin{cases} 1, & \text{if } r_{i,t}^{MM} - \overline{r}_{i,t}^{MM} \le -2\sigma_{i,t}; \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

$$r_{i,t}^{MM} \equiv r_{i,t} - (r_{f,t} + \beta_{i,t}(r_{m,t} - r_{f,t})) \tag{6}$$

Finally, in order to capture the tendency of insider buy-herding prior to a jump, we construct the base line variables for a jump, *RETJUMP*, *ERJUMP*, and *MMJUMP*. These jump variables are defined in a symmetric way as crash variable counterparts in Equation (3) ~ (5).

4. Empirical results

4.1 Summary statistics

Table 2 describes the summary statistics of our sample. As shown in Table 1, insider sell-herding (SHERD) is smaller than insider buy-herding (BHERD) with a mean of 0.0359 compared to 0.0509. In terms of insider herding in the presence of the largest shareholder, *SHDINCLUDE* exhibits a lower mean value of 0.0085 versus 0.0113 for *BHDINCLUDE*. Turning to the insider hierarchy level, both *SLARGEST* and *BLARGEST* exhibit a higher mean value of 0.0716 and 0.0272, respectively, than other insider groups do. Table 2 also reports the mean and median values of firm characteristics for our sample. The mean value of *CHAEBOL* is 0.1513 which means 13,835 firm-months in our total sample.

Table 3 presents mean value of key firm characteristics for insider sell-herding, insider buy-herding, and non-herding, respectively. Cumulative abnormal returns over the previous 12 months (PCAR) show the highest insider sell-herding (21.08%) and the lowest insider buy-herding (-0.34%). The difference in means between the three groups is all significant. Therefore, insiders tend to engage in sell-herding with high past stock returns and trade buy-herding with low past returns. Insider buy-herding shows the lowest market-to-book ratio of 1.1677 compared to 1.6556 for insider sell-herding. Insiders prosecute insider sell-herding with growth-stocks and insider buy-herding with value–stocks. In sum, they show discrete herding behavior.

4.2 Insider herding and stock price crash risk

In this section, we first examine whether a crash and a jump can be predicted by insider herding. As noted by Cohen et al. (2012), our analysis builds on the idea that stripping away uninformative trades can better identify unpredictable insider trades. This new approach is pertinent to examine the informativeness of insider trading. Therefore, we provide a new perspective that complements previous studies for thinking about insider herding.

Table 4 presents the results for the relation between insider herding and a crash (or jump). The dependent variables are binary monthly crash dummy variables according to the estimate in Equation (3) ~ (5). $SHERD_{t-1}$ is an indicator equal to one if insider sell-herding occurs in the prior month and zero otherwise. $SHERD_{t-2,t-12}$ is the sum of monthly insider herding that takes value of one if there is at least one insider sell-herding during the period t-12 to t-2. Regression results from Column (1) to (3) regarding insider sell-herding activity are qualitatively similar. In Column (1) of Table 4, the coefficient estimate of the interaction between $SHERD_{t-1}$ and a crash is positive and statistically significant (= 0.467). $SHERD_{t-1}$ in Columns (2) and (3) has the consistent results with Column (1), with statistically significant coefficients of 0.485, and 0.462, respectively. Hence, we naturally interpret the coefficients on a crash as suggesting that insider sell-herding in the nearby month raises the likelihood of a crash in the event month. On the contrary, we do not find significant relation for $SHERD_{t-2,t-12}$ in all regressions. Hence, insider sell-herding in the immediate past increases the likelihood of a crash.

Marin and Olivier (2008) report opposite results for insider sales in the far past (from t-2 months to t-12 months) before crashes occur and jumps are preceded by the prior month of insider purchases trading activity. They primarily focus on insider sales and evaluate informational value of sales trades. The presence of informed traders such as firm insider sales slowly reveal bad information to the market, however the absence of insider trading stacks worse information which causes a large stock price drop (the dog that didn’t bark effect). Nonetheless, Marin and Oliver (2008) contain routine insider trades on their work. However, Cohen et al. (2012) posit that stripping away predictable routine trades can better identify informative insider trades. Alldgredge and Blank (2017) document that the 60-day cumulative abnormal returns on insider sell-herding two days away from independent insider trades realize negative *CAR*s, notably the possibility of having negative *CAR*s is larger, as the number of sellers is greater. In turn, insider sell-herding that occurred over a short period increased chances of a crash more lucrative. This result implies that insider sell-herding over a short period strongly and meaningfully relates to negative private information.

The relation between insider buy-herding of the entire insider universe and a jump is also reported in Table 4. We create a dummy variable for the fraction of the insider trades that equal one if insider buy-herding occur in the prior month ($BHERD_{t-1}$). $BHERD_{t-2,t-12}$ is the sum of insider trading that equal one if insider buy-herding occurs within a certain period between t-12 and t-2.

We obtain similar results and insights from Columns (4) ~ (6). The coefficient on the previous month's insider buy-herding ($BHERD_{t-1}$) in Column (4) has a negative, but not significant. The coefficients in Columns (5) and (6) are also insignificant. Furthermore, the coefficient estimate on the far past insider trading is 0.141 in Model (4) and statistically significant, while the coefficients on $BHERD_{t-2,t-12}$ in Columns (5) and (6) are positive but not significant. Hence, these findings together establish that insider buy-herding in the far past does not predict a jump in the following month.

The overall idea we develop from these tests is that crashes are most likely to be preceded by the immediate period of insider sell-herding rather than those of the far past (months t-2, t-12). Interestingly, though, insider buy-herding before jumps are highly irrelevant to the far and near past's insider trading activity. The asymmetry of this finding supports a conclusion that insider mutually share bad information just right before a large stock price drop.

4.3 Insider herding in the presence of the largest shareholder

Access to private information differs within an insider group to which insiders belong. As shown by Wang et al. (2012), CFOs derive statistically and economically higher abnormal returns from insider trading than CEOs do. Also, Ahern (2017) propose that social relationships based on family, friends and co-workers influence the flow of information. The largest shareholders privately convey information by tipping them. Thus, the shared information eventually flows through insider traders with similar networks which lead to insider herding. Therefore, the empirical literature allows for the possibility that the presence of the largest shareholders may exhibit differential impact on stock price variation.

