INFORMATION ENVIRONMENT, SYSTEMATIC VOLATILITY AND STOCK RETURN SYNCHRONICITY

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Abstract

The stock return synchronicity decreases when the general information environment improves. I theoretically demonstrate that if investors can learn the firm's future performance based on all noisy signals in the market, the systematic volatility would be largely reduced even when the incremental information content of each particular firm's signal is modest. I build up a theoretical model which allows for multiple firms whose cash flows are correlated, and characterize the information as noisy signals about future cash flows. Based on this information structure, the systematic volatility decreases with the resolution of market-level uncertainty when a large amount of public news is released. Since the idiosyncratic volatility would not be affected by the clustered announcements, the stock return synchronicity is predicted to be lower when the information environment becomes better.

The earnings season serves as a proper empirical setting to demonstrate how the general information environment would fluctuate the stock return synchronicity in a dynamic manner. Consistent with the information interpretation of R^2, I find that the dramatically increased intensity of information disclosures could significantly decrease the stock return synchronicity in China. This dynamic pattern is robust after control for the change of fundamentals, the effect of corporate events, the abnormal returns around the earnings announcements and the change of liquidity. More importantly, the driving force of this dynamic pattern is the reduction of the systematic volatility rather than the increment of the idiosyncratic volatility, and this dynamic pattern is more pronounced for older firms. These findings are not special to China. With the sample of 40 countries around the world, I find that the stock return synchronicity and the systematic volatility are lower in the earnings season than they are in the non-earnings seasons in both country-level and firm-level analyses.

Key words: Stock return synchronicity; information environment; cross-assets learning; earnings season.

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Chapter 1. Introduction

1.1 Motivations

Stock return synchronicity, measured as the R^2 from the extended market model regression, has attracted much research attention both across firms and over time. Roll (1988) finds that the systematic economic influences, industry innovations and public firm-specific news can only explain a relatively small portion of stock price movement. Since then, the mystery of the underlying causes for the lower value of R^2 has triggered considerable research interest and debate in the literature.

A large number of studies take the perspective that more informative stock price should be associated with lower R^2 by incorporating more firm-specific information into the stock prices (Morck, Yeung and Yu (2000)). This line of work suggests that the stock return synchronicity is negatively associated with the disclosure quality (Jin and Myers (2006); Haggard, Martin, and Pereira (2008); Hutton, Marcus and Tehranian (2009); Gul, Kim and Qiu (2010)), the information about future earnings contained in the current stock prices (Durnev, Morck, Yeung and Zarowin (2003)), the corporate governance quality (Ferreira and Laux (2007); Ferreira, Ferreira and Raposo (2011); Gul, Ng and Srinidhi (2011); Armstrong, Balakrishnan, and Cohen (2012)), the activity of informed investors (Piotroski and Roulstone (2004); Crawford, Roulstone and So (2012)) and the efficiency of investment (Durnev, Morck and Yeung (2004); Chen, Goldstein and Jiang (2007)).

However, a growing body of research holds the opposite view that the stocks with better information environment are actually associated with higher R^2 (West (1988); Teoh, Yang and Zhang (2009); Chan and Chan (2014); Kelly (2014)) and the increase of idiosyncratic volatility is due to deteriorating earnings quality (Rajgopal and Venkatachalam (2011); Chen, Huang and Jha (2012)). The R^2 may be just an indicator of noise or investors' sentiment and frictions (Barberis, Shleifer and Wurgler (2005); Kumar and Lee (2006); Li, Rajgopal and Venkatachalam (2014)).

Among the studies of the stock return synchronicity, little attention has been paid to the dynamic nature of R^2. For example, Brockman, Liebenberg and Schutte (2010) confirm the countercyclical pattern of stock return comovement and its negative relationship with information production in the country level. While Dasgupta, Gan and Gao (2010) demonstrate that the improved transparency can increase the future R^2, since the news about the future firm-specific events has been already impounded into the stock price. In fact, it is important to note that with time-varying information flows, R^2 may change and present corresponding dynamic patterns. Motivated by this argument, this thesis makes an attempt to understand the relationship between the information and stock return synchronicity by taking the dynamic pattern of R^2 into consideration, which provides more direct evidence for the information interpretation of R^2 than the static, cross-sectional research in the literature.

