경영학석사 학위논문

Financial Reporting Opacity, R^2, and Crash Risk in the Korean Market

한국 시장에서 회계적 불투명성, R^2, 그리고 주가 급락 위험과의 관계

2017년 2월

서울대학교 대학원

경영학과 재무금융전공

전 세 은

Abstract

I examine the relation between financial reporting opacity and R^2 as well as the relation between opacity and the likelihood of experiencing stock price crash. Following Hutton et al. (2009), I conduct firm-level study for firms listed in Korea Composite Stock Price Index (KOSPI) from 1995 to 2015. Using discretionary accruals as a proxy for reporting opacity, I find positive relation between opacity and crash risk. Moreover, through investigation of outside monitoring effect on crash risk, I conclude that firms with high institutional investors' trading ratio are less subject to crash risk. I also test whether the adoption of K-IFRS has any effect on the relation between opacity and R^2 and the relation between opacity and crash risk. Through regression analysis, I conclude that market-wide accounting transparency improved after the adoption of K-IFRS in 2011.

주요어 : financial reporting opacity, stock returns, stock price crash, R^2
학 번 : 2015-20661

Table of Contents

Tables

1 Introduction

Roll (1988) finds that broad economic and industry influences, and specific news events have relatively small explanatory power for stock prices by examining R^2s of Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT). Lower R^2 means that firm-specific information drives future stock prices, whereas higher R^2 implies that public information in the market explains large portion of future stock prices.

Previous literatures have shown that R^2 is lower when firm-specific information is embedded in stock prices through industry- and country-level analyses. Dunrev et al. (2003) find that firms and industries with lower R^2 have stock prices that have better information about future earnings. Also, Morck et al. (2000) show that stock comovement is higher in poor countries than in rich countries, and that higher firm-specific return variation is related to strong property rights in developed countries.

After Sloan (1996) finds that accruals anomaly exists, there have been numerous studies regarding earnings management and accounting opacity. According to Bhattacharya et al. (2003) and Leuz et al. (2003), the magnitude of earnings opacity and earnings management is relatively high in South Korea when compared to other countries.

Jin and Myers (2006) and Hutton et al. (2009) show that firms whose financial reports are opaque have higher R^2, and they are more subject to

stock price crashes both in country- and firm-level. When a firm experiences bad news, managers have incentives to hide the bad news privately. However, it is impossible to keep the bad news for themselves forever. Thus, at some point, the bad news have to be released, and this increases the possibility of stock price crashes.

In this paper, I would like to examine both the relationship between R^2 and earnings opacity, and the relationship between crash risk and earnings opacity in the Korean stock market. Earnings opacity is measured as the moving average of discretionary accruals. Lim et al. (2013) and Lee et al. (2014) studied the relationship between opacity and crash risk in the Korean market, but they have not examined whether firms with opaque financial statements have high R^2. Therefore, I would like to examine whether the two relations exist in the Korean market. Moreover, I would further study the relations after K-IFRS were mandatorily adopted in Korea in 2011.

2 Hypothesis Development

In this study, I would like to test three main hypotheses. The first two hypotheses follow Jin and Myers (2006) and Hutton et al. (2009). Firms with more opaque financial statements reveal less firm-specific information to the market. As not enough firm-specific information is released, stock prices of such firms cannot fully reflect firm-specific information; rather,

market returns better explain stock price movements. Thus, the first hypothesis is that firms with opaque financial statements have higher R^2.

[Hypothesis 1] Firms with more opaque financial statements have higher R^2.

Even if managers withdraw bad news or manage earnings with discretionary accruals, bad news will have to be released or the accruals have to be reversed at some point. If so, there is high possibility that the firm will experience stock price crash. Many researchers have investigated the topic of crash risk. Jin and Myers (2006) show that at a country-level, there is a positive relation between opacity and crash risk. Following their research, Hutton et al. (2009) devise a simpler firm-level analysis model to measure financial reporting opacity and crash risk and find that a positive relation between opacity and crash risk exists in the firm level as well. The second hypothesis of this study is that firms with more opaque financial statements have higher likelihood of experiencing stock price crashes.

[Hypothesis 2] Firm with more opaque financial statements have higher likelihood of experiencing stock price crashes

Kim et al. (2011) find that tax avoidance which is used as a proxy of a firm's activity of hoarding bad news is positively related with firm stock

price crash risk. They also find that when outside monitoring such as institutional ownership, analyst coverage, and takeover threat is high, the relation between tax avoidance and crash risk attenuates. Lim et al. (2013) examine whether outside monitoring has any effect on opacity and crash risk and find that the crash risk of firms with large size, high analyst coverage, government regulation and high outside monitoring is less sensitive to opacity. Lee et al. (2014) also study the relation of opacity and crash risk in Korean market and conclude that monitoring by institutional investors enhances the quality of discretionary accruals. In this study, I examine whether outside monitoring, which is measured by trading of institutional and foreign investors, and whether a firm is defined as '*Chaebol'* or not. I hypothesize that when there is high external monitoring, then it is hard for a firm to hide firm-specific information, and thus the firm will experience less stock price crash.

[Hypothesis 3] Firms with high outside monitoring will experience less crashes than firms with low outside monitoring

Starting 2011, Korea adopted K-IFRS (Korea-International Financial Reporting Standards). One of the purposes of the adoption of the accounting standards is to improve accounting transparency. Despite the purpose of improving reporting quality, there are concerns that earnings quality would decrease due to increased management discretion regarding earnings under

the new standards. Nevertheless, Yoo et al. (2015) show that the adoption of K-IFRS decreased discretionary accruals and real earnings management. I hypothesize that after 2011, the market-wide accounting transparency improved by examining how the relation between opacity and R^2 and the relation between opacity and crash risk differ before and after the adoption of the new international accounting standards.

[Hypothesis 4] After the mandatory adoption of K-IFRS in 2011, the market-wide accounting transparency improved

3 Data and Research Methodology

3.1 Sample Data

The sample includes non-financial firms in Korea listed in Korea Composite Stock Price Index (KOSPI) which have weekly stock data and financial reporting data from 1995 to 2015. Weekly stock data and annual accounting data are collected from DataGuide 5.0. The weekly stock returns are assigned to each firm's year. For each year, I exclude firms with less than 20 weeks of stock return data. Also, firms which have one or more missing values for calculating three-year average of discretionary accruals and control variables are excluded. The final sample includes 9,652 firm

years from 1999 to 2015.

[Insert Table 1 here]

Panel A of Table 1 presents the number of firm years for each category of Korean Standard Industrial Classification (KSIC). The industries included in the sample are Manufacturing, Construction, Wholesale and Retail Trade, Transportation, Information and Communications, and Professional, Scientific and Technical Activities. Manufacturing industry accounts for more than 70% of the whole sample. Panel B of Table 1 shows the number of observations for each year. The number of observations per year is relatively constant with average observation of approximately 567 firm years per year.