As Table 5 shows, we test whether the existence of the largest shareholder exhibits a differential effect on a crash or a jump. Results for crashes are reported in the first three columns and for jumps are reported in the remaining columns. $SHDINCLUDE_{t-1}$ in Columns (1) ~ (3) is a dummy variable equal to one if there is any insider sell-herding in the presence of the largest shareholders in the prior month and zero otherwise. $SHDINCLUDE_{t-2,t-12}$ is the sum of a dummy variable for monthly insider sell-herding that equals one if they include the largest shareholder's trading during the period t-12 to t-2. $BHDINCLUDE_{t-1}$ in the far right columns is a dummy variable equal to one if there is any insider buy-herding in the presence of the largest shareholders in the prior month and zero otherwise. $BHDINCLUDE_{t-2,t-12}$ is the sum of a dummy variable for monthly insider buy-herding that equal one if they include the largest shareholder's trading during the period t-12 to t-2.

In general, the results for crashes appear to be persistent in the first through third columns of Table 5. The coefficient on $SHDINCLUDE_{t-1}$ (Column 1) is positive and significant 0.491. Furthermore, we find that the probability of a crash is positively correlated with the existence of the largest shareholder in the regressions of Columns (2) to (3). These findings together establish that a crash in the event month is more likely to occur when the largest shareholders have been trading in the prior month, $SHDINCLUDE_{t-2,t-12}$, although it is insignificant in all regressions. The results reveal that insider sell-herding of the largest shareholders in the far past is largely uncorrelated with crashes occurred in the event month. These results imply that the largest shareholders share bad information with other insiders just right before a large stock price drop.

However, further analysis reveals that no such pattern is observed for jumps in Columns (4) ~ (6). $BHDINCLUDE_{t-1}$ in Columns (4) ~ (6) have negative and insignificant coefficients. Hence, we naturally interpret the results as evidence that a jump occurred in the event month are less responsive to insider buy-herding of the largest shareholder in the previous month. The coefficients on $BHDINCLUDE_{t-2,t-12}$ in Column (4) ~ (6) have positive signs, whereas those coefficients are statistically insignificant. These results are unlike insider sell-herding with a constraint in which noise is added through the presence of the largest shareholder, showing much less significant relations between the existence of the largest shareholder and a jump.

4.4 Insider herding of the each insider group

Overall, the results of Table 4 and Table 5 suggest that insider sell-herding occurs near a crash, and the likelihood of a crash increases in the presence of the largest shareholder. We focus solely on the trading patterns of each insider group regarding insider herding and examine how their insider herding influences the stock price variation. The largest shareholder group (the largest shareholder and special relation with the largest shareholder such as family, relatives) may have a distinct information advantage over major shareholders or officers, and are more likely to hold private information. Accordingly, we run additional tests to evaluate differential movements in the largest shareholder group.

Table 6 contains the results of the regression of crashes on insider sell-herding conducted by the largest shareholders, major shareholders, and other officers, separately. Regarding independent variables: $SLARGEST_{t-1}$ are equal to one if there is insider herding solely conducted by the largest shareholder group and zero otherwise, $SHDLARGEST_{t-2,t-12}$ is the sum of monthly insider herding that takes value of one if there is only insider sell-herding led by the largest shareholder group during the period t-12 to t-2. We apply the same procedure to the remainder variables, a major shareholder group (SMAJOR), an officer group (SOFFICER).

$SLARGEST_{t-1}$ in Columns (1) and (2) are statistically significant, with coefficients of 0.528, and 0.559, respectively. This observation suggests that the previous month's insider herding conducted by the largest shareholder group is highly likely to increase the probability of a crash. The coefficient estimates on $SLARGEST_{t-2,t-12}$ are insignificantly correlated, indicating that the frequency of insider sell-herding in the past is largely irrelevant for a crash. We also find no significant empirical relation between insider sell-herding performed by major shareholders, other officers and a crash as opposed to the largest shareholders.

Overall, our results confirm that a strong tendency of insider sell-herding by the largest shareholder group during the nearby past (month t-1) raises the probability of crashes in the event month. Therefore, these point at a clear pattern of insider herding led by the largest shareholders in the prior month.

In table 7, we show the regression results of insider buy-herding conducted by each tier on a jump. The coefficient for $BLARGEST_{t-1}$ is insignificantly negative -0.172 in Column (1) and is, again, statistically insignificant in Column (2). Indeed, the estimated coefficients on $BLARGEST_{t-2,t-12}$ are positively insignificant in both columns. In addition, we present the results of regressions in which we run *ERJUMP* and *MMJUMP* against $SLARGEST_{t-2,t-12}$ and find that the coefficients are insignificant in Columns (1) and (2). As the empirical exploration of insider buy-herding of major shareholders and other officers, they are all insignificant in the third through sixth to columns of Table 7.

If the largest shareholders trade on short-lived private information, insider sell-herding by the largest shareholders should take place a month before a crash and insider buy-herding should occur a month before a jump. Interestingly, herding patterns of the largest shareholders in the prior month of a crash are identical to those of other insiders. Consequently, our results suggest that insider-sell herding by the largest shareholder group contains robust negative information.

5. Additional analyses

In this section, we test our base regressions to reinforce the robustness. We take into account the direct relation between the numbers of net insiders (RAW) instead of previously described dummy variables.

Next, we adjust the previous period over a six month window. Finally, we divide our sample period in halves for the period before and after the Capital Market Act in Korea of 2009.

5.1 Using the ratio of the number of net insiders

To check the robustness of our findings, we first use a continuous variable, *RAW* (the ratio of net purchasers) as the independent variable for the magnitude of insider herding.