In addition, from an econometric perspective, the R^2 can be decomposed into (1) the systematic volatility, which is the variation in returns that can be explained by the market factors and (2) the idiosyncratic volatility, which is the variation of residuals from the market model regression. Therefore, the higher R^2 can be caused by either elevated systematic volatility or depressed idiosyncratic volatility or both. However, most of the previous work simply assumes that only the idiosyncratic volatility matters and overlooks the impact on the systematic volatility. In this thesis, I demonstrate how the systematic volatility varies with the clustered public individual news in a multi-firms setting, which generates important implications for the puzzle of the stock return synchronicity.

1.2 Theoretical Model and Predictions

I develop a one-period rational model with multiple risky assets in the economy to demonstrate the information updating process and the underlying mechanism of the dynamic R^2. The random end-of-period cash flows are determined by a linear combination of the market and firm-specific factors. The cash flows are correlated across assets because of the existence of the common component. The homogeneous prior beliefs about future cash flows would be updated based on the information set which contains noisy signals for the future cash flows. Unlike the previous literature, I assume that the information for the market and firm-specific factors cannot be perfectly separated, which makes the cross-assets learning possible[1]. The signals can be easily learned by all investors, and the information quality is defined as the reverse of the error term's variance in the signal.

R^2 as well as the systematic and idiosyncratic volatilities is estimated using the standard asset pricing model of CAPM, which can be expressed using the items from the variance-covariance structure of cash flows for the individual firms and the aggregate market. I first illustrate that the R^2 is negatively associated with not only the information quality of that particular firm, but also the general information environment of the whole market. I then explore how the information environment would fluctuate the R^2 by decomposing it into systematic and idiosyncratic volatilities. The intuition is

[1] The independence of the information structure across firms is widely assumed in the models of the R-square studies (Jin and Myers (2006), Peng and Xiong (2006), Dasgupta, Gan and Gao (2010) and Hou, Peng and Xiong (2013)).

straightforward. When investors receive new information about one particular firm, they could update their prior beliefs about all firms' future cash flows since their beliefs about the common component are updated. Therefore, other firms' information would be finally reflected into the systematic volatility in this dynamic learning process, but would impose no effect on the idiosyncratic volatility. As a result, the stock return synchronicity would decrease when the general information environment is improved.

Moreover, the model indicates that the systematic volatility can effectively capture the accumulated change of the information quality which cannot be detected by the idiosyncratic volatility. As long as the market factor is not perfectly revealed, each individual news could provide additional information to depress the systematic volatility further. Therefore, even though each firm's information quality in the market is only slightly improved, if the number of the improved signals is large, the systematic volatility would still be largely reduced with the improved information environment. The situation is different to the idiosyncratic volatility. Since the idiosyncratic volatility can only reflect the information learned from that particular firm, the dynamic pattern would be weak if the incremental information content for that firm is modest.

Based on the implications of the model, several testable hypotheses are developed for the empirical analysis. The earnings season provides a natural framework to test how the general information environment would fluctuate the stock return synchronicity. When firms jointly announce their annual earnings reports in the earnings season, the increased disclosure intensity as well as the activated learning process would lower the stock return synchronicity compared with other normal periods. This dynamic pattern of R^2 around the earnings season is claimed in the first hypothesis.

Next, I propose that the dominant effect of the dynamic pattern of R^2 around the earnings season is coming from the systematic volatility rather than the idiosyncratic volatility. That is because when investors update their beliefs about the common component in the earning season, a large number of effective signals could compensate for the modest information content provided by one particular earnings announcement, and lower the systematic volatility rather than the idiosyncratic volatility. Finally, since the firms with relatively lower firm-specific uncertainty would be more sensitive to the change of the information environment, I propose that older firms would present more pronounced dynamic patterns of R^2 around the earnings season than the younger firms.