3.2 Variable Definitions

A. Opacity of Financial Statements Measure

A firm's net income consists of operating cash flows and accruals. The operating cash flows are objective numbers which cannot be manipulated, whereas accruals are subjective numbers and thus subject to manipulation. Previous literatures have used a firm's accruals to measure a firm's accounting opacity. However, under accrual accounting, some levels of accruals are necessary and unavoidable. Thus, following Hutton et al.

(2009), I employ only discretionary accruals (not normal accruals) to measure opacity of financial statements using the modified Jones model (Dechow, Sloan, and Sweeney, 1995).

The process of calculating discretionary accruals for a firm is basically a two-step procedure. First, I run a cross-sectional regression of equation (1) for each year for each KSIC industry. For each year, if the observations for an industry is less than 20, then the firms in the industry are excluded for that year.

$$\frac{Accruals_{jt}}{Assets_{jt-1}} = \alpha\left(\frac{1}{Assets_{jt-1}}\right) + \beta_1\left(\frac{\Delta Sales_{jt}}{Assets_{jt-1}}\right) + \beta_2\left(\frac{PPE_{jt}}{Assets_{jt-1}}\right) + \varepsilon_{j,t} \qquad (1)$$

where $Accruals_{jt}$ denotes total accruals for firm *j* in year *t*, calculated by subtracting operating cash flows from net income, $Assets_{jt-1}$ denotes total assets for firm *j* at year *t-1*, $\Delta Sales_{jt}$ denotes change in sales for firm *j* in year *t*, and PPE_{jt} denotes Property, Plant, and Equipment for firm *j* in year *t*.

The second step is to calculate discretionary accruals using parameter estimates from equation (1). For each industry year, $\hat{\alpha}$, $\hat{\beta}_1$, and $\hat{\beta}_2$ are estimated. With these estimates, discretionary accruals are calculated following equation (2).

$$DA_{jt} = \frac{Accruals_{jt}}{Assets_{jt-1}} - \left(\hat{\alpha}\left(\frac{1}{Assets_{jt-1}}\right) + \hat{\beta}_1\left(\frac{\Delta Sales_{jt} - \Delta Receivables_{jt}}{Assets_{jt-1}}\right) + \hat{\beta}_2\left(\frac{PPE_{jt}}{Assets_{jt-1}}\right)\right) \quad (2)$$

where DA_{jt} denotes discretionary accruals for firm *j* in year *t* and $\Delta Receivables_{jt}$ denotes change in receivables for firm *j* in year *t*.

Following Hutton et al. (2009), I constructed a key variable "*OPAQUE*" measuring a firm's financial reporting opacity through equation (3). The opacity measure is a three-year moving average of absolute values of discretionary accruals from equation (2).

$$OPQAUE = AbsV(DA_{t-3}) + AbsV(DA_{t-2}) + AbsV(DA_{t-1}) \quad (3)$$

The reason for using three-year moving average of accruals is to measure how consistently firms report opaque financial statements. If a firm reported a large amount of discretionary accruals for the past three years, then the firm has a high possibility of managing earnings. Thus, the variable *OPAQUE* is used as a key variable in the following analyses in the study.

B. R^2 Measure

R^2 is to measure how well the market return explains stock prices. I used weekly stock and market returns. Following Hutton et al. (2009) and Kim et al. (2011), R^2 and firm-specific returns are measured using the expanded index model regression.

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-2} + \beta_{2,j} r_{m,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{m,t+1} + \beta_{5,j} r_{m,t+2} + \epsilon_{j,t} \quad (4)$$

where $r_{j,t}$ denotes weekly return of stock j on week t and $r_{m,t}$ denotes KOSPI weekly return on week t.

The regression using equation (4) is run for each firm year, and R^2 from the regression is used as the measure of how stock prices commove with the market index. For the regression analyses, a variable *IDIOSYN* is constructed as a substitute for R^2. *IDIOSYN* is calculated as equation (5). Weekly Residuals from equation (4) are used to measure *Firm-specific Weekly Return* which is calculated as $\log(1 + \epsilon_{j,t})$.

$$IDIOSYN = ln\left(\frac{1-R^2}{R^2}\right) \quad (5)$$

According to the hypotheses mentioned in Section 2, I expect that *OPAQUE* is positively correlated with R^2, and negatively correlated with *IDIOSYN* because R^2 and *IDIOSYN* retain the same information but move in the opposite direction.

C. Crash/Jump Measure

Stock price crashes and jumps are measured using residuals from equation (4). More specifically, the mean and standard deviation of *Firm-specific Weekly Returns* for each firm year are calculated. Following Hutton et al. (2009), if a *Firm-specific Weekly Return* falls below 3.09 standard

deviations from its mean, then the firm experiences a stock price crash for that week. Also, if a *Firm-specific Weekly Return* rises above 3.09 standard deviations from the mean, then the firm experiences a stock price jump for that week. If a firm experiences one or more crashes for a year, then CRASH variable is 1 and 0 otherwise. If a firm experiences one or more jumps for a year, then JUMP variable is 1 and 0 otherwise.

[Insert Table 2 here]

[Insert Table 3 here]

Table 2 presents the number of weeks that experience crash and the percentage of crash weeks in the total weeks for a year. The average percentage of experiencing weekly stock price crash is 0.2383% and the crash percentage is highest in 2001. Table 3 presents number of weeks that experience jump and the percentage of jump weeks in the total weeks for a year. Jump percentage is highest in 2002 and the average jump percentage is 0.7865%.

D. Control Variables

Control variables include generally used firm characteristics that explain stock returns. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1}

denotes market value of equity divided by book value of equity in year *t-1*. *SKEW* and *KURT* are skewness and kurtosis of *Firm-specific Weekly Returns* respectively.

[Insert Table 4 here]

Table 4 presents descriptive statistics and correlation matrix of key variables used in the regression analyses. Panel A of Table 4 shows number of observations, mean, standard deviation, 1st quarter and 3rd quarter values of each variable. Panel B of Table 4 reports Pearson correlation coefficients and p-values. As expected, *OPAQUE* has a significant negative correlation with *IDIOSYN* and a significant positive correlation with *CRASH*. $SIZE_{t-1}$ is negatively correlated with *IDIOSYN* because if a firm's market capitalization is large, then the firm's stock price will account for larger portion of the market index than firms with smaller size. All independent variables used in the regression analyses have relatively small correlation coefficient, and thus I concluded that the variables can be used in the same regression model altogether.

3.3 Research Methodology

For each hypothesis, I run pooled regression as well as panel regressions to account for errors in standard errors. To investigate the

relation between financial reporting opacity and R^2, cross-sectional ordinary least square (OLS) regression and panel regression that clusters standard errors by firm and year are used. The dependent variable is *IDIOSYN*, which is used as a substitute variable for R^2, and independent variables include *OPAQUE* and other control variables.

To investigate the relation between financial reporting opacity and crash(jump) risk, pooled logit regression and panel logit regression that clusters standard errors by firm and year are used. The dependent variable is *CRASH(JUMP)*, and independent variables include *OPAQUE* and other control variables.

To test hypothesis 3, which is to investigate whether firms with outside monitoring have lower likelihood of experiencing stock price crashes, I construct three variables: dummy variable for '*Chaebol*,' trading of foreign traders, and trading of institutional traders. I run logit and panel logit regressions with the three outside monitoring variables included as independent variables.