As shown in Table 8, the results are qualitatively unchanged in the additional test using *RAW*. RAW_{t-1} are negatively significant with coefficients of -0.165, -.0.274, and -0.276 (i.e., RETCRASH, ERCRASH, and MMCRASH) in crashes, respectively. However, the coefficients for $RAW_{t-2,t-12}$ in the window from t-2 to t-12 are insignificant except for *RETCRASH*. As a result, we interpret these results as suggestive that a decrease in *RAW* increases the possibility of a crash, which is consistent with the results of Table 4.

Interestingly, we find mixed results in a jump. In Table 4, the coefficient for $BHERD_{t-2,\, t-12}$ is insignificant in the far past. However, the coefficients of $RAW_{t-2,t-12}$ using *RETJUMP* and *ERJUMP* are positive and significant, 0.132, and 0.106, respectively. These results suggest that an increase in the ratio of the number of purchasers raises the likelihood of a jump. However, we find that the results of RAW_{t-1} are insignificant with the same as the results of Table 4.

Overall, this evidence is robust enough to conclude that insider sell-herding in the immediate past month (t-1) increase the likelihood of crashes, while insider buy-herding in the far past (t-2, t-12) are partially attributable to a jump. In other words, it is possible that jumps are driven by insider buy-herding in the past. However, mixed evidence from Table 4 suggests that there is a low likelihood of a jump before insider buy-herding.

5.2 Considering over a 6-month window

To mitigate concerns over potential effects of overlapping periods on the computed abnormal returns, we examine stock returns over a 6-month window. Table 9 describes the results for the relation between insider herding and a crash (or jump) over a 6-month window. The results correspond to the period analyzed in the Section 4.2. The indicator for the occurrence of insider sell-herding, $SHERD_{t-1}$ is strongly associated with a crash. For a crash, $SHERD_{t-1}$ is positively significant with a coefficient of 0.462, 0.464, and 0.449, respectively. In case of a jump, the coefficients on $BHERD_{t-1}$ are all insignificant. We find that the remaining results are also almost identical with those of longer periods as reported in Table 4 and therefore they are not reported.

For crashes, the coefficient of $SHERD_{t-6}$ is 0.091 in *RETCRASH*, whereas crash measures using *ERCRASH* and *MMCRASH*, the coefficients of SHD_{t-6} are not significant. Given the evidence described above, insider sell-herding both 6-months and 12-months are unrelated to a crash.

The coefficients on $SHERD_{t-1}$ in the immediate past are positively significant, likewise the coefficients on $SHERD_{t-2,t-6}$ are positive and insignificant in all crash regressions at conventional levels. Overall, our finding is consistent with our earlier results that insider sell-herding unlikely to raise the likelihood of a crash. On the contrary, we do not find significant correlations for $BHERD_{t-1}$ and $BHERD_{t-2,t-6}$ on a jump. This exhibits the same result as Table 5. Therefore, our robustness check confirms that insider buy-herding in the past is unlikely to raise the likelihood of jumps regardless of time frame.

5.3 Impact of changes in the Capital Market Act in Korea

We split the sample into two periods before and after the Capital Market Act in Korea of 2009. As noted earlier, the Capital Market Act may have changed the likelihood of crashes (or jumps). Table 10 and Table 11 present the regression analyses in the pre- and post- Capital Market Act periods.

For crashes, we find that the results are essentially same in both the early (2003~2008) and late (2009~2015) periods. The coefficients on $SHERD_{t-1}$ are significantly positive in both the pre- and post- Capital Market Act periods. Otherwise, $SHERD_{t-2,t-12}$ are statistically significant in both periods as shown in Table 4. In the case of insider buy-herding, the coefficients of $BHERD_{t-1}$ on all three jump measures are negative and significant before the Capital Market Act was enacted. Contrary to the pre-regulation period, insider buy-herding does not show any significant results in both immediate and far past month after the Capital Market Act was enacted. After all, the rest of findings provide conclusive evidence that the Capital Market Act does not affect our results.

Overall, insider sell-herding prior to a crash occurs before and after the Capital Market Act which confirms that insider herding especially sales contains short-term negative information on firm value.

6. Concluding remarks

In this paper, we employ the herding of corporate insiders traded on the Korea stock market. Our findings provide new insights into insider trading, private information of insider herding, and the relation between insider herding and a crash (jump). We analyze not only the impact of insider sell-herding on a crash but also the impact of insider buy-herding on a jump by examining insider trading. We also conduct additional tests finding a relatively informational advantage above others within the firm at the insider hierarchy level.

We find that insider sell-herding in the nearby month (month t-1) is associated with the high likelihood of a crash, while insider sell-herding in the far past (months t-12, t-2) is not associated with a crash. Further, we find a crash occurs in the following month when there is a presence of the largest shareholders along with insider sell-herding. Additional analysis at the insider hierarchy level shows that these results are especially robust to the largest shareholders. On the other hand, we find evidence that neither insider buy-herding nor the presence of the largest shareholders' trades contributes to a jump.

Collectively, our results are consistent with Ahren (2017) whereby they document that insiders share information. The herding behavior of corporate insiders contains robust private information, as suggested by Alldredge and Blank (2017). We provide ample evidence that insiders share bad information just before crashes. Moreover, we show a relatively informational advantage above others even within the firm insiders; especially the largest shareholders possess more valuable private information. These insights could allow us to better develop a richer understanding of insider trading and private information from a new perspective.