As a by-product, the model also provides theoretical support for the empirical findings which study the effect of the particular firm's information on the stock return synchronicity. For example, Cheng, Leung and Yu (2014) examine the changes of R^2 upon compliance disclosures of the earnings in China. Within a 60-days window before and after the annual earnings announcement, they find the R^2 decreases after the information arrival, which is consistent with the predictions of the model in this thesis. Furthermore, I extend the model by adding dummies to the information structure to illustrate how R^2 changes when the particular firm's information is purely firm-specific. Consistent with Dasgupta, Gan and Gao (2010) who find the stock return synchronicity would increase after the seasonal equity offerings and the cross-listings of ADRs, the model demonstrates that if investors receive signals only with respect to the firm-specific factors, R^2 will increase as a result of decreased idiosyncratic volatility and unchanged systematic volatility. To sum up, my model reconciles this conflict by emphasizing the differences in the information structures.

The model also makes implications for the cross-sectional analysis of R^2. Consistent with the previous literature (Morck, Yeung and Yu (2000); Durnev, Morck, Yeung and Zarowin (2003); Jin and Myers (2006)), the model predicts that the stock return synchronicity is negatively associated with the informativeness of the stock prices, and the R^2 is lower for the stocks with lower market uncertainty and higher firm-specific uncertainty, lower fundamental correlation with the market and higher extent of cross-assets learning. In addition, the model indicates that both the systematic volatility and the idiosyncratic volatility are negatively associated with the information quality, which is consistent with the empirical findings of Li, Rajgopal and Venkatachalam (2014) who claim that the R^2 and the idiosyncratic volatility are not interchangeable.

1.3 China and International Empirical Findings

I conduct the empirical tests of the dynamic pattern of R^2 around the earnings season using both China and international data. I first choose a typical emerging market with 2036 Chinese listed firms from 2003 to 2015, and test whether the stock return synchronicity as well as the systematic volatility would decrease in the earnings season within this framework. Then I provide the international evidence with the sample of 40 countries to examine whether this dynamic pattern can be generalized to other markets around the world.

The dynamic pattern of R^2 with the changing information environment around the earnings season should be more pronounced using Chinese data for the following reasons. First, as a typical emerging market with inadequate informed arbitrage, the higher market-wide uncertainty reflected in the elevated systematic volatility is more likely to be resolved when the information environment becomes better. Second, the information environment presents very clear changing pattern in China. On one hand, the earnings statements are important information sources for Chinese investors in addition to other kinds of disclosures; on the other hand, the earnings announcements are highly clustered in China with almost 98 percentages of firms releasing their annual earnings reports within three months.

The main findings using Chinese data are summarized as follows. Consistent with the hypothesis, I find a clear and significant dynamic pattern of stock return synchronicity around the earnings season. The average R^2 estimated from the standard market model decreases about 16% in the earnings season, and this pattern cannot be explained by the change of the fundamental values, the effect of major corporate events, the abnormal returns when earnings reports are released and the change of the price liquidity[2].

Furthermore, I decompose the R^2 into the systematic and idiosyncratic volatilities. I test how these two components of R^2 would change with different information environment around the earnings season. I find that the systematic volatility is significantly lower in the earnings season than that in the normal period, with a decrease ratio of almost 36% for the standard market model and 31% for the industry-augmented model[3]. However, the idiosyncratic volatility does not change significantly in different periods, indicating that the incremental information content revealed by the particular firm's earnings announcement is too modest to be reflected. I then conclude that the improved general information environment and the reduced systematic volatility are the

[2] In the normal years, the equal-weighted average of R^2 estimated from the standard market model decreases from 0.4210 in the non-earnings seasons to 0.3528 in the earnings season.
[3] In the normal years, the equal-weighted average of the systematic volatility decreases from 0.0163 in the non-earnings seasons to 0.0105 in the earnings season for the standard market model, and from 0.0202 to 0.0140 for the industry-augmented market model.

primary causes for the dynamic pattern of the stock return synchronicity around the earnings season.

Finally, I find the dynamic pattern of R^2 around the earnings season is more pronounced for older firms whose uncertainty about the firm-specific factors is relatively lower. Since the information environment decreases the stock return synchronicity by resolving the uncertainty of the market factors, the learning effect would be more important to the firms with relatively higher uncertainty of the systematic component. The empirical results confirm this prediction and document a positive association between the firm age and the change of R^2 around the earnings season.