Lastly, to test whether the adoption of K-IFRS increased the market-wide transparency of financial statements, I construct *IFRS dummy*, which is 1 for year 2011 and after and 0 otherwise. Also, interaction variable of *IFRS* and *OPAQUE* is included as an independent variable.

4 Empirical Results

4.1 Opacity and R^2

[Insert Table 5 here]

This section presents empirical results of testing the relation between opacity and R^2. More specifically, variable *IDIOSYN* is used instead of R^2. Table 5 presents firm characteristics for each group sorted by opacity and size. I sort the sample into three opacity groups (1=low opacity, 3=high opacity) and five size groups (1=small size, 5=large size). Each breakpoint is sorted independently. Panel A of Table 5 presents the number of firm years in each group. The whole sample has 9,652 firm years from 1999 to 2015, and the number of firm years per group differs from 487 to 782. In Panel B of Table 5, I examine how the variable *OPAQUE* differs for each group. Except for opacity group (3), there is a general trend of decreasing opacity as size increases, but the trend is not a monotonic decrease. Panel C of Table 5 presents how the variable *IDIOSYN* differs for each group. According to Hypothesis 1, R^2 should be higher for firms with higher opacity; in other words, *IDIOSYN* should be lower as opacity increases. The result shows that for Size groups (3), (4), and (5), *IDIOSYN* generally decreases with opacity and the differences of *IDIOSYN* between Opacity

group (3) and (1) are statistically significant.

[Insert Table 6 here]

For the main empirical analysis, I use regression models to examine whether firms with opaque financial statements have high R^2. Table 6 presents results of the regression analysis. The regression models are as follows:

[Model 1] $IDIOSYN_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \epsilon_{j,t}$

[Model 2]
$IDIOSYN_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \beta_2 SIZE_{j,t-1} + \beta_3 MTB_{j,t-1} + \beta_4 LEV_{j,t-1} + \beta_5 ROE_{j,t} + \epsilon_{j,t}$

[Model 3]
$IDIOSYN_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \beta_2 SIZE_{j,t-1} + \beta_3 MTB_{j,t-1} + \beta_4 LEV_{j,t-1} + \beta_5 ROE_{j,t} + \beta_6 SKEW + \beta_7 KURT + \epsilon_{j,t}$

First, I run ordinary least square regression of *IDIOSYN* on *OPAQUE*. Without control variables, the coefficient of *OPAQUE* is negative and highly significant. As expected in Hypothesis 1, there is a positive relation between opacity and R^2.

In order to examine whether the relation exists after controlling for firm characteristics that are generally known to explain variation of stock

returns, I run ordinary least square regression of *IDIOSYN* on *OPAQUE* and other control variables. The control variables include firm size, market-to-ratio, leverage, and return on equity. The result shows that after controlling for firm characteristics, the relation between opacity and R^2 disappears.

Model 2 of Table 6 shows that firm size is positively related to R^2. This is a reasonable result because larger firms account for larger portion of the market index, and thus their stock returns should have higher R^2. Market-to-book ratio has significant negative relation with R^2. Also, leverage is positively related to R^2. This can be explained that firms with large leverage are more subject to macroeconomic shock and fluctuations in the market.

Following Jin and Myers (2006) and Hutton et al. (2009), I also include skewness and kurtosis of *Firm-specific Weekly Returns* to control for variations of stock returns. Both skewness and kurtosis are positively correlated with *IDIOSYN*. Even after controlling for skewness and kurtosis, the significance of firm size, market-to-book ratio, and leverage remains.

In the last column of Table 6, I run panel regression to cluster standard errors by firm and year. The significance of firm size and market-to-book ratio remains, but leverage is no longer significantly related with R^2.

4.2 Earnings Opacity and Crash/Jump Risk

[Insert Table 7 here]

As in Table 5, I sort the sample into three opacity groups and five size groups. In Table 7, I examine whether crash and jump probabilities differ for each group. According to Hypothesis 2 and Hutton et al. (2009), crash probability should increase with opacity and jump probability should not have any apparent relation with opacity.

In Panel A of Table 7, average crash probability per group, differences of the mean from Opacity group (3) to (1), and t-Statistics of the differences are presented. For all size groups, crash probability for Opacity group (3) is higher than Opacity group (1). For Size group (5), the difference of crash probability from Opacity group (3) to (1) is statistically significant.

Panel B of Table 7 presents average jump probability per group, differences of the mean from Opacity group (3) to (1), and t-Statistics of the differences. There is not a general trend in the jump probabilities with opacity. For Size groups (1), (2), and (5), the differences of jump probability from Opacity group (3) to (1) are negative, whereas for Size groups (3) and (4), the difference is positive. Thus, it is hard to conclude that there is a meaningful relation between opacity and the likelihood of stock price jumps.

[Insert Table 8 here]

In Table 8, I run logit and panel logit regression to investigate the

relation between opacity and crash or jump risk. I include firm size, market-to-book ratio, leverage, and return on equity as control variables. The regression models are as follows:

[Panel A] $CRASH_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \beta_2 SIZE_{j,t-1} + \beta_3 MTB_{j,t-1} + \beta_4 LEV_{j,t-1} + \beta_5 ROE_{j,t} + \epsilon_{j,t}$

[Panel B] $JUMP_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \beta_2 SIZE_{j,t-1} + \beta_3 MTB_{j,t-1} + \beta_4 LEV_{j,t-1} + \beta_5 ROE_{j,t} + \epsilon_{j,t}$

Panel A of Table 8 shows regression results of crash risk and opacity. After controlling for firm characteristics, opacity is positively correlated with crash risk at 1% significance level. This means that firms with more opaque financial statements are more subject to stock price crashes. Firm size is negatively correlated with crash risk, which implies that smaller firms are more likely to experience crashes. Leverage also has a significant relation with crash risk. The positive relation between leverage and crash risk implies that firms with more leverage are more subject to stock price crashes. In the last column of Table 8, p-values under panel logit regression are presented. After clustering by firm and year, the significance of opacity and firm size remains, but leverage is no longer significantly related to crash risk.

Panel B of Table 8 presents regression results of stock price jump and opacity. After controlling for firm characteristics, opacity is not significantly

related to stock price jumps. This result is consistent with Hutton et al. (2009). Under panel logit regression, opacity is positively correlated with jump at 10% significance level. Interaction and firm size are highly significant in both pooled and panel logit regression model. Since it is hard to find an apparent relation between likelihood of stock price jump and opacity, I would only focus on the relation between opacity and crash risk for further analyses in this study.

4.3 Outside Monitoring and Crash Risk

To test Hypothesis 3, which is to examine whether firms with high outside monitoring are less subject to crash risk, added three new variables to the regression model in Panel A of Table 8. The three outside monitoring variables are *CHAEBOL dummy*, trading of foreign investors, and trading of institutional investors.

[Insert Table 9 here]

Table 9 presents regression results of opacity and crash risk with *CHAEBOL dummy* and interaction term of crash risk and *CHAEBOL dummy*. A firm is defined as '*Chaebol'* and given 1 for *CHAEBOL dummy* if the firm is included in the 'Large Business Group' provided by Korean Fair Trade Commission, and 0 otherwise. Since Korean Fair Trade Commission

provides 'Large Business Group' data since 2010, the sample for the analysis includes 9,120 firm years from 2000 to 2015.

After including the dummy and interaction variable, opacity is still positively related with crash risk with high statistical significance. *CHAEBOL* and the interaction term do not have significant effect on crash risk.

[Insert Table 10 here]

Table 10 provides regression results of opacity and crash risk with the effect of foreign investors. Following Lee et al. (2014), the variable for trading by foreign investors '*FOREIGN*' is constructed through equation (6).

$$FOREIGN_{j,t} = \frac{\left(\frac{1}{2}\right)\left(Foreign\ Trader\ Buy_{j,t} + Foreign\ Trader\ Sell_{j,t}\right)}{Total\ Trading\ Volume_{j,t}} \quad (6)$$

where $FOREIGN_{j,t}$ denotes percentage of foreign investors' trading volume in the total trading volume for firm *j* in year *t*, $Foreign\ Trader\ Buy_{j,t}$ denotes buy trading volume by foreign investors for firm *j* in year *t*, $Foreign\ Trader\ Sell_{j,t}$ denotes sell trading volume by foreign investors for firm *j* in year *t*, and $Total\ Trading\ Volume_{j,t}$ denotes total trading volume for firm *j* in year *t*.

The regression results show that after including the new variable,

opacity still has significant positive relation with crash risk. Moreover, firm size remains its significance. Under pooled logit regression, foreign investors' trading is negatively related with crash risk, which is consistent with Hypothesis 3. However, the significance dissipates under panel logit regression which clusters by firm and year.

[Insert Table 11 here]

Lastly, I investigate whether institutional investors' trading lowers crash risk. The variable for institutional investors' trading is constructed as the same way as *FOREIGN* is constructed.

$$INST_{j,t} = \frac{\left(\frac{1}{2}\right)\left(Institutional\ Trader\ Buy_{j,t} + Institutional\ Trader\ Sell_{j,t}\right)}{Total\ Trading\ Volume_{j,t}} \qquad (7)$$

where $INST_{j,t}$ denotes percentage of institutional investors' trading volume in the total trading volume for firm *j* in year *t*, $Institutional\ Trader\ Buy_{j,t}$ denotes buy trading volume by institutional investors for firm *j* in year *t*, $Institutional\ Trader\ Sell_{j,t}$ denotes sell trading volume by institutional investors for firm *j* in year *t*, and $Total\ Trading\ Volume_{j,t}$ denotes total trading volume for firm *j* in year *t*.

Table 11 presents regression results of crash risk and opacity with institutional investor trading. After the addition of the new variable, opacity

is still positively correlated with crash risk. The coefficient for *INST* is negative and highly significance. The significance does not disappear under panel logit regression. Firms that institutional investors trade more are less subject to stock price crashes. This result is consistent with Hypothesis 3.

From the three regression analyses of testing whether outside monitoring decreases the likelihood of crash risk, only institutional investors' trading yields robust and significant result.

4.4 Adoption of K-IFRS on R^2 and Crash Risk

Hutton et al. (2009) examine the effect of Sarbanes-Oxley Act by adding *SOX dummy* and interaction term of *SOX* and *OPAQUE*. Following their research methodology, I construct *IFRS dummy* and interaction term of *IFRS* and *OPAQUE*. From year 2011 and beyond, *IFRS* is 1 and 0 otherwise.

There have been studies regarding the adoption of K-IFRS in Korea and its effect on earnings quality.

[Insert Table 12 here]

Table 12 presents results of regression analysis of *IDIOSYN* and *OPAQUE* with *IFRS dummy*. This regression analysis is to examine whether the adoption of K-IFRS has any significant effect on R^2. For Model 1 where opacity and control variables for firm characteristics are included,

IFRS is highly significant and positive. After controlling for skewness and kurtosis, and even under panel regression results, the *IFRS* remain highly significant. This can be interpreted that after 2011, the baseline of R^2 decreased. The decrease in R^2 implies that stock returns are more explained by firm-specific information than market returns. In other words, firms better reveal firm-specific information after 2011 than before. I interpret this result as the general transparency of financial statements improved, and thus the result of Table 12 is consistent with Hypothesis 4.

[Insert Table 13 here]

In Table 13, I examine whether the adoption of K-IFRS has any effect on crash risk and the relationship with opacity and crash risk. With the addition of the dummy variable and interaction term, the significance of *OPAQUE* somewhat dissipates. Under pooled logit regression, both the dummy variable and the interaction term are not statistically significant. However, under panel logit regression, the interaction term is highly significant and positive. From Table 12, the result implies that the market-wide transparency improved. With this interpretation, I conclude that as the transparency of financial statements generally improved, firms which actually have opaque financial statements are highly likely to experience crash risk.

5 Conclusion

Through this study, I examine whether financial reporting opacity measured as three-year moving average of discretionary accruals have significant relation with R^2 and stock price crashes. The regression results show that opacity has a positive correlation with R^2, but after controlling for firm characteristics, there is no significant relation between the two. In terms of crash risk, there is a highly significant positive relation between opacity and crash risk. This implies that if firms withhold firm-specific bad news, they are more subject to stock price crashes when the bad news is released to the market at some point in the future. I also test whether outside monitoring decreases the likelihood of crashes, but C*haebol* and foreign investors' trading do not have significant effect on crash risk. However, firms with high institutional trading ratio are less subject to crashes. Lastly, after the mandatory adoption of K-IFRS in 2011, the baselines of R^2 decreased, implying that more firm-specific information is embedded in stock returns. Moreover, after K-IFRS, firms that actually report opaque financial statements are subject to crash risk under the new transparent accounting policy.

References

An, H., Zhang, T., 2013. Stock price synchronicity, crash risk, and institutional investors. Journal of Corporate Finance 21, 1-15.

Bhattacharya, U., Daouk, H. and Welker, M. 2003. The World Price of Earnings Opacity. The Accounting Review 78(3): 641-678

Callen, J., Fang, X., 2013. Institutional investor stability and crash risk: Monitoring versus short-terism? Journal of Banking & Finance 37, 3047-3063.

Dechow, P., Sloan, R., Sweeney, A., 1995. Detecting earnings management. Accounting Review 70, 193-225.

Dechow, P., Sloan, R., Sweeney, A., 1996. Causes and consequences of earnings manipulation: an analysis of firms subject to enforcement actions by the SEC. Contemporary Accounting Research 13, 1-36.

Dunrev, A., Morck, R., Yeung, B., Zarowin, P., 2003. Does greater firm-specific return variation mean more or less informed stock pricing? Journal of Accounting Research 41, 797-836.

Hutton, A., Marcus, A., Tehranian, H., 2009. Opaque financial reports, R^2, and crash risk. Journal of Financial Economics 94, 67-86.

Jin, L., Myers, S.C., 2006. R^2 around the world: new theory and new tests. Journal of Financial Economics 79, 257-292.

Kim, J., Li, Y., Zhang, L., 2011. Corporate tax avoidance and stock price crash risk: firm-level analysis. Journal of Financial Economics 100, 639-662.

Lee, J., Cho, J., Im, C., 2014. The impact of reporting quality on crash risks in the Korean stock market. Korean Accounting Review 39, 361-394.

Leuz, C., Nanda, D. and Wysocki, P. 2003. Earnings Management and Investor Protection: an International Comparison. Journal of Financial Economics 69: 505-527

Lim, H., Kim, M., 2013. Corporate opacity and crash risk: evidence from Korean listed firms. Journal of Money & Finance 28, 89-121.

Morck, R., Yeung, B., Yu, W., 2000. The information content of stock markets: why do emerging markets have synchronous stock price movements? Journal of Financial Economics 58, 215-260.

Roll, R., 1988. R^2. Journal of Finance 43, 541-566.

Sloan, R., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? Accounting Review 71, 289-315.

Yoo, H., Kim, Y., Jeon, K. 2015. The Effects of K－IFRS Adoption on the Quality of Earnings －A Focusing on Firm`s Characteristics－. Journal of Taxation and Accounting 16(2): 85-130

[Tables]

Table 1

Panel A of Table 1 presents the number of firm years in the sample data for each category of Korean Standard Industrial Classification (KSIC). Industry codes are presented in the parentheses. Panel B of Table 1 presents number of firm years in the sample data for each year. The whole sample includes 9,652 firm years from 1999 to 2015.

Panel A

Industry	Number of obs.
Manufacturing (C)	6857
Construction (F)	608
Wholesale and Retail Trade (G)	826
Transportation (H)	141
Information and Communications (J)	316
Professional, Scientific and Technical Activities (M)	904
Total	9652

Panel B

Year	Number of obs.
1999	533
2000	540
2001	536
2002	530
2003	539
2004	542
2005	547
2006	549
2007	560
2008	563
2009	579
2010	580
2011	592
2012	611
2013	613
2014	619
2015	619
Total	9652

Table 2

Table 2 presents the number of weeks that do not experience crash and the number of weeks that experience crash. Crash % denotes the percentage of crash weeks in the total weeks for a given year. The sample period is from 1999 to 2015. From the expanded index model regression, *Firm-specific Return* is defined as $\ln(1+\epsilon_{j,t})$. If *Firm-specific Return* falls below (rises above) 3.09 standard deviation from the mean, then the firm experiences a stock price crash(jump) for that particular week.

Year		Number of Weeks	Crash %
1999	No Crash	27,600	0.2746%
	Crash	76	
2000	No Crash	27,989	0.2317%
	Crash	65	
2001	No Crash	27,670	0.3422%
	Crash	95	
2002	No Crash	27,111	0.2979%
	Crash	81	
2003	No Crash	27,881	0.3111%
	Crash	87	
2004	No Crash	28,496	0.2800%
	Crash	80	
2005	No Crash	28,104	0.1953%
	Crash	55	
2006	No Crash	28,497	0.1786%
	Crash	51	
2007	No Crash	28,958	0.1620%
	Crash	47	
2008	No Crash	29,204	0.2459%
	Crash	72	
2009	No Crash	30,519	0.1701%
	Crash	52	
2010	No Crash	30,040	0.1794%
	Crash	54	
2011	No Crash	30,592	0.2511%
	Crash	77	
2012	No Crash	31,672	0.2237%
	Crash	71	
2013	No Crash	31,767	0.2136%
	Crash	68	
2014	No Crash	32,015	0.3114%
	Crash	100	
2015	No Crash	31,395	0.1971%
	Crash	62	
Total	No Crash	499,510	0.2383%
	Crash	1,193	

Table 3

Table 3 presents the number of weeks that do not experience jump and the number of weeks that experience jump. Jump % denotes the percentage of jump weeks in the total weeks for a given year. The sample period is from 1999 to 2015. From the expanded index model regression, *Firm-specific Return* is defined as $\ln(1+\epsilon_{j,t})$. If *Firm-specific Return* falls below (rises above) 3.09 standard deviation from the mean, then the firm experiences a stock price crash(jump) for that particular week.

Year		Number of Weeks	Jump %
1999	No Jump	27,522	0.5564%
	Jump	154	
2000	No Jump	27,863	0.6808%
	Jump	191	
2001	No Jump	27,585	0.6483%
	Jump	180	
2002	No Jump	26,830	1.3313%
	Jump	362	
2003	No Jump	27,763	0.7330%
	Jump	205	
2004	No Jump	28,312	0.9239%
	Jump	264	
2005	No Jump	27,837	1.1435%
	Jump	322	
2006	No Jump	28,366	0.6375%
	Jump	182	
2007	No Jump	28,754	0.8654%
	Jump	251	
2008	No Jump	29,117	0.5431%
	Jump	159	
2009	No Jump	30,323	0.8112%
	Jump	248	
2010	No Jump	29,835	0.8606%
	Jump	259	
2011	No Jump	30,418	0.8184%
	Jump	251	
2012	No Jump	31,533	0.6616%
	Jump	210	
2013	No Jump	31,619	0.6785%
	Jump	216	
2014	No Jump	31,875	0.7473%
	Jump	240	
2015	No Jump	31,213	0.7757%
	Jump	244	
Total	No Jump	496765	0.7865%
	Jump	3938	

Table 4

Table 1 shows descriptive statistics and correlation matrix of key variables. The sample covers non-financial firms from 1999 to 2015 listed in KOSPI. *IDIOSYN* is $\ln((1-R^2)/R^2)$ from expanded index model regression. *OPAQUE* is three-year moving average of discretionary accruals. From expanded index model regression, *Firm-specific Return* is defined as $\ln(1+\epsilon_{j,t})$. If *Firm-specific Return* falls below (rises above) 3.09 standard deviation from the mean, then the firm experiences a stock price crash(jump) for that particular week. If a firm experiences one or more crashes(jumps) for a year, then *CRASH(JUMP)* is 1 and 0 otherwise. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1} denotes market value of equity divided by book value of equity in year *t-1*. *SKEW* and *KURT* are skewness and kurtosis of *Firm-specific Weekly Returns* respectively

Panel A: Summary Statistics of Key Variables

	N	Mean	St. dev	Q1	Q3
IDIOSYN	9744	1.3857	0.9401	0.7511	1.9952
OPAQUE	10600	0.3599	0.8477	0.1318	0.3450
CRASH	9764	0.1205	0.3256	0	0
JUMP	9764	0.3434	0.4749	0	1
SIZE t-1	9670	18.3506	1.8095	17.1162	19.2868
LEV t-1	9670	0.6532	0.8340	0.3595	0.6830
ROE	9670	-0.1990	12.1898	0.0062	0.1215
MTB t-1	9670	1.6983	15.9062	0.3616	1.1517
SKEW	9752	0.3642	0.7736	-0.0700	0.7798
KURT	9751	1.9917	2.8873	0.3046	2.6278

Panel B: Pearson Correlation Matrix of Key Variables

	IDIOSYN	*OPAQUE*	*CRASH*	*JUMP*	*SIZE t-1*	*LEV t-1*	*ROE*	*MTB t-1*	*SKEW*	*KURT*
IDIOSYN	1									
OPAQUE	-0.0560	1								
	(<.0001)									
CRASH	0.0651	0.0261	1							
	(<.0001)	(0.0100)								
JUMP	0.1696	-0.0335	-0.1233	1						
	(<.0001)	(0.0009)	(<.0001)							
SIZE t-1	-0.2842	0.2048	-0.0471	-0.1986	1					
	(<.0001)	(<.0001)	(<.0001)	(<.0001)						
LEV t-1	-0.0772	0.1750	0.0147	-0.0358	0.1918	1				
	(<.0001)	(<.0001)	(0.1491)	(0.0004)	(<.0001)					
ROE	-0.0040	0.0197	0.0095	-0.0164	0.0319	0.0042	1			
	(0.6949)	(0.0523)	(0.3519)	(0.1079)	(0.0017)	(0.6793)				
MTB t-1	-0.0125	0.2361	-0.0006	-0.0303	0.1130	0.0462	0.0090	1		
	(0.2187)	(<.0001)	(0.9543)	(0.0029)	(<.0001)	(<.0001)	(0.3738)			
SKEW	0.1576	-0.0527	-0.4646	0.5984	-0.1517	-0.0564	-0.0059	-0.0188	1	
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.5655)	(0.0649)		
KURT	0.2558	-0.0198	0.2678	0.5075	-0.2007	-0.0309	0.0041	-0.0266	0.3185	1
	(<.0001)	(0.0502)	(<.0001)	(<.0001)	(<.0001)	(0.0024)	(0.6895)	(0.009)	(<.0001)	

Table 5

Table 5 presents firm characteristics for groups sorted by opacity and size. I sort the sample into three opacity groups (1=low financial reporting opacity, 3=high financial reporting opacity) and five size groups (1=small size, 5=large size). Each breakpoint is sorted independently. Panel A presents the number of observations per group. Panel B presents mean *OPAQUE* for each group. *OPAQUE* is three-year moving average of discretionary accruals. Panel C presents mean *IDIOSYN* for each group and t-Statistics of the difference (3)-(1). *IDIOSYN* is $\ln((1-R^2)/R^2)$ from expanded index model regression. There are 9,652 firm years in the sample period from 1999 to 2015.

Panel A: Number of Observations per Group

	Opacity		
Size	1	2	3
1	487	661	782
2	614	703	614
3	691	702	537
4	764	639	528
5	661	513	756
Total	3217	3218	3217

Panel B: *OPAQUE* per Group

	Opacity		
Size	1	2	3
1	0.1085	0.2150	0.6117
2	0.1049	0.2144	0.5126
3	0.1016	0.2124	0.4793
4	0.0992	0.2138	0.5640
5	0.0981	0.2128	1.4248

Panel C: *IDIOSYN* per Group

	Opacity			
Size	1	2	3	t-stat:(3)-(1)
1	1.5347	1.5128	1.6980	(3.30)
2	1.4552	1.4286	1.4922	(0.70)
3	1.5603	1.4149	1.3848	(-3.33)
4	1.4607	1.4182	1.3150	(-2.72)
5	1.1719	1.1863	0.8381	(-6.75)

Table 6

[Model 1] $IDIOSYN_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \epsilon_{j,t}$

[Model 2] $IDIOSYN_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \beta_2 SIZE_{j,t-1} + \beta_3 MTB_{j,t-1} + \beta_4 LEV_{j,t-1} + \beta_5 ROE_{j,t} + \epsilon_{j,t}$

[Model 3] $IDIOSYN_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \beta_2 SIZE_{j,t-1} + \beta_3 MTB_{j,t-1} + \beta_4 LEV_{j,t-1} + \beta_5 ROE_{j,t} + \beta_6 SKEW + \beta_7 KURT + \epsilon_{j,t}$

Table 6 shows results of regression analyses of *IDIOSYN* on financial reporting opacity and control variables. Model specifications are presented above. Model 1, 2, and 3 are all pooled cross-sectional regression results. The last column reports results of panel regression that clusters by both firm and year.. *IDIOSYN* is $\ln((1-R^2)/R^2)$ from expanded index model regression. *OPAQUE* is three-year moving average of discretionary accruals. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1} denotes market value of equity divided by book value of equity in year *t-1*. *SKEW* and *KURT* are skewness and kurtosis of *Firm-specific Weekly Returns* respectively. There are 9,652 firm-years in the sample period from 1999 to 2015. t-Statistics are presented in parentheses. *, **, *** denotes statistical significance at 10%, 5%, and 1% level respectively.

Regression Analysis of *IDIOSYN* and *OPAQUE*

	Model 1		Model 2		Model 3		Panel	
Intercept	1.4133	***	4.0925	***	3.4969	***	3.4969	***
	(137.41)		(42.99)		(36.10)		(8.02)	
OPAQUE	-0.0592	***	0.0032		-0.0006		-0.0006	
	(-5.41)		(0.29)		(-0.05)		(-0.03)	
SIZE t-1			-0.1463	***	-0.1219	***	-0.1219	***
			(-27.87)		(-23.24)		(-4.36)	
MTB t-1			0.0012	**	0.0013	**	0.0013	**
			(1.96)		(2.18)		(1.95)	
LEV t-1			-0.0268	**	-0.0263	**	-0.0263	
			(-2.37)		(-2.38)		(-1.07)	
ROE			0.0004		0.0002		0.0002	
			(0.51)		(0.32)		(0.83)	
SKEW					0.0697	***	0.0697	***
					(5.69)		(2.65)	
KURT					0.0612	***	0.0612	***
					(18.53)		(11.09)	
Adj. R^2	0.0030		0.0812		0.1249		0.1255	

Table 7

Table 7 presents crash and jump probabilities for groups sorted by opacity and size. I sort the sample into three opacity groups (1=low financial reporting opacity, 3=high financial reporting opacity) and five size groups (1=small size, 5=large size). Each breakpoint is sorted independently. Difference (3)-(1) and t-Statistics are presented in separate columns. From the expanded index model regression, firm-specific return is defined as $\ln(1+\epsilon_{j,t})$. If weekly stock return for a firm falls below(rises above) 3.09 standard deviations from the mean firm-specific return, then the firm experienced a crash(jump) for that particular week. If a firm experiences one or more crashes(jumps) in a year, the firm is assigned 1 for *CRASH(JUMP)* and 0 otherwise. There are 9,652 firm years in the sample period from 1999 to 2015.

Panel A: Crash Probability per Group

	Opacity				
Size	1	2	3	(3)-(1)	t-stat: (3)-(1)
1	0.1663	0.1573	0.1867	0.0204	(0.93)
2	0.1238	0.1152	0.1498	0.0261	(1.33)
3	0.1027	0.1197	0.1229	0.0202	(1.10)
4	0.0851	0.0923	0.1098	0.0248	(1.46)
5	0.0817	0.0897	0.1164	0.0347	(2.20)

Panel B: Jump Probability per Group

	Opacity				
Size	1	2	3	(3)-(1)	t-stat: (3)-(1)
1	0.4148	0.4251	0.4079	-0.0069	(-0.24)
2	0.3941	0.3926	0.3893	-0.0049	(-0.18)
3	0.3734	0.4145	0.4153	0.0419	(1.49)
4	0.2840	0.3083	0.3693	0.0853	(3.20)
5	0.2027	0.1930	0.1653	-0.0374	(-1.81)

Table 8

[Panel A]

$$CRASH_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \beta_2 SIZE_{j,t-1} + \beta_3 MTB_{j,t-1} + \beta_4 LEV_{j,t-1} + \beta_5 ROE_{j,t} + \epsilon_{j,t}$$

[Panel B]

$$JUMP_{j,t} = \alpha_0 + \beta_1 OPAQUE_{j,t} + \beta_2 SIZE_{j,t-1} + \beta_3 MTB_{j,t-1} + \beta_4 LEV_{j,t-1} + \beta_5 ROE_{j,t} + \epsilon_{j,t}$$

Table 8 shows results of logit regression of stock price crash(jump) on financial reporting opacity and control variables. For pooled logit regression, Chi^2 values and p-values are presented as separate columns and for panel logit regression that clusters by both firm and year, p-values are presented. From the expanded index model regression, firm-specific return is defined as $\ln(1 + \epsilon_{j,t})$. If weekly stock return for a firm falls below(rises above) 3.09 standard deviations from the mean firm-specific return, then the firm experienced a crash(jump) for that particular week. If a firm experiences one or more crashes(jumps) in a year, the firm is assigned 1 for *CRASH(JUMP)* and 0 otherwise. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1} denotes market value of equity divided by book value of equity in year *t-1*.There are 9.652 firm-years in the sample period from 1999 to 2015. *, **, *** denotes statistical significance at 10%, 5%, and 1% level respectively.

Panel A : Regression Analysis of *CRASH* and *OPAQUE*

		Pooled Logit Regression			Panel Logit Regression	
	Coefficient	Chi^2	p-value		p-value	
Intercept	-0.2369	0.5159	0.4726		0.747	
OPAQUE	0.0886	8.6152	0.0033	***	0.013	**
SIZE t-1	-0.0999	29.5644	<.0001	***	0.015	**
MTB t-1	-0.0008	0.0928	0.7606		0.549	
LEV t-1	0.0729	4.0952	0.0430	**	0.108	
ROE	0.0194	2.3863	0.1224		0.107	

Panel B: Regression Analysis of *JUMP* and *OPAQUE*

		Pooled Logit Regression			Panel Logit Regression	
	Coefficient	Chi^2	p-value		p-value	
Intercept	3.9656	256.8094	<.0001	***	0.000	***
OPAQUE	0.0090	0.0586	0.8087		0.091	*
SIZE t-1	-0.2531	337.9626	<.0001	***	0.000	***
MTB t-1	-0.0035	0.9073	0.3408		0.067	*
LEV t-1	-0.0155	0.2355	0.6275		0.711	
ROE	-0.0018	0.7291	0.3932		0.453	

Table 9

Table 9 presents results of logit regression of stock price crash(jump) on financial reporting opacity, control variables, and *CHAEBOL* dummy. For pooled logit regression, Chi^2 values and p-values are presented as separate columns and for panel logit regression that clusters by both firm and year, p-values are presented. From the expanded index model regression, firm-specific return is defined as $\ln(1+\epsilon_{j,t})$. If weekly stock return for a firm falls below(rises above) 3.09 standard deviations from the mean firm-specific return, then the firm experienced a crash(jump) for that particular week. If a firm experiences one or more crashes(jumps) in a year, the firm is assigned 1 for *CRASH(JUMP)* and 0 otherwise. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1} denotes market value of equity divided by book value of equity in year *t-1*. A firm is defined 'CHAEBOL' and given 1 for *CHAEBOL* dummy variable if it is included in the 'Large Business Group' provided by Korean Fair Trade Commission and 0 otherwise. *CHAEBOL*OPAQUE* is the interaction term of *CHAEBOL* and *OPAQUE*. There are 9,120 firm-years in the sample period from 2000 to 2015. *, **, *** denotes statistical significance at 10%, 5%, and 1% level respectively.

Regression Analysis of *CRASH* and *OPAQUE* with *CHAEBOL*

		Pooled Logit Regression			Panel Logit Regression	
	Coefficient	Chi^2	p-value		p-value	
Intercept	-0.2216	0.3857	0.5345		0.791	
OPAQUE	0.0981	9.7964	0.0017	***	0.019	**
SIZE t-1	-0.1010	25.7465	<.0001	***	0.030	**
MTB t-1	-0.0010	0.1293	0.7191		0.512	
LEV t-1	0.0683	3.3735	0.0663	*	0.145	
ROE	0.0180	2.0100	0.1563		0.151	
CHAEBOL	0.1533	0.5106	0.4749		0.484	
*CHAEBOL*OPAQUE*	-0.2069	0.9841	0.3212		0.232	

Table 10

Table 10 presents results of logit regression of stock price crash on earnings opacity, control variables, and trading of foreign investors. For pooled logit regression, Chi^2 values and p-values are presented as separate columns and for panel logit regression that clusters by both firm and year, p-values are presented. From the expanded index model regression, firm-specific return is defined as $\ln(1+\epsilon_{j,t})$. If weekly stock return for a firm falls below(rises above) 3.09 standard deviations from the mean firm-specific return, then the firm experienced a crash(jump) for that particular week. If a firm experiences one or more crashes(jumps) in a year, the firm is assigned 1 for *CRASH(JUMP)* and 0 otherwise. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1} denotes market value of equity divided by book value of equity in year *t-1*. *FOREIGN* is defined as $1/2\,(foreign\ trader\ buy + foreign\ trader\ sell)$ divided by total trading volume for each firm in a given year. There are 9,652 firm-years in the sample period from 1999 to 2015. *, **, *** denotes statistical significance at 10%, 5%, and 1% level respectively.

Regression Analysis of *CRASH* and *OPAQUE* with Foreign Investor Trading

		Pooled Logit Regression			Panel Logit Regression	
	Coefficient	Chi^2	p-value		p-value	
Intercept	-0.8640	3.7338	0.0533	*	0.333	
OPAQUE	0.0907	9.1039	0.0026	***	0.012	**
SIZE t-1	-0.0621	5.7894	0.0161	**	0.220	
MTB t-1	-0.0006	0.0636	0.8009		0.598	
LEV t-1	0.0756	4.4150	0.0356	**	0.095	*
ROE	0.0199	2.5137	0.1129		0.099	*
FOREIGN	-1.0690	4.2067	0.0403	**	0.155	

Table 11

Table 11 presents results of logit regression of stock price crash on earnings opacity, control variables, and trading of institutional investors. For pooled logit regression, Chi^2 values and p-values are presented as separate columns and for panel logit regression that clusters by both firm and year, p-values are presented. From the expanded index model regression, firm-specific return is defined as $\ln(1+\epsilon_{j,t})$. If weekly stock return for a firm falls below(rises above) 3.09 standard deviations from the mean firm-specific return, then the firm experienced a crash(jump) for that particular week. If a firm experiences one or more crashes(jumps) in a year, the firm is assigned 1 for *CRASH(JUMP)* and 0 otherwise. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1} denotes market value of equity divided by book value of equity in year *t-1*. *INST* denotes $[1/2\,(institutional\ trader\ buy + institutional\ trader\ sell)]/total\ trading\ volume$ for each firm in a given year. There are 9,652 firm-years in the sample period from 1999 to 2015. *, **, *** denotes statistical significance at 10%, 5%, and 1% level respectively.

Regression Analysis of *CRASH* and O*PAQUE* with Institutional Investor Trading

		Pooled Logit Regression			Panel Logit Regression	
	Coefficient	Chi^2	p-value		p-value	
Intercept	-1.3291	10.0191	0.0015	***	0.102	
OPAQUE	0.0812	7.1674	0.0074	***	0.014	**
SIZE t-1	-0.0317	1.6810	0.1948		0.490	
MTB t-1	-0.0010	0.1289	0.7195		0.495	
LEV t-1	0.0695	3.6816	0.0550	*	0.125	
ROE	0.0205	2.7115	0.0996	*	0.079	*
INST	-1.7112	17.2287	<.0001	***	0.002	***

Table 12

Table 12 presents results of regression analyses of *IDIOSYN* on financial reporting opacity with *IFRS dummy*. Model 1 and 2 are all pooled cross-sectional regression results. The third column reports results of panel regression that clusters by both firm and year. *IDIOSYN* is $\ln((1-R^2)/R^2)$ from expanded index model regression. *OPAQUE* is three-year moving average of discretionary accruals. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1} denotes market value of equity divided by book value of equity in year *t-1*. *SKEW* and *KURT* are skewness and kurtosis of *Firm-specific Weekly Returns* respectively. *IFRS* variable is 1 in 2011 and beyond and 0 otherwise. *IFRS*OPAQUE* is the interaction term of *IFRS* and *OPAQUE*. There are 9,652 firm-years in the sample period from 1999 to 2015. t-Statistics are presented in parentheses. *, **, *** denotes statistical significance at 10%, 5%, and 1% level respectively.

Regression Analysis of *IDIOSYN* and *OPAQUE* with *IFRS Dummy*

	Model 1		Model 2		Panel	
Intercept	4.7371	***	4.1645	***	4.1645	***
	(51.16)		(44.09)		(10.82)	
OPAQUE	0.0243	*	0.0209		0.0209	
	(1.86)		(1.63)		(1.16)	
SIZE t-1	-0.1930	***	-0.1689	***	-0.1689	***
	(-37.30)		(-32.57)		(-6.86)	
MTB t-1	0.0010	*	0.0011	**	0.0011	**
	(1.85)		(2.06)		(2.27)	
LEV t-1	-0.0240	**	-0.0235	**	-0.0235	
	(-2.24)		(-2.24)		(-1.08)	
ROE	0.0002		0.0001		0.0001	
	(0.33)		(0.16)		(0.43)	
SKEW			0.0652	***	0.0652	***
			(5.61)		(2.81)	
KURT			0.0563	***	0.0563	***
			(17.95)		(10.56)	
IFRS	0.6490	***	0.6273	***	0.6273	***
	(31.44)		(31.06)		(3.22)	
*IFRS*OPAQUE*	-0.0164		-0.0179		-0.0179	
	(-0.80)		(-0.90)		(-0.48)	
Adj. R^2	0.1754		0.2124		0.2131	

Table 13

Table 10 presents results of logit regression of stock price crash on earnings opacity with *IFRS dummy*. For pooled logit regression, Chi^2 values and p-values are presented as separate columns and for panel logit regression that clusters by both firm and year, p-values are presented. From the expanded index model regression, firm-specific return is defined as $\ln(1+\epsilon_{j,t})$. If weekly stock return for a firm falls below(rises above) 3.09 standard deviations from the mean firm-specific return, then the firm experienced a crash(jump) for that particular week. If a firm experiences one or more crashes(jumps) in a year, the firm is assigned 1 for *CRASH(JUMP)* and 0 otherwise. $SIZE_{t-1}$ denotes natural log value of market value of equity in year *t-1*. LEV_{t-1} is total liability divided by total assets in year *t-1*. ROE is net income divided by book value of equity in year *t*. MTB_{t-1} denotes market value of equity divided by book value of equity in year *t-1*. *IFRS* variable is 1 in 2011 and beyond and 0 otherwise. *IFRS*OPAQUE* is the interaction term of *IFRS* and *OPAQUE*. There are 9,652 firm-years in the sample period from 1999 to 2015. *, **, *** denotes statistical significance at 10%, 5%, and 1% level respectively.

Regression Analysis of *CRASH* and *OPAQUE* with *IFRS Dummy*

		Pooled Logit Regression			Panel Logit Regression	
	Coefficient	Chi^2	p-value		p-value	
Intercept	-0.0793	0.0537	0.8168		0.911	
OPAQUE	0.0666	3.2730	0.0704	*	0.067	*
SIZE t-1	-0.1099	32.2466	<.0001	***	0.006	***
MTB t-1	-0.0012	0.1495	0.6990		0.335	
LEV t-1	0.0698	3.7145	0.0539	*	0.119	
ROE	0.0196	2.4523	0.1174		0.098	*
IFRS	0.0833	1.2794	0.2580		0.413	
*IFRS*OPAQUE*	0.0699	1.5907	0.2072		0.000	***

초 록

한국 시장에서 회계적 불투명성, R^2, 그리고 주가 급락 위험과의 관계

전 세 은
경영학과 재무금융전공

본 연구는 회계적 불투명성과 R^2의 관계, 그리고 불투명성과 주가 급락을 맞을 확률의 관계에 대해 알아보았다. Hutton et al. (2009)을 따라, 1995년부터 2015년 사이 KOSPI에 상장되었던 회사들에 대한 연구를 진행하였다. 재량적 발생액을 회계적 불투명성의 기준으로 삼았을 때, 불투명성과 주가 급락 위험 사이에 양의 상관관계가 존재한다는 것을 관찰하였다. 외부 모니터링이 주가 급락 위험에 미치는 영향을 분석하였을 때, 기관투자자들의 투자비율이 높을수록 주가 급락 위험이 높아진다고 실증적으로 확인하였다. 또한, K-IFRS의 도입이 불투명성과 R^2 의 관계, 그리고 불투명성과 주가 급락 위험의 관계에 영향을 미쳤는지 알아보았다. 회귀분석을 통해, 2011년 K-IFRS의 도입 이후 시장의 전체적인 회계적 투명성이 높아졌다는 결론을 내렸다.

주요어 : 회계적 불투명성, 주가, 주가 급락 위험, R^2
학 번 : 2015-20661