Appendix

Table A. Description of variables

Proxies for Insider Herding	
SHERD	Insiders' sell herding in the prior month equals 1 and 0 otherwise
BHERD	Insiders' buy herding in the prior month equals 1 and 0 otherwise
SHDINCLUDE	Insiders' sell herding including largest shareholders equals 1 and 0 otherwise
BHDINCLUDE	Insiders' buy herding including largest shareholders equals 1 and 0 otherwise
SLARGEST	Insiders' sell herding only led by the largest shareholders equals 1and 0 otherwise
BLARGEST	Insiders' buy herding only led by the largest shareholders equals 1and 0 otherwise
SMAJOR	Insiders' sell herding only led by the major shareholders equals 1 and 0 otherwise
BMAJOR	Insiders' buy herding only led by the major shareholders equals 1 and 0 otherwise
SOFFICER	Insiders' sell herding only led by the officers equals 1 and 0 otherwise
BOFFICER	Insiders' buy herding only led by the officers equals 1 and 0 otherwise
Firm characteristic variables	
CHAEBOL	A dummy variable that equals 1 if the firm belongs to a member of largest business group and 0 otherwise
PCAR	Cumulative abnormal returns over the previous 12 months
TURNOVER	Average monthly share turnover over the previous 12 months: Trading volume / shares outstanding
ASSET	Previous year-end total asset
MB	(Stock price X shares outstanding) / book value of equity
ROA	EBITDA / total asset
OWN	Previous year-end ownership of the largest shareholders
DEBT	Total debt / total asset

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Table 1. Distribution of insider herding over the sample period

This table presents the number of the crashes (RETCRASH, ERCRASH, MMCRASH), jumps (RETJUMP, ERJUMP, MMJUMP), the frequency of insider sell-herding (SHERD), and insider buy-herding (BHDERD) over our 2004 to 2015 sample period.

YEAR	N	RET CRASH	ER CRASH	MM CRASH	RET JUMP	ER JUMP	MM JUMP	SHERD	BHERD
2004	4,548	19	18	21	72	69	77	90	377
2005	5,330	51	107	101	361	271	334	207	233
2006	6,923	94	96	114	132	180	185	164	335
2007	7,748	175	204	215	364	294	319	267	367
2008	8,264	799	355	400	161	326	294	148	652
2009	9,005	86	186	172	391	367	352	427	407
2010	8,881	99	132	139	209	274	282	408	414
2011	8,881	200	164	165	252	310	306	362	523
2012	8,715	140	172	165	257	292	301	364	376
2013	7,956	84	91	94	118	166	168	278	295
2014	7,596	127	138	136	206	235	244	292	339
2015	7,597	192	227	222	377	398	398	279	336

Table 2. Summary statistics

This table presents summary statistics for the final sample. *SHERD* (BHERD) is an indicator equal to one if an insider conducted at least one insider sell(buy)-herding in the prior month and zero otherwise. *SHDINCLUDE* (BHDINCLUDE) equals one for insider sell(buy)-herding in the presence of the largest shareholders and zero otherwise. *SLARGEST* (BLARGEST) equals to one if there exists only insider herding led by the largest shareholders and zero otherwise. *SMAJOR* (BMAJOR) equals to one if there is insider sell(buy)-herding only led by major shareholder and zero otherwise. *SOFFICER* (BOFFICER) equals to one if there is insider sell(buy)-herding only conducted by other officers and zero otherwise. The definitions of the variables are provided in Table A. We winsorize all variables at the 1% and 99% levels to mitigate the impact of outliers.

	N	Mean	Median	St. Dev	Max	Min
SHERD	91,444	0.0359	0.0000	0.1861	1.0000	0.0000
BHERD	91,444	0.0509	0.0000	0.2198	1.0000	0.0000
SHDINCLUDE	91,444	0.0085	0.0000	0.0918	1.0000	0.0000
BHDINCLUDE	91,444	0.0113	0.0000	0.1057	1.0000	0.0000
SLARGEST	91,444	0.0177	0.0000	0.1316	1.0000	0.0000
BLARGEST	91,444	0.0272	0.0000	0.1628	1.0000	0.0000
SMAJOR	91,444	0.0055	0.0000	0.0737	1.0000	0.0000
BMAJOR	91,444	0.0095	0.0000	0.0969	1.0000	0.0000
SOFFICER	91,444	0.0037	0.0000	0.0603	1.0000	0.0000
BOFFICER	91,444	0.0024	0.0000	0.0485	1.0000	0.0000
CHAEBOL	91,444	0.1513	0.0000	0.3584	1.0000	0.0000
PCAR	91,444	0.0248	0.0080	0.4719	3.7186	-3.9562
TURNOVER	91,444	0.3388	0.1537	0.5660	12.3132	0.0012
ASSET(Billion)	91,444	10290.06	1449.83	36900.44	526000.00	76.33
MB	91,444	1.2733	0.9141	1.0675	8.0017	0.1115
ROA	91,444	0.0390	0.0389	0.0705	0.2936	-0.2886
OWN	91,444	0.3967	0.3887	0.1615	0.8599	0.0502
DEBT	91,444	0.9557	0.7150	0.9021	12.4664	0.0140

Table 3. Insider herding and firm characteristics

This table presents characteristics of insider sell-herding, insider buy-herding, and none. The final three columns report the difference in means between the three groups. *PCAR* and *TURNOVER* are cumulative abnormal returns and the average monthly share turnover over the previous 12 months, respectively. ln(*ASSET*) is the logarithm of the previous year-end total asset. *MB* is the previous year-end market value of equity divided by the book value of equity. *ROA* is calculated as lagged EBITDA divided by total asset. *OWN* is the previous year-end ownership of the largest shareholders and those who have special relationship with the largest shareholders. *DEBT* is defined as the previous year-end total debt divided by total asset. t-statistics are reported under each estimates in parentheses. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%.

	SHERD (a)	BHERD (b)	Non-HERD (c)	Mean Difference Test		
				(a)-(b)	(a)-(c)	(b)-(c)
PCAR	0.2108	-0.0034	0.0190	0.2142 (20..06)***	0.1918 (22.74)***	-0.0224 (-3.18)***
TURNOVER	0.3438	0.1917	0.3468	0.1521 (14.90)***	-0.0030 (-0.30)	-0.1551 (-18.22)***
ln(ASSET)	26.6332	26.3836	25.9592	0.2496 (6.58)***	0.6740 (25.52)***	0.4244 (19.11)***
MB	1.6556	1.1677	1.2641	0.4879 (19.66)***	0.3915 (20.57)***	-0.0964 (-6.06)***
ROA	0.0502	0.0494	0.0380	0.0008 (0.55)	0.0122 (9.68)***	0.0114 (10.74)***
OWN	0.3870	0.3924	0.3973	-0.0054 (1.51)	-0.0103 (-3.57)***	-0.0049 (-2.01)**
DEBT	0.9486	0.8931	0.9595	0.0555 (2.92)***	-0.0109 (-0.68)	-0.0664 (-4.90)***

Table 4. Insider herding and a crash (jump)

This table presents regression results of a crash and a jump on insider herding. $SHERD_{t-1}$ is an indicator equal to one if insider sell-herding occurred in the prior month, and zero otherwise. $SHERD_{t-2,t-12}$ is the sum of monthly insider sell-herding that takes value of one if there is at least one insider sell-herding during the period t-12 to t-2. $BHERD_{t-1}$ equals to one if insider buy-herding occurred in the prior month. $BHERD_{t-2,t-12}$ is the sum of insider trading that equals to one if insider buy-herding occurs within a certain period between t-12 and t-2. The definitions of other variables are provided in Table A. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%.

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	CRASH			JUMP		
	(1) RET	(2) ER	(3) MM	(4) RET	(5) ER	(6) MM
$SHERD_{t-1}$	0.467	0.485	0.462			
	(0.103)***	(0.103)***	(0.102)***			
$\ln(SHERD_{t-2, t-12})$	0.071	0.031	0.042			
	(0.064)	(0.066)	(0.065)			
$BHERD_{t-1}$				-0.122	-0.148	-0.170
				(0.099)	(0.096)	(0.095)*
$\ln(BHERD_{t-2, t-12})$				0.141	0.063	0.039
				(0.048)***	(0.046)	(0.046)
CHAEBOL	0.678	0.688	0.521	0.243	0.372	0.335
	(0.209)***	(0.218)***	(0.212)**	(0.181)	(0.174)**	(0.173)*
PCAR	1.206	1.424	1.425	0.021	-0.055	-0.037
	(0.057)***	(0.060)***	(0.059)***	(0.047)	(0.045)	(0.045)
TURNOVER	-0.017	-0.005	-0.018	-0.427	-0.412	-0.453
	(0.053)	(0.053)	(0.053)	(0.056)***	(0.054)***	(0.055)***
ln(ASSET)	0.025	0.225	0.172	-0.383	-0.268	-0.333
	(0.070)	(0.072)***	(0.071)**	(0.058)***	(0.055)***	(0.055)***
MB	-0.744	-0.576	-0.583	0.511	0.442	0.445
	(0.046)***	(0.044)***	(0.044)***	(0.027)***	(0.025)***	(0.025)***
ROA	-1.178	-1.866	-2.016	-3.285	-3.213	-3.210
	(0.502)**	(0.517)***	(0.506)***	(0.418)***	(0.394)***	(0.393)***
OWN	-1.411	-1.376	-1.346	1.422	1.409	1.364
	(0.331)***	(0.348)***	(0.34)***	(0.277)***	(0.267)***	(0.264)***
DEBT	0.069	0.152	0.144	0.066	0.071	0.097
	(0.043)	(0.041)***	(0.041)***	(0.038)*	(0.035)**	(0.035)***
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,444	91,444	91,444	91,444	91,444	91,444
Pseudo Adj. R^2	0.0453	0.0539	0.0532	0.0318	0.0248	0.0260

Table 5. Insider herding in the presence of the largest shareholders and a crash (jump)

This table presents the results of estimating the relation between a crash (jump) and insider herding in the presence of the largest shareholder group. $SHDINCLUDE_{t-1}$($BHDINCLUDE_{t-1}$) equals to one for insider sell(buy)-herding in the presence of the largest shareholders in the previous month and zero otherwise. $SHDINCLUDE_{t-2,t-12}$ ($BHDINCLUDE_{t-2,t-12}$) is the sum of monthly insider herding that takes value of one if there is at least one insider sell(buy)-herding in the existence of the largest shareholder group during the period t-12 to t-2. The definitions of other variables are provided in Table A. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%.

	CRASH			JUMP		
	(1) RET	(2) ER	(3) MM	(4) RET	(5) ER	(6) MM
$SHDINCLUDE_{t-1}$	0.491 (0.204)**	0.423 (0.204)**	0.383 (0.206)*			
$\ln(SHDINCLUDE_{t-2, t-12})$	-0.081 (0.123)	0.057 (0.120)	0.005 (0.120)			
$BHDINCLUDE_{t-1}$				-0.081 (0.208)	-0.287 (0.210)	-0.139 (0.197)
$\ln(BHDINCLUDE_{t-2, t-12})$				0.091 (0.095)	0.035 (0.090)	0.007 (0.090)
CHAEBOL	0.682 (0.209)***	0.685 (0.217)***	0.525 (0.212)**	0.246 (0.180)	0.372 (0.173)**	0.333 (0.172)*
PCAR	1.227 (0.057)***	1.444 (0.060)***	1.446 (0.059)***	0.023 (0.047)	-0.054 (0.045)	-0.035 (0.045)
TURNOVER	-0.007 (0.052)	-0.005 (0.052)	-0.015 (0.052)	-0.436 (0.056)***	-0.415 (0.054)***	-0.454 (0.055)***
ln(ASSET)	0.045 (0.069)	0.236 (0.072)***	0.185 (0.071)***	-0.388 (0.058)***	-0.268 (0.055)***	-0.333 (0.055)***
MB	-0.740 (0.046)***	-0.574 (0.044)***	-0.581 (0.043)***	0.509 (0.027)***	0.441 (0.025)***	0.445 (0.025)***
ROA	-1.198 (0.503)**	-1.887 (0.517)***	-2.033 (0.506)***	-3.275 (0.418)***	-3.213 (0.394)***	-3.213 (0.393)***
OWN	-1.410 (0.331)***	-1.362 (0.348)***	-1.343 (0.340)***	1.426 (0.277)***	1.412 (0.267)***	1.370 (0.264)***
DEBT	0.068 (0.043)	0.152 (0.041)***	0.144 (0.041)***	0.067 (0.038)*	0.071 (0.035)**	0.098 (0.035)***
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,444	91,444	91,444	91,444	91,444	91,444
Pseudo Adj. R^2	0.0442	0.0527	0.0520	0.0314	0.0247	0.0258

Table 6. Insider sell-herding and a crash at the insider hierarchy level

This table presents the link between a crash and Insider sell-herding at the insider group level. $SLARGEST_{t-1}$ is indicators equal to one if there is only insider sell-herding performed by the largest shareholders in the prior month, and zero otherwise. $SLARGEST_{t-2,t-12}$ is the sum of monthly insider sell-herding that takes value of one if there is only insider sell-herding led by the largest shareholders during the period t-12 to t-2. $SMAJOR_{t-1}$, $SMAJOR_{t-2,t-12}$, $SOFFICER_{t-1}$, $SOFFICER_{t-2,t-12}$ are applied in the same procedure. The definitions of other variables are provided in Table A. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%

	(1) ER	(2) MM	(3) ER	(4) MM	(5) ER	(6) MM
$SLARGEST_{t-1}$	0.528 (0.136)***	0.559 (0.133)***				
$\ln(SLARGEST_{t-2\ t-12})$	0.072 (0.090)	0.091 (0.089)				
$SMAJOR_{t-1}$			0.429 (0.281)	0.271 (0.290)		
$\ln(SMAJOR_{t-2\ t-12})$			0.127 (0.153)	0.196 (0.147)		
$SOFFICER_{t-1}$					0.062 (0.377)	-0.066 (0.398)
$\ln(SOFFICER_{t-2\ t-12})$					-0.373 (0.207)*	-0.401 (0.211)*
CHAEBOL	0.697 (0.217)***	0.534 (0.211)**	0.683 (0.217)***	0.517 (0.212)**	0.690 (0.217)***	0.526 (0.211)**
PCAR	1.429 (0.060)***	1.427 (0.059)***	1.449 (0.060)***	1.449 (0.059)***	1.452 (0.060)***	1.452 (0.059)***
TURNOVER	-0.011 (0.053)	-0.024 (0.053)	-0.003 (0.052)	-0.015 (0.052)	0.000 (0.052)	-0.012 (0.052)
ln(ASSET)	0.233 (0.072)***	0.179 (0.071)**	0.242 (0.072)***	0.188 (0.071)***	0.253 (0.072)***	0.199 (0.071)***
MB	-0.575 (0.044)***	-0.583 (0.044)***	-0.573 (0.044)***	-0.580 (0.043)***	-0.572 (0.044)***	-0.579 (0.043)***
ROA	-1.869 (0.517)***	-2.012 (0.506)***	-1.905 (0.517)***	-2.051 (0.506)***	-1.904 (0.517)***	-2.045 (0.506)***
OWN	-1.401 (0.348)***	-1.378 (0.340)***	-1.354 (0.348)***	-1.330 (0.340)***	-1.379 (0.348)***	-1.359 (0.340)***
DEBT	0.152 (0.041)***	0.144 (0.041)***	0.151 (0.041)***	0.142 (0.041)***	0.150 (0.041)***	0.142 (0.041)***
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,444	91,444	91,444	91,444	91,444	91,444
Pseudo Adj. R^2	0.0534	0.0530	0.0526	0.0520	0.0526	0.0521

Table 7. Insider buy-herding and a jump at insider hierarchy level

This table presents the link between a jump and insider buy-herding at the insider group level. $BLARGEST_{t\text{-}1}$ is an indicator equal to one if there is only insider buy-herding performed by the largest shareholders in the prior month, and zero otherwise. $BLARGEST_{t\text{-}2,t\text{-}12}$ is the sum of monthly (clustered) insider herding that takes value of one if there is only insider buy-herding led by the largest shareholders during the period t-12 to t-2. $BMAJOR_{t\text{-}1}$, $BMAJOR_{t\text{-}2,t\text{-}12}$, $BOFFICER_{t\text{-}1}$, $BOFFICER_{t\text{-}2,t\text{-}12}$ are applied in the same procedure. The definitions of other variables are provided in Table A. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%.

	(1) ER	(2) MM	(3) ER	(4) MM	(5) ER	(6) MM
$BLARGEST_{t\text{-}1}$	-0.172	-0.184				
	(0.127)	(0.125)				
ln($BLARGEST_{t\text{-}2\ t\text{-}12}$)	0.078	0.079				
	(0.057)	(0.057)				
$BMAJOR_{t\text{-}1}$			-0.036	-0.231		
			(0.212)	(0.227)		
ln($BMAJOR_{t\text{-}2\ t\text{-}12}$)			0.050	0.032		
			(0.095)	(0.095)		
$BOFFICER_{t\text{-}1}$					0.408	0.164
					(0.402)	(0.431)
ln($BOFFICER_{t\text{-}2\ t\text{-}12}$)					-0.167	-0.256
					(0.248)	(0.247)
CHAEBOL	0.373	0.335	0.368	0.334	0.369	0.330
	(0.174)**	(0.173)*	(0.174)**	(0.173)*	(0.173)**	(0.173)*
PCAR	-0.054	-0.036	-0.054	-0.035	-0.053	-0.035
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
TURNOVER	-0.413	-0.451	-0.415	-0.454	-0.416	-0.454
	(0.054)***	(0.055)***	(0.054)***	(0.055)***	(0.054)***	(0.055)***
ln(ASSET)	-0.266	-0.331	-0.268	-0.333	-0.267	-0.330
	(0.056)***	(0.055)***	(0.055)***	(0.055)***	(0.056)***	(0.055)***
MB	0.442	0.446	0.441	0.445	0.441	0.445
	(0.025)***	(0.025)***	(0.025)***	(0.025)***	(0.025)***	(0.025)***
ROA	-3.217	-3.216	-3.212	-3.212	-3.213	-3.217
	(0.394)***	(0.394)***	(0.394)***	(0.393)***	(0.394)***	(0.393)***
OWN	1.403	1.360	1.419	1.370	1.413	1.372
	(0.267)***	(0.264)***	(0.267)***	(0.264)***	(0.267)***	(0.264)***
DEBT	0.071	0.097	0.071	0.098	0.071	0.098
	(0.035)**	(0.035)***	(0.035)**	(0.035)***	(0.035)**	(0.035)***
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,444	1,444	1,444	1,444	1,444	1,444
Pseudo Adj. R^2	0.0248	0.0260	0.0246	0.0259	0.0247	0.0259

Table 8. Insider herding using RAW and a crash (jump)

This table explores the link between *RAW* and a crash (jump). *RAW* is equal to the ratio of net purchasers for each month as calculated in Equation (2). RAW_{t-1} is the value of the immediate past (month t-1) and $RAW_{t-2,t-12}$ is the mean value for the far past (months t-12 to t-2). The definitions of other variables are provided in Table A. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%.

	CRASH			JUMP		
	(1) RET	(2) ER	(3) MM	(4) RET	(5) ER	(6) MM
RAW_{t-1}	-0.165 (0.086)*	-0.274 (0.088)***	-0.267 (0.087)***	-0.122 (0.076)	-0.095 (0.072)	-0.128 (0.071)*
$RAW_{t-2,\ t-12}$	-0.099 (0.047)**	-0.020 (0.049)	-0.046 (0.049)	0.132 (0.041)***	0.106 (0.039)***	0.058 (0.038)
CHAEBOL	0.679 (0.208)***	0.686 (0.217)***	0.528 (0.211)**	0.243 (0.180)	0.368 (0.174)**	0.332 (0.173)*
PCAR	1.218 (0.057)***	1.436 (0.06)***	1.435 (0.059)***	0.022 (0.048)	-0.055 (0.045)	-0.039 (0.045)
TURNOVER	-0.031 (0.054)	-0.011 (0.053)	-0.027 (0.053)	-0.407 (0.057)***	-0.390 (0.054)***	-0.441 (0.056)***
ln(ASSET)	0.029 (0.069)	0.232 (0.072)***	0.176 (0.071)**	-0.376 (0.058)***	-0.260 (0.056)***	-0.330 (0.055)***
MB	-0.745 (0.046)***	-0.576 (0.044)***	-0.584 (0.044)***	0.511 (0.027)***	0.442 (0.025)***	0.445 (0.025)***
ROA	-1.187 (0.502)**	-1.872 (0.517)***	-2.015 (0.506)***	-3.265 (0.418)***	-3.201 (0.394)**	-3.199 (0.393)***
OWN	-1.425 (0.331)***	-1.399 (0.348)***	-1.377 (0.34)***	1.421 (0.277)***	1.415 (0.267)***	1.366 (0.264)***
DEBT	0.069 (0.043)	0.151 (0.041)***	0.143 (0.041)***	0.067 (0.038)*	0.071 (0.035)**	0.097 (0.035)***
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,444	91,444	91,444	91,444	91,444	91,444
Pseudo Adj R^2	0.0444	0.0531	0.0526	0.0320	0.0251	0.0261

Table 9. Insider herding and a crash (jump) over a 6-month window

This table explores the link between a crash and a jump on insider herding over a 6-month window. $SHDINCLUDE_{t-1}$ ($\mathrm{BHDINCLUDE}_{t-1}$) equals one for insider sell(buy)-herding in the presence of the largest shareholders in the previous month and zero otherwise. $SHDINCLUDE_{t-2,t-12}$ ($\mathrm{BHDINCLUDE}_{t-2,t-12}$) is the sum of monthly insider herding that takes value of one if there is at least one insider sell(buy)-herding in the existence of the largest shareholder group during the period t-12 to t-2. The definitions of other variables are provided in Table A. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%.

	CRASH			JUMP		
	(1) RET	(2) ER	(3) MM	(4) RET	(5) ER	(6) MM
SHERD_{t-1}	0.462 (0.103)***	0.464 (0.103)***	0.449 (0.103)***			
$\ln(\mathrm{SHERD}_{t-2,\ t-6})$	0.091 (0.083)**	0.136 (0.082)	0.110 (0.082)			
BHERD_{t-1}				-0.112 (0.100)	-0.141 (0.096)	-0.163 (0.096)*
$\ln(\mathrm{BHERD}_{t-2,\ t-6})$				0.100 (0.064)	0.037 (0.062)	0.014 (0.061)
CHAEBOL	0.678 (0.210)***	0.689 (0.218)***	0.520 (0.212)**	0.245 (0.180)	0.372 (0.173)**	0.335 (0.172)*
PCAR	1.204 (0.057)***	1.417 (0.060)***	1.420 (0.059)***	0.024 (0.047)	-0.054 (0.045)	-0.036 (0.045)
TURNOVER	-0.012 (0.053)	-0.008 (0.052)	-0.017 (0.052)	-0.434 (0.056)***	-0.415 (0.054)***	-0.455 (0.055)***
ln(ASSET)	0.027 (0.069)	0.220 (0.072)***	0.170 (0.071)***	-0.386 (0.058)***	-0.268 (0.055)***	-0.334 (0.055)***
MB	-0.744 (0.046)***	-0.577 (0.044)***	-0.584 (0.044)***	0.510 (0.027)***	0.441 (0.025)***	0.445 (0.025)***
ROA	-1.173 (0.502)**	-1.865 (0.517)***	-2.015 (0.506)***	-3.284 (0.418)***	-3.212 (0.394)**	-3.209 (0.393)***
OWN	-1.416 (0.331)***	-1.378 (0.348)***	-1.348 (0.34)***	1.427 (0.277)***	1.411 (0.267)***	1.364 (0.264)***
DEBT	0.069 (0.043)	0.152 (0.041)***	0.144 (0.041)***	0.067 (0.038)*	0.071 (0.035)**	0.097 (0.035)***
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,444	91,444	91,444	91,444	91,444	91,444
Pseudo Adj R^2	0.0453	0.0541	0.0533	0.0315	0.0247	0.0260

Table 10. Insider herding and a crash (jump) in the pre period of the Capital Market Act

This table explores the link between a crash and a jump on insider herding in the pre-regulation period (2003-2008). $SHDINCLUDE_{t-1}$ ($BHDINCLUDE_{t-1}$) equals one for insider sell(buy)-herding in the presence of the largest shareholders in the previous month and zero otherwise. $SHDINCLUDE_{t-2,t-12}$ ($BHDINCLUDE_{t-2,t-12}$) is the sum of monthly insider herding that takes value of one if there is at least one insider sell(buy)-herding in the existence of the largest shareholder group during the period t-12 to t-2. The definitions of other variables are provided in Table A. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%.

	CRASH			JUMP		
	(1) RET	(2) ER	(3) MM	(4) RET	(5) ER	(6) MM
$SHERD_{t-1}$	0.403 (0.152)***	0.509 (0.151)***	0.362 (0.156)**			
$\ln(SHERD_{t-2,\ t-12})$	-0.088 (0.104)	-0.104 (0.112)	-0.118 (0.111)			
$BHERD_{t-1}$				-0.317 (0.139)**	-0.318 (0.140)**	-0.361 (0.140)***
$\ln(BHERD_{t-2,\ t-12})$				0.191 (0.069)***	0.075 (0.069)	0.082 (0.068)
CHAEBOL	0.970 (0.342)	0.917 (0.368)**	1.149 (0.403)***	0.660 (0.342)*	0.588 (0.311)*	0.573 (0.330)*
PCAR	1.256 (0.080)***	1.702 (0.091)***	1.710 (0.089)***	-0.038 (0.070)	-0.179 (0.068)**	-0.153 (0.068)**
TURNOVER	-0.405 (0.107)***	-0.272 (0.104)***	-0.281 (0.100)***	-0.691 (0.097)***	-0.677 (0.095)***	-0.689 (0.094)***
ln(ASSET)	0.992 (0.139)***	0.762 (0.150)***	0.791 (0.148)***	-0.340 (0.131)***	-0.169 (0.123)	-0.327 (0.122)***
MB	-1.106 (0.079)***	-0.637 (0.075)***	-0.690 (0.075)***	0.743 (0.051)***	0.555 (0.044)***	0.548 (0.046)***
ROA	-3.468 (0.837)***	-2.090 (0.881)**	-2.245 (0.846)***	-3.484 (0.705)***	-3.455 (0.660)***	-3.280 (0.661)***
OWN	-2.205 (0.541)***	-2.060 (0.600)***	-2.108 (0.580)***	1.315 (0.491)***	0.778 (0.469)*	0.770 (0.465)*
DEBT	-0.143 (0.085)*	0.155 (0.076)**	0.090 (0.075)***	-0.092 (0.077)	-0.052 (0.071)	0.003 (0.070)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,444	91,444	91,444	91,444	91,444	91,444
Pseudo Adj R^2	0.0696	0.0735	0.0742	0.0419	0.0288	0.0287

Table 11. Insider herding and a crash (jump) in the post period of the Capital Market Act

This table explores the link between a crash and a jump on insider herding in the post-regulation period (2009-2015). *SHDINCLUDE*$_{t-1}$(BHDINCLUDE$_{t-1}$) equals one for insider sell(buy)-herding in the presence of the largest shareholders in the previous month and zero otherwise. *SHDINCLUDE*$_{t-2,t-12}$ (BHDINCLUDE$_{t-2,t-12}$) is the sum of monthly insider herding that takes value of one if there is at least one insider sell(buy)-herding in the existence of the largest shareholder group during the period t-12 to t-2. The definitions of other variables are provided in Table A. *, **, and *** respectively indicate significance levels at 10%, 5%, and 1%.

	CRASH			JUMP		
	(1) RET	(2) ER	(3) MM	(4) RET	(5) ER	(6) MM
SHERD$_{t-1}$	0.426 (0.147)***	0.354 (0.150)**	0.407 (0.141)***			
ln(SHERD$_{t-2, t-12}$)	0.145 (0.102)	0.135 (0.099)	0.107 (0.097)			
BHERD$_{t-1}$				0.079 (0.145)	-0.046 (0.134)	-0.029 (0.132)
ln(BHERD$_{t-2, t-12}$)				0.054 (0.081)	-0.007 (0.073)	-0.053 (0.073)
CHAEBOL	0.715 (0.518)	0.113 (0.432)	-0.025 (0.416)	0.334 (0.348)	0.299 (0.313)	0.376 (0.301)
PCAR	1.592 (0.101)***	1.634 (0.098)***	1.664 (0.098)***	-0.216 (0.073)***	-0.235 (0.069)***	-0.209 (0.068)***
TURNOVER	0.197 (0.098)*	0.143 (0.092)	0.161 (0.094)**	-0.451 (0.088)***	-0.474 (0.084)***	-0.535 (0.086)***
ln(ASSET)	1.229 (0.232)***	1.580 (0.217)***	1.278 (0.211)***	0.112 (0.150)	-0.148 (0.140)	-0.186 (0.138)
MB	-0.602 (0.074)***	-0.615 (0.069)***	-0.588 (0.068)***	0.511 (0.040)***	0.475 (0.037)***	0.486 (0.037)***
ROA	0.425 (1.034)	-1.648 (0.962)*	-1.619 (0.975)*	-3.254 (0.735)***	-2.599 (0.685)***	-2.901 (0.681)***
OWN	-1.054 (0.825)	-1.971 (0.750)***	-1.669 (0.737)**	2.583 (0.559)***	2.255 (0.533)***	2.271 (0.530)***
DEBT	0.280 (0.091)***	0.267 (0.085)***	0.240 (0.084)***	0.082 (0.071)	0.137 (0.063)**	0.119 (0.063)*
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,444	91,444	91,444	91,444	91,444	91,444
Pseudo Adj R^2	0.0689	0.0715	0.0705	0.0293	0.0258	0.0274