The challenge to the international study comes from how clear the information environment would change around the earnings season. Only a few countries present identical fiscal year end dates for all firms as China, and the extent of the clustering for the earnings announcements is quite different across countries[4]. To obtain a relatively clear changing pattern of the information environment, I first exclude the firms whose fiscal year end months are different from the month of the majority firms in that country. In my sample, the majority of firms end their fiscal years in December except for Australia, India, Japan, Pakistan, South Africa and Sri Lanka. Then I carefully identify the period of the earnings season which covers the largest number of earnings announcements and lasts for three months for each country. R^2s are estimated for the earnings season and non-earnings seasons respectively, and the dynamic pattern is tested in both country-level and firm-level analyses around the world.

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[4] In my sample countries, only Chile, China, Israel, Mexico, Peru and Romania present identical fiscal year end dates for all firms in that country.

For the country-level analysis, both equal-weighted and variance-weighted R^2s are lower in the earnings season than they are in the non-earnings seasons. 31 countries out of 40 countries present decreased stock return synchronicity in the earnings season, and the dynamic patterns are most pronounced in Egypt, China and Indonesia. In addition, the dominate effect of this dynamic pattern is coming from the systematic volatility rather than the idiosyncratic volatility. On average, the systematic volatility is 0.0148 in the non-earnings seasons and decreases about 8% to 0.0136 in the earnings season. In contract, the idiosyncratic volatility is 0.0507 in the non-earnings seasons and 0.0502 in the earnings season. I then classify the countries into high income countries and middle income countries according to the World Bank. Substantial changes of R^2 around the earnings season are presented for both high income countries and middle income countries, indicating that the findings in this thesis are general issues around the world. Finally, the dynamic pattern is robust for the firm-level analysis as well.

1.4 Contributions

This thesis contributes to the literature by providing new evidence for the information interpretation of stock return synchronicity. I join the debate by emphasizing the time varying nature of the R^2 which decreases when the general information environment becomes better. The dynamic response of stock return synchronicity to the information is also studied by Dasgupta, Gan and Gao (2010), who find the stock return synchronicity would increase after seasoned equity offerings (SEOs) and cross-listings of ADRs. I extend their work by exploring the dynamic pattern of R^2 in a more general setting for the regular earnings announcements and introducing a more comprehensive information structure with learning mechanism across assets. The general dynamic pattern highlights the limitations of static, cross-sectional approaches which are commonly used in the previous literature. My thesis also makes important implications for the change of market volatility.

Second, although most of the literature focuses on the firm-specific variations when analyzing the R^2, I reconsider this issue from the perspective of the systematic volatility which is closely related to the general information environment. In a multi-firms setting, I demonstrate how the systematic volatility would be fluctuated with the individual firms' earnings announcements when investors learn across assets, and this dynamic risk cannot be diversified in the portfolio. The property of the systematic volatility has also been studied by Morck, Yeung and Yu (2000). In a cross-country study, they find that the negative relationship between the private property protection and the stock return synchronicity is mainly driven by the market-wide variations in the emerging markets. They blame the elevated systematic risk to the increased noise trader risk with deterred informed arbitrage (DeLong, Shleifer, Summers and Waldmann (1989, 1990)). My thesis provides a rational explanation for the findings of Morck, Yeung and Yu (2000) by establishing a direct link between the general information environment and the systematic volatility. My thesis also casts doubt about the practices of controlling systematic volatility in the R^2 study, which is recommended by several papers such as Dasgupta, Gan and Gao (2010) and Li, Rajgopal and Venkatachalam (2014).

Finally, this thesis highlights an information structure which combines the information about the market-wide and firm-specific factors in one noisy signal. The previous literature supposes that the market-wide and firm-specific information can be perfectly separated. They either assume that the macroeconomic news can be easily observed than the firm-specific news (Jin and Myers (2006); Dasgupta, Gan and Gao (2010)), or the investors can process these two kinds of information through separated tasks (Peng and Xiong (2006); Hou, Peng and Xiong (2013)). I claim that the integrated information structure is important to the price generation process by allowing investors to learn across assets, and it can generate an endogenous ratio of the systematic volatility and the idiosyncratic volatility which makes important implications for the cross-sectional analysis.

1.5 Thesis Structure

The remainder of the thesis is organized as follows. Chapter 2 reviews the literature about the stock return synchronicity, the learning process in financial markets and the information content in the earnings season. Chapter 3 constructs the theoretical model with important implications and develops testable hypotheses for the empirical analysis. The empirical evidence for the dynamic pattern of R^2 around the earnings season in China is presented in Chapter 4. And Chapter 5 generalizes the findings in the international framework. Chapter 6 concludes and discusses potential directions for future research.

Chapter 2. Literature Review

In this chapter, I introduce the concept of the stock return synchronicity and the decomposition process of R^2 in section 2.1. I also review the information interpretation of the stock return synchronicity and its discussions in this section. In section 2.2, I review the Bayesian updating rules and discuss how learning can induce excess comovement in the previous literature. Finally, since I use the earnings season as the empirical setting, the response of investors to the earnings announcements and the information transfer during the earnings season are reviewed in section 2.3.

2.1 Stock Return Synchronicity and the Informativeness of Stock Prices

2.1.1 Definition of Stock Return Synchronicity

The stock return synchronicity measures to what extent the individual stock returns may co-move with the market. In the theories of the asset pricing, the individual stock returns can be explained by one or more economy-level common pricing factors (Sharpe (1964); Ross (1976)). Taking the Capital Asset Pricing Model (CAPM) as an example, the expected returns can be explained by a single pervasive market factor and the risk free rate[5]. Approximately, the standard market model regression derived from the CAPM model can be expressed as

$$r_{jt} = \alpha + \beta_j r_{m,t} + \varepsilon_{jt}, \qquad (2\text{-}1)$$

where r_{jt} is the total return for stock j at time t, $r_{m,t}$ is the market return at time t, β_j is the estimated coefficient, and ε_{jt} is the unexpected return. The variance of $(\beta_j r_{m,t})$ is noted as the systematic volatility since it cannot be diversified in the portfolio, while the variance

[5] The stock return synchronicity can also be estimated using multiple-factors model.

of the error term (ε_{jt}) is firm-specific and noted as the idiosyncratic volatility. The sum of these two volatilities is the total variance of the stock returns.

From an econometric perspective, the R^2 extracted from the regression of Equation (2-1) is used to measure the goodness of fit of the market model. While according to Roll (1988), it can also measure the fraction of the stock returns explained by the common factors:

$$R^2 = \frac{var(\beta_j r_{m,t})}{var(\beta_j r_{m,t}) + var(\varepsilon_{jt})}$$

$$= \frac{systematic\ volatility}{systematic\ volatility + idiosyncratic\ volatility}. \qquad (2\text{-}2)$$

Furthermore, according to Morck, Yeung and Yu (2000), the stock return synchronicity can be measured as a logarithmic transformation of R^2 as

$$SYNCH = \ln\left(\frac{R^2}{1-R^2}\right) = \ln\left(\frac{var(\beta_j r_{m,t})}{var(\varepsilon_{jt})}\right)$$

$$= \ln(systematic\ volatility) - \ln(Idiosyncratic\ volatility). \qquad (2\text{-}3)$$

As shown in Equation (2-3), the stock return synchronicity equals to the logarithm of the systematic volatility minus the logarithm of the idiosyncratic volatility. That means the stock return synchronicity is associated with both the systematic volatility and the idiosyncratic volatility. In another word, the higher stock return synchronicity could be caused by either higher systematic volatility or lower idiosyncratic volatility or both.

Roll (1988) draws the first attention to R^2. He finds that in US, the average adjusted R^2 is only about 0.35 with monthly data and 0.20 with daily data, which is far below the expectations of the asset pricing theories. He argues that the stock returns cannot be mainly explained by the movements in pervasive economic factors, the changes of the industry information or the effects of unpredictable firm-specific events. The large proportion of the firm-specific price movements in the stock return variations may imply either private information or else occasional frenzy unrelated to concrete information. Following Roll (1988), substantial evidence is provided to explore the interpretation of R^2. However, what R^2 captures, the information or noise, is still under debate nowadays.

2.1.2 The Interpretation of R^2

The information interpretation of R^2 is first confirmed in Morck, Yeung and Yu's paper in 2000. By studying the stock return synchronicity across 40 countries in 1995, they find the stock return synchronicity is lower in rich economies with stronger property rights protection, which promotes informed arbitrage and capitalizes more firm-specific information. The higher systematic volatility in the emerging markets appears unrelated to the fundamentals but consistent with the noise trader risk. This explanation of investors' property rights protection for the variation of R^2 across countries is admitted by Jin and Myers (2006), who step further to emphasize the role of transparency to this mechanism. The imperfect protection with completely transparency would not increase R^2, but the lack of transparency combined with insiders' capture would increase R^2 by reducing firm-specific risk absorbed by outside investors. With several measures of opaqueness, they find the R^2 is positively associated with the opaqueness as well as the frequency of crashes. Consistent with these arguments, Dang, Moshirian and Zhang (2015) find that the comovement of firm-level news is higher in the countries with weaker institutional environments and the positive relationship between the news commonality and the stock return synchronicity is more pronounced in the countries with stronger institutions.

The information interpretation of R^2 at the country level has been easily adopted at the firm level after Durnev, Morck, Yeung and Zarowin (2003) who find that the firms and industries with lower R^2s have more information-laden stock prices about future earnings. As a widely accepted measure of stock price informativeness, they find the explanation power of the future earnings to the current stock prices is larger for the stocks with lower R^2s in US industries. Consistent with their findings, the negative association between the stock return synchronicity and the disclosure quality is also documented by the following papers. Hutton, Marcus and Tehranian (2009) find that the higher R^2 is associated with more opacity of the financial statements and a higher probability of crash[6]. The opaqueness is measured by the earnings management, which is a three years' sum of the absolute value of discretionary accruals from Jones (1991) model. Haggard, Martin, and Pereira (2008) find that the enhanced voluntary disclosure using the analyst evaluation of disclosure quality is negatively associated with the stock return synchronicity, indicating a negative relationship between R^2 and the transparency. While Gul, Kim and Qiu (2010) find that the synchronicity of Chinese listed firms is lower if the financial reports are audited by big-four auditors who would provide more credible information to the investors. To sum up, this line of literature argues that by improving the firm's transparency, the higher disclosure quality could help to incorporate more firm-specific information into the stock prices, thus leading to a lower R^2.

The effect of the corporate governance to the stock return synchronicity is widely studied based on the information interpretation of R^2. Ferreira and Laux (2007) find that

[6] Datta, Iskandar-Datta and Singh (2014) challenge the results of Hutton, Marcus and Tehranian (2009) and find that the positive relationship between R^2 and opacity is not robust with different time period, different empirical technique and the estimation method for the discretionary accruals suggested by Kothari, Leone and Wasley (2005).

the firms' antitakeover provisions are positively associated with the stock return synchronicity. They argue that the openness of the corporate control to the market could encourage investors to collect and trade on the private information, which would improve the informativeness of the stock price and reduce the stock return synchronicity. To support this argument, they also find that the firms with fewer antitakeover propositions would display higher trading activity, higher private information flow and more information about the future earnings. Consistent with their findings, Armstrong, Balakrishnan, and Cohen (2012) find the stock return synchronicity decreases following the passage of the antitakeover laws, indicting an increase of financial statement informativeness after this important change of governance rules. The effect of the improved corporate governance to the stock return synchronicity is also studied by Fernandes and Ferreira (2008). By triggering the collection and trading process of the private information, they find that the cross-listing in US helps to improve the price informativeness of the firms in other developed markets, thus leading to a lower stock return synchronicity for the cross-listed firms.

In addition, several papers document that the board and shareholder structures are also associated with the stock return synchronicity. Ferreira, Ferreira and Raposo (2011) find that the price informativeness measured as the inversed stock return synchronicity is negatively associated with the board independence, indicating a less demand for the board structure for the firms with more informative stock prices. While Gul, Ng and Srinidhi (2011) argue that the gender diversity in boards decreases the stock return synchronicity through increased public disclosure or private information collection. They find that the firms which have lower return synchronicity are more likely to have a higher proportion of women on their boards. Furthermore, Brockman and Yan (2009) document that the block holders decrease the firm's stock return synchronicity with the advantage of information precision and lower acquisition costs, thus playing an important role on the shaping of information environment. While a strong relationship between the stock return synchronicity and the interlocking directorates is documented by Khanna and Thomas (2009), who investigate the effect of different kinds of firm interlocks and control groups to the synchronicity in Chile and argue that the presence of share directors indicates either lower firm level transparency or higher fundamentals correlations. In China, the stock return synchronicity is a concave function of the ownership by the largest shareholder as stated by Gul, Kim and Qiu (2010).

If the stock return synchronicity reflects the relative information incorporated into the stock price, the effect of the trading activities by the market participants is an essential issue in the R^2 study. Piotroski and Roulstone (2004) use stock return synchronicity to test the type of price-relevant information conveyed by financial analysts, institutional investors and insiders. They find the stock return synchronicity is inversely related to insider and institutional trading by incorporating firm-specific information, while positively associated with analysts' activities by incorporating industry-level information through intra-industry information transfers. The positive relationship between the financial analyst coverage and the stock return synchronicity is confirmed by Chan and Hameed (2006) in the setting of the emerging markets and by Fernandes and Ferreira (2008) who find an increase of stock return synchronicity of the firms in the emerging markets after the cross-listing in US due to the increased analyst following. The stock return synchronicity increases after the initial analyst coverage (Schutte and Unlu (2009)), while decreases with further analyst following (Crawford, Roulstone and So 2012). They argue that the initial analyst coverage would provide more market or industry-level information but the followers would provide more firm-specific information to distinguish with the existing analyst.

The informed or sophisticated investors also help to reduce the stock return synchronicity. An and Zhang (2013) find that the dedicated institutional investors help to reduce the stock return synchronicity by limiting the extent of managers' extraction of the cash flows (Jin and Myers (2006)) through monitoring. While Ye (2012) separates the active institutional investors from the passive ones and finds that the R^2 decreases with the increase of active ownership. The ownership by the foreign investors affects the stock return synchronicity by providing more private information. In the framework of Chinese A-H shares, Gul, Kim and Qiu (2010) find that the foreign ownership is inversely associated with the stock return synchronicity.

Finally, the stock price informativeness could help improve the efficiency of investment, which is negatively associated with the stock return synchronicity. Wurgler (2000) finds that the efficiency of the capital allocation is negatively associated with the stock return synchronicity across 65 countries. Due to effective arbitrage and low transaction costs, the countries with more informative prices and lower R^2s could help investors and managers find good investments. In the firm level analysis, Durnev, Morck and Yeung (2004) find a positive association between the economic efficiency of corporate investment and the firm-specific variation, and argue that the quickly and accurately reflection of the firm-specific information could facilitate more efficient corporate investment. Similarly, Chen, Goldstein and Jiang (2007) document a learning process of managers from the private information reflected in the stock price to the corporate investment decisions, which leads to a positive effect of firm-specific variation on the sensitivity of corporate investment to the stock price. Their argument is also supported by Bakke and Whited (2010) that the managers consider the private information in the stock price when making investment decisions.

However, the reasonability to use the stock return synchronicity as a measure of information is always questioned by the scholars. They argue that the lower stock return synchronicity is actually associated with less informed stock prices. West (1988) shows that the excess price variance is higher when the expectations are based on a smaller information set. If the discount rates are constant, the changes of the expected firm values which realized earlier would be more heavily discounted. Therefore, the rapid information incorporation based on a better information set should lead to lower volatility. Rajgopal and Venkatachalam (2011) show that the increased idiosyncratic volatility from 1962 to 2001 in US (Campbell, Lettau, Malkiel, and Xu (2001)) is caused by the deteriorating earnings quality, which increases the dispersion in analysts' forecasts and makes the analysts to place a higher weight on the firm-specific information. Furthermore, Chen, Huang and Jha (2012) demonstrate that the time trend of the idiosyncratic volatility is not only related to the operating uncertainty, but also associated with the managerial discretion in accruals. Contrary to the information interpretation of R^2, they find that the poor information quality is actually associated with higher idiosyncratic volatility.

In the cross-sectional analysis, Chan and Chan (2014) find a significant negative relationship between stock return synchronicity and the information asymmetry measured by SEO discounts. This relationship declines with the increase of the analyst coverage which means the extent of the information asymmetry can be mitigated by the analyst following. As a result, the firms with more analyst following should display higher stock return synchronicity due to the reduced information asymmetry rather than providing more industry-level information. Their perspectives are also supported by the empirical evidence indicating that the lower R^2 is associated with higher information costs and greater impediments to informed trades, less market efficiency and poorer information quality as suggested by Kelly (2014), Teoh, