

# The Impact of Institutional Ownership on Stock Price Synchronicity and Crash Risk

**Arezoo Haghghat**

M.A. of Finance  
University of Isfahan  
Isfahan, Iran

**Banafsheh Farhangzadeh**

M.A. of Finance  
University of Tehran  
Tehran, Iran

**Mohammad Haghghat**

M.A. student of Finance  
University of Allameh Tabataba'i  
Tehran, Iran

## Abstract

*The aim of this paper is to analyze and to test the impact of institutional ownership on stock price synchronicity and crash risk. To test the research hypotheses we use a logistic transformation of  $R^2$  as a measure of stock price synchronicity and Down-Up volatility, NCSKEW and CRASH as measures of crash risk. The result of the linear regression model shows that institutional ownership is negatively affected firms' stock price synchronicity because institutional transactions improve the flow of firm-specific information into individual stock prices. Moreover, institutional monitoring mitigates managerial bad-news hoarding, which results in a stock price crash when the accumulated bad news is finally released. As a result, institutional ownership is negatively affected firms' crash risk.*

**Keywords:** Institutional Ownership, Stock Price Synchronicity, Crash Risk

## 1. Introduction

One of the most important features of emerging markets especially in developing countries is the presence of major investors and owned a considerable portion of the shares by them. The large presence of institutional investors has important implications for both corporate decisions and stock price behavior. Monitoring by large shareholders has long been considered an important governance solution to agency problems (Shleifer and Vishny, 1986). As institutional ownership increases over time, many researchers have looked to institutional investors as potential monitors due to their monitoring advantage over diffuse shareholders (An and Zhang, 2013). According to Chen et al. (2007), investor monitoring consists of both gathering firm-specific information and influencing management to protect investors' property rights. Investor monitoring affects limited information and the division of risk-bearing between managers and outside investors. Managers capture part of the firm's operating cash flows. That is, they extract more cash than they would receive if investors' property rights could be completely protected. The limits to capture are based on outside investors' perception of the firm's cash flow and value. When cash flows are higher than investors think, managers' capture increases. When cash flows are lower than investors think, managers are forced to reduce capture if they want to keep running the firm. Increased capture therefore reduces the amount of firm-specific risk absorbed by outside investors (Jin and Myers, 2006). Strong investor monitoring, which limits managers' capture of the firm's cash flows, should reduce the stock price synchronicity.

In Jin and Myers (2006), lack of full transparency concerning firm performance enables managers to capture portion of cash flow, in the process absorbing (and making nonvisible) part of the variation in firm-specific performance. This increases stock price synchronicity.

Managers are willing to personally absorb losses due to temporary bad performance to protect their jobs. However, following a run of sufficiently bad news, they are unwilling or unable to absorb any more losses; in other words, they have an abandonment option.

If they abandon their positions, all of the hitherto unobserved negative firm-specific shocks become public at once, resulting in a crash (Hutton et al, 2009).

The aim of this paper is to investigate the impact of institutional investors on the higher moments of return distributions, specifically the stock price synchronicity and crash risk of their holding firms. The remainder of this paper is organized as follows. Section 2 reviews related literature. Section 3 describes variables. Section 4 provides research methodology. Section 5 discusses the empirical design and findings and Section 6 concludes the paper.

## **2. Literature Review**

### **2.1. Stock Price Synchronicity**

Financial economists and accountants have long viewed stock price changes as tied to new information about firms' prospects. However, Roll (1988) finds that only a relatively small portion of price movements can be explained by contemporaneous public news and speculates that traders acting on nonpublic firm-specific information could drive returns. These results have stimulated considerable interest in the relation between information and stock price dynamics and, in particular, between the  $R^2$  from a modified index-model regression as a common measure of stock price synchronicity and a proxy for stock price informativeness, and the revelation of firm-specific news (Hutton et al, 2009).

Since Morck et al. (2000), a growing number of studies have used stock price synchronicity as an inverse measure of the relative amount of firm-specific information impounded in price. Stock price synchronicity is defined as "the extent to which market returns explain variation in firm-level stock returns" (Piotroski and Roulstone, 2004). Stock price synchronicity measures the ability of market returns to explain firm-level returns. The residual component of returns represents firm-specific information or idiosyncratic noise. Existing evidence suggests that stock price synchronicity is inversely related to the relative amount of firm-specific information influencing prices. Given this evidence, stock price synchronicity is a reasonable benchmark for measuring the relative amount of firm-specific versus market -level information influencing prices.

Measurement of stock price synchronicity is typically derived from  $R^2$  of a market pricing model (e.g. the Capital Asset Pricing Model (CAPM)). Firms displaying low stock return synchronicity imply that their price depends less on market movements because there is a greater amount of firm-specific information that market participants rely on. In theory, ceteris paribus, a firm with higher degree of firm-specific information impounded in price will increase the variation in stock prices unrelated to systematic variance, hence, report a lower  $R^2$  from CAPM. However, the converse is not true. That is, lower  $R^2$  does not necessarily mean a higher degree of firm-specific information. This is because noise (either from the trading process or from non-information based trading) will also increase idiosyncratic volatility, hence, reduce  $R^2$  (Johnston, 2009).

Jin and Myers (2006) conclude lack of firm-specific information "affects the division of risk bearing between inside managers and outside investors". In their model, a lack of firm-specific information allows insiders to capture part of the firm's cash flows and effectively increases the amount of firm-specific risk that they bear. In contrast, firm opacity forces outside investors to rely largely on publicly known market and industry information, which contributes to greater stock price co movement with market factors (Haggard, 2008).

Strong investor monitoring, which limits managers' capture of the firm's cash flows, should reduce the  $R^2$  of the firm's stock price. According to Chen et al. (2007), investor monitoring consists of both gathering firm-specific information and influencing management to protect investors' property rights. The limitation of managers' extraction of private benefits depends on the strength of investor monitoring. Under strong investor monitoring, managers have to reduce their capture, thereby absorbing less firm-specific risk during the process. This then decreases the  $R^2$ . In contrast,  $R^2$  would increase when investor monitoring is weak, as managers are able to increase their capture, everything else equal. Therefore, there should be a negative relation between  $R^2$  and the strength of investor monitoring (An and Zhang, 2013).

## 2.2. Crash Risk

According to Jin and Myers (2006), when cash flow is lower than investors expect, managers hide the bad news and reduce their capture in an effort to protect their jobs. However, when the accumulated bad news finally crosses a tipping point, managers give up trying to conceal the information and all the bad news is released at once, which then results in a stock price crash (An and Zhang, 2013).

Crash risk or more generally negative skewness in stock market returns is asymmetrically distributed. This asymmetry can be measured in several ways. First, and most simply, the very largest movements in the market are usually decreases, rather than increases because; the stock market is more prone to melt down than to melt up. Second, a large literature documents that market returns exhibit negative skewness, or a closely related property, “asymmetric volatility” a tendency for volatility to go up with negative returns. Finally, since the crash of October 1987, the prices of stock index options have been strongly indicative of a negative asymmetry in returns, with the implied volatilities of out-of-the money puts far exceeding those of out-of-the-money calls; this pattern has come to be known as the “smirk” in index-implied volatilities. While the existence of negative asymmetries in market returns is generally not disputed, it is less clear what underlying economic mechanism these asymmetries reflect (Chen et al, 2001). An extensive literature documents the asymmetrical distribution of stock returns. Several economic theories have been proposed to explain the mechanism generating this asymmetry, including leverage effects, volatility feedback mechanism, and stochastic bubbles models. Since the theories all focus on mechanisms in the aggregate, they could be formulated as are presentative-agent model (Hueng and McDonald, 2004). It is well known that trading among investors who have different opinions could reveal the private signals of others and move prices even in the absence of new fundamental information (Romer, 1993). In Hong and Stein (2003), this process, combined with short sale constraints, imparts an asymmetry in which market declines differentially reveal the private signals of relatively pessimistic investors. Such revelation could lead other investors to downgrade their assessments of a firm’s prospects, thereby reinforcing the decline. Other sources of negative skewness focus on volatility feedback effects (e.g., French, Schwert, and Stambaugh, 1987 or Campbell and Hentschel, 1992). For example, big price movements could cause investors to reassess market volatility and increase required risk premia. An increased risk premium reduces equilibrium prices, which reinforces the impact of bad news but offsets the impact of good news, thus generating negative skewness (Hutton et al, 2009).

The model of Hutton et al. (2009) envisions firm managers controlling at least a portion of the public access to fundamental information about the firm. Managers have incentives to stock pile bad news, but in some circumstances those incentives collapse, leading to a sudden release of accumulated negative information and a stock price crash. The management of firm-specific information increases crash risk. To the extent that monitoring by investors attenuates the bad-news hoarding, so would expect that institutional ownership have negative influence on stock price crash.

Based on the developments of the literature, two hypotheses are developed. The first hypothesis is stated:

**H<sub>1</sub>:** The institutional holdings have negative impact on stock price synchronicity.

The second hypothesis is as follows:

**H<sub>2</sub>:** The institutional holdings have negative impact on crash risk.

## 3. Variables

### 3.1. Measuring Stock Price Synchronicity

Our measure of stock price synchronicity follows Morck et al. (2000). We estimate the linear regression

$$R_{i,t} = \beta_{i0} + \beta_{i1} R_{m,t} + \varepsilon_{i,t} \quad (1)$$

Where  $R_{i,t}$  is the return of stock  $i$  at month  $t$  and  $R_{m,t}$  is the market return at month  $t$ .

Since the  $R^2$  is highly skewed and bounded between unit and zero, we apply a logistic transformation to obtain a near normally distributed variable, SYNCH. A higher value of SYNCH indicates that the stock price is more synchronized.

$$\text{SYNCH}_{i,t} = \ln \left( \frac{R_{i,t}^2}{1 - R_{i,t}^2} \right) \quad (2)$$

Where  $R^2$  is the coefficient of determination from the estimation of Eq. (1) for firm  $i$  in year  $t$ .  $SYNCH_{i,t}$  is measured for each firm based on the monthly return observations of the year (An and Zhang, 2013)

### 3.2. Measuring Crash Risk

We follow the literature and construct measure of firm-specific crash risk. Our first measure of crash risk is DUVOL, down-to-up volatility. Following Kim et al. (2011b), for each firm year we calculate the standard deviations of firm-specific monthly returns during the up (down) months when the firm-specific monthly returns are above (below) its annual mean. DUVOL is the log of the ratio of the standard deviation on down months to the standard deviation on up months. The convention is that a higher value of DUVOL suggests a more left-skewed distribution. Our second measure of crash risk is the negative conditional return skewness (NCSKEW) measure of Chen, Hong, and Stein (2001). Specifically, we calculate NCSKEW for a given firm in a fiscal year by taking the negative of the third moment of firm-specific monthly returns for each sample year and dividing it by the standard deviation of firm-specific monthly returns raised to the third power. Specifically, for each firm  $i$  in year  $t$ , we compute NCSKEW as

$$NCSKEW_{i,t} = - \left[ \frac{N(N-1)^{3/2} \sum W_{i,t}^3}{(N-1)(N-2) \left( \sum W_{i,t}^2 \right)^{3/2}} \right]$$

(Kim et al, 2011b).

Finally to calculate our third measure of crash risk means CRASH, we first estimate firm-specific monthly returns for each firm and year. Specifically, the firm-specific monthly return, denoted by  $W$ , is defined as the natural log of one plus the residual return from the market model regression. The firm-specific monthly return for firm  $i$  in month  $t$  is measured by the natural log of one plus the residual return in Eq (1), that is,  $W_{i,t} = \ln(1 + \varepsilon_{i,t})$ . We define crash months in a given fiscal year for a given firm as those months during which the firm experiences firm-specific monthly returns 3.2 standard deviations below the mean firm-specific monthly returns over the entire fiscal year, with 3.2 chosen to generate a frequency of 0.1% in the normal distribution.

Following Hutton et al (2009), our first measure of crash likelihood for each firm in each year, denoted by CRASH, is an indicator variable that equals one for a firm-year that experiences one or more crash months (as defined above) during the fiscal year period, and zero otherwise (Kim et al, 2011a).

### 3.3. Identification of Institutional Investors

In the present study, the institutional investors is determined based on the Accounting Standard of Iran No.20 and Accounting Principles Board No.18 was appointed Iran's statement. Based on these statements, direct or indirect investments in at least 20% of shares with voting rights invested unit, will lead to the leveraging effect in the unit, unless the contrary is observed (Technical Committee on Corporate Audit, 2007). After identifying institutional investors, for calculating the percentage of institutional ownership in each firm, the number of shares owned of institutional is divided by total of common stock issued by the firm at the end of the period.

## 4. Research Methodology

This research is categorized in empirical researches and also type of this study is descriptive-correlation research. To obtain research results via referred variables in last section, Multivariate regression and panel data model has been used.

Spatial domain of research (statistical population) in the research is all Tehran Stock Exchange firms from 2005 to 2011. Delisted firms, firms transferred to informal panel and investment companies were eliminated from population. Finally the research sample includes 95 firms. In order to gather required quantitative data including market value, stock price, equity, assets and others, Tehran Stock Exchange website, Tehran Stock Exchange data base and CODAL network were used.

## 5. Results

### 5.1. Summary Statistics

As it is mentioned, the sample is composed of 95 companies listed in Tehran Stock Exchange. The methodology for analyzing data is based on panel modeling. In the first, the Stock price synchronicity is based on near normally distributed variable. The data being in both time series and cross sectional. We have thus made regression using a panel data.

Table 1, hereafter resumes the descriptive statistics of the variables on the whole period (2005-2011): mean, median, maximum, minimum and standard deviation. SYNCH is the logistic transformed R<sup>2</sup>. DUVOL is down-to-up volatility calculated as the log of the ratio of the standard deviation of firm-specific monthly return on up months to that on down months. CRASH is an indicator variable. CRASH, is set equal to one for a firm-year if the firm experiences one or more Firm-Specific monthly Returns falling 3.2 standard deviations below the mean monthly firm-specific return for that fiscal year; otherwise, CRASH is set equal to zero. NCSKEW is the negative conditional skewness of firm-specific monthly return. IO is the percentage of total institutional ownership in the firm. SIZE is the natural log of the firm’s market value of equity at the end of last fiscal year. MTB is the ratio of the market value of equity to the book value of equity at the end of last fiscal year. LEV is the book value of all liabilities scaled by total assets at the end of last fiscal year. ROE is the net income divided by the book value of equity. ROA is the net income divided by the book value of total assets. SKEW is the skewness of firm-specific monthly return over the fiscal year. KURT is the kurtosis of firm-specific monthly return over the fiscal year. VOL is the standard deviation of firm-specific monthly return over the fiscal year. DTURN is the detrended turnover, which is calculated as the difference between average monthly turnover over fiscal year t-1 and the prior fiscal year's average monthly turnover. SIGMA is the standard deviation of the firm-specific return over the fiscal year. RET is the average of firm-specific return over the fiscal year. The number of observations is 475.

**Table 1: Descriptive Statistics**

Variables	N/valid	Mean	Median	Std. Deviation	Maximum	Minimum
Synch	475	-2.65	-2.16	2.10	1.59	-10.61
DUVOL	464	-0.20	-0.21	0.35	0.94	-1.26
NCSKEW	475	-21.52	-22.30	36.56	95.25	-115.82
IO	450	0.54	0.53	0.23	0.96	0.00
ROE	474	31.73	32.36	18.82	73.83	-10.42
MTB	475	2.10	1.73	1.62	12.44	-0.88
Size	475	26.90	26.86	1.51	31.33	22.82
LEV	475	0.58	0.60	0.19	1.19	0.10
Skew	475	0.64	0.66	1.11	3.17	-3.09
kurt	475	1.84	1.10	2.64	10.52	-1.99
VOL	475	10.44	9.34	6.09	44.58	0.00
Dturn	475	0.00	0.00	0.02	0.13	-0.09
Sigma	475	10.66	9.58	6.64	61.75	0.00
RET	475	2.75	2.28	4.85	26.57	-8.92
ROA	475	13.93	12.40	11.30	52.34	-17.18

In this study we have two hypotheses. For each hypothesis, we analyze data.

**5.2. The Results of the First Hypothesis Test**

**5.2.1. Panel Analysis H<sub>1</sub>**

For data analysis, the panel analysis (Panel) without fixed effects, with fixed effects and with random effects is used. To determine the effectiveness of model with fixed or random effects Limer (Chav) test and Houseman test is used. As the table 2 shows, the results of Chav test is indicate that "Pooled regression model", is preferred to "Panel regression model".

**Table 2: Redundant Fixed Effects Tests of Hypothesis 1**

Effects Test	Statistic	d.f.	Prob.
Cross- section F	1.284211	(93,347)	0.0570
Cross- section Chi- square	132.808232	93	0.0043

The supposed model to test the hypothesis 1 is as follow

$$\begin{aligned}
 \text{SYNCH}_{i,t} = & \beta_0 + \beta_1 \cdot \text{IO}_{i,t-1} + \beta_2 \cdot \text{ROE}_{i,t} + \beta_3 \cdot \text{MTB}_{i,t-1} \\
 & + \beta_4 \cdot \text{SIZE}_{i,t-1} + \beta_5 \cdot \text{LEV}_{i,t-1} + \beta_6 \cdot \text{SKEW}_{i,t-1} \\
 & + \beta_7 \cdot \text{KURT}_{i,t-1} + \beta_8 \cdot \text{VOL}_{i,t-1} + \varepsilon_{i,t}
 \end{aligned}
 \tag{3}$$

In order to review the heteroskedasticity in the Error Component Model, Likelihood-ratio test was used. Table 3 shows the results of Likelihood-ratio test.

**Table 3: Heteroskedasticity Test in the Error Component Model of Hypothesis 1**

Likelihood-ratio test	Statistic	d.f.	Prob.
chi <sup>2</sup>	135.24	93	0.0028

As p-value of LR test is less than 5%, this model is heteroskedastic so OLS<sup>1</sup> estimators cannot be used and Instead, GLS<sup>2</sup> estimators are used.

Table (4) shows that Institutional ownership, Size, Skew, Kurt variables have significant influence on stock price synchronicity and other variables, regardless of their sign, and the effects on dependent variable are not significant. The results of pooled model show that significant of chi<sup>2</sup> Statistics of Wald test is equal 0.000. This result means that there is a significant model. Durbin-Watson statistic for model is 2.203 which suggests that there is no evidence of autocorrelation.

**Table 4. Generalized least squares of Hypothesis 1**

Variables	Prob.	z-Statistics	Std. Error	Coefficient
C	-6.363	1.503	-4.41	0.00
IO	-1.488	0.298	-4.98	0.00
ROE	-0.004	0.004	-0.96	0.337
MTB	0.076	0.054	1.4	0.163
Size	0.177	0.054	3.26	0.001
LEV	0.25	0.036	0.7	0.484
Skew	0.291	0.074	3.91	0.00
Kurt	-0.133	0.028	-4.03	0.00
VOL	0.004	0.012	0.3	0.761
<b>Wald chi<sup>2</sup> (Prob)</b>	86.03 (0.000)		<b>Durbin-Watson stat</b>	2.203

The results of hypothesis 1 indicate that institutional ownership has negative impact on stock price synchronicity.

### 5.3. The Results of the Second Hypothesis Test

#### 5.3.1. Panel Analysis of the First Model of Hypothesis 2

For data analysis, the panel analysis (Panel) without fixed effects, with fixed effects and with random effects is used. To determine the effectiveness of model with fixed or random effects Limer (Chav) test is used. As the table 5 shows, the results of Chav test is indicate that pooled model is better than the model with effects.

**Table 5: Redundant Fixed Effects Tests of first model of Hypothesis 2**

Effects Test	Statistic	d.f.	Prob.
Cross- section F	1.239	(93,337)	0.089
Cross- section Chi- square	129.366	93	0.008

The first supposed model to test the hypothesis 2 is as follow:

$$\begin{aligned} \text{DUVOL}_{i,t} = & \beta_0 + \beta_1 \cdot \text{IO}_{i,t-1} + \beta_2 \cdot \text{DTURN}_{i,t-1} + \beta_3 \cdot \text{NCSKEW}_{i,t-1} \\ & + \beta_4 \cdot \text{SIGMA}_{i,t-1} + \beta_5 \cdot \text{RET}_{i,t-1} + \beta_6 \cdot \text{ROA}_{i,t} \\ & + \beta_7 \cdot \text{SIZE}_{i,t-1} + \beta_8 \cdot \text{MTB}_{i,t-1} + \beta_9 \cdot \text{LEV}_{i,t-1} + \epsilon_{i,t} \end{aligned} \quad (4)$$

As table (6) shows p-value of LR test is less than 5%, so model is heteroskedastic and GLS estimators are used for evaluate model.

<sup>1</sup> Ordinary Least Square

<sup>2</sup> Generalized Least Square

**Table 6. Heteroskedasticity Test in the Error Component Model of first model of Hypothesis**

Likelihood-ratio test	Statistic	d.f.	Prob.
chi <sup>2</sup>	126.50	93	0.0120

Table (7) shows that Institutional ownership, ROA, MTB variables have significant influence on the first measure of crash risk means. Down-up volatility and other variables, regardless of their sign, and the effects on dependent variable are not significant. The results of pooled model show that significant of chi<sup>2</sup> Statistics of Wald test is equal 0.000. This result means that there is a significant model. Durbin-Watson statistic for model is 1.969 which suggests that there is no evidence of autocorrelation.

**Table 7: Generalized Least Squares of First Model of Hypothesis 2**

Variables	Coefficient	Std. Error	z-Statistics	Prob.
$\beta_0$	-0.26	0.267	-0.97	0.334
IO	-0.187	0.06	-3.16	0.002
DTURN	-0.482	0.576	-0.84	0.403
NCSKEW	-0.006	0.004	-1.4	0.163
SIGMA	-0.002	0.003	-0.73	0.465
RET	-0.004	0.003	-1.43	0.154
ROA	-0.004	0.001	-2.68	0.007
SIZE	0.005	0.009	0.57	0.570
MTB	0.34	0.009	3.44	0.001
LEV	0.047	0.087	0.54	0.588
<b>Wald chi<sup>2</sup> (Prob)</b>	15.35(0.00)		<b>Durbin-Watson stat</b>	1.969

**5.3.2. Panel Analysis of the Second Model of Hypothesis 2**

For data analysis, the panel analysis (Panel) without fixed effects, with fixed effects and with random effects is used. To determine the effectiveness of model with fixed or random effects Limer (Chav) test is used. As the table 8 shows, the results of Chav test is indicate that pooled model is better than the model with effects.

**Table 8: Redundant Fixed Effects Tests of second model of Hypothesis 2**

Effects Test	Statistic	d.f.	Prob.
Cross- section F	1.245	(93,347)	0.083
Cross- section Chi- square	129.609	93	0.007

The second supposed model to test the hypothesis 2 is as follow:

$$\begin{aligned}
 NCSKEW_{i,t} = & \beta_0 + \beta_1 \cdot IO_{i,t-1} + \beta_2 \cdot DTURN_{i,t-1} + \beta_3 \cdot NCSKEW_{i,t-1} \\
 & + \beta_4 \cdot SIGMA_{i,t-1} + \beta_5 \cdot RET_{i,t-1} + \beta_6 \cdot ROA_{i,t} \\
 & + \beta_7 \cdot SIZE_{i,t-1} + \beta_8 \cdot MTB_{i,t-1} + \beta_9 \cdot LEV_{i,t-1} + \epsilon_{i,t}
 \end{aligned}
 \tag{5}$$

As table (9) shows p-value of LR test is less than 5%, so model is heteroskedasic and GLS estimators are used for evaluate model.

**Table 9: Heteroskedasticity Test in the Error Component Model of Second Model of Hypothesis 2**

Likelihood-ratio test	Statistic	d.f.	Prob.
chi <sup>2</sup>	138.99	93	0.0014

Table (10) shows that Institutional ownership, ROA, MTB variables have significant influence on the second measure of crash risk means NCSKEW and other variables, regardless of their sign, and the effects on dependent variable are not significant. The results of pooled model show that significant of chi<sup>2</sup> Statistics of Wald test is equal 0.005. This result means that there is a significant model. Durbin-Watson statistic for model is 1.909 which suggests that there is no evidence of autocorrelation.

**Table 10: Generalized Least Squares of the Second Model of Hypothesis 2**

Variables	Coefficient	Std. Error	z-Statistics	Prob.
$\beta_0$	-5.68	25.2	-0.23	0.822
IO	-15.59	6.414	-2.414	0.015
DTURN	-25.8	52.289	-0.49	0.622
NCSKEW	-0.02	0.042	-0.51	0.607
SIGMA	0.68	0.226	0.3	0.764
RET	-0.34	0.291	-119	0.233
ROA	-0.34	0.149	-2.24	0.025
SIZE	-0.41	0.91	-0.46	0.649
MTB	3.16	0.89	3.56	0.000
LEV	2.51	7.824	0.32	0.748
<b>Wald chi<sup>2</sup> (Prob)</b>	23.83(0.005)		<b>Durbin-Watson stat</b>	1.909

### 5.3.2. Panel Analysis of the third Model of Hypothesis 2

As same as the past models, we first use Limer (Chav) test for determining the effectiveness of model with fixed or random effects. As the table 11 shows, the results of Chav test is indicate that pooled model is better than the model with effects.

As previously mentioned, CRASH (dependent variable) is index variable that takes values 1 or 0. Also, Since the model is pooled, We use the Logit Regression.

**Table 11: Redundant Fixed Effects Tests of third Model of Hypothesis 2**

Effects Test	Statistic	d.f.	Prob.
Cross- section F	1.256	(93,384)	0.0749
Cross- section Chi- square	130.808	93	0.0060

The third supposed model to test the hypothesis 2 is as follow:

$$\begin{aligned} \text{CRASH}_{i,t} = & \beta_0 + \beta_1 \cdot \text{IO}_{i,t-1} + \beta_2 \cdot \text{DTURN}_{i,t-1} + \beta_3 \cdot \text{NCSKEW}_{i,t-1} \\ & + \beta_4 \cdot \text{SIGMA}_{i,t-1} + \beta_5 \cdot \text{RET}_{i,t-1} + \beta_6 \cdot \text{ROA}_{i,t} \\ & + \beta_7 \cdot \text{SIZE}_{i,t-1} + \beta_8 \cdot \text{MTB}_{i,t-1} + \beta_9 \cdot \text{LEV}_{i,t-1} + \varepsilon_{i,t} \end{aligned} \quad (6)$$

**Table 12: The Result of the Third Model of Hypothesis 2**

Variables	Coefficient	Std. Error	Wald-Statistics	Prob.
$\beta_0$	-3.119	3.522	0.784	0.376
IO	-2.034	0.774	6.901	0.009
DTURN	-3.181	8.590	0.137	0.711
NCSKEW	-0.003	0.005	0.370	0.543
SIGMA	0.002	0.029	0.004	0.950
RET	-0.008	0.047	0.003	0.863
ROA	-0.042	0.019	4.984	0.026
SIZE	0.072	0.127	0.317	0.574
MTB	0.307	0.130	5.61	0.018
LEV	-1.621	1.192	1.851	0.174
<b>Hosmer and Lemeshow chi<sup>2</sup> (Prob)</b>	2.8(0.946)		<b>Naglekerke R Square</b>	0.1
<b>Chi-Square</b>	21.13(0.012)			

Table (12) shows that Institutional ownership, ROA, MTB variables have significant influence on the third measure of crash risk means CRASH and other variables, regardless of their sign, and the effects on dependent variable are not significant.



The Nagelkerke R square is 0.1 and Chi-Square statistics is equal 21.13, also significance level of the test is less than 0.05, this means hypothesis 2 is not rejected at the 95 percent confidence level. The total, the third model of hypothesis 2 is significant. The Hosmer and Lemeshow's Chi-Square represents overall fit of model. Since the significance of it is more than 0.05, so acceptable explanation of the data is confirmed by the model.

## 6. Conclusion

This paper examines the influence of institutional investors on both the stock price synchronicity and the crash risk of their holding firms. We find that institutional ownership is negatively affected firms' stock price synchronicity because institutional transactions improve the flow of firm-specific information into individual stock prices. These results are consistent with the theory of Jin and Myers (2006) that limited information enables managers to capture more of the firm's cash flow, while in the process absorbing more firm-specific variance, which leads to a higher stock price synchronicity. Moreover, we find that institutional investors are negatively affected firms' crash risk. Hutton et al. (2009) show that Managers are willing to personally absorb losses due to temporary bad performance to protect their jobs. However, following a run of sufficiently bad news, they are unwilling or unable to absorb any more losses; in other words, they have an abandonment option. If they abandon their positions, all of the hitherto unobserved negative firm-specific shocks become public at once, resulting in a crash. Institutional monitoring mitigates managerial bad-news hoarding so reduce the probability of firm's crash risk.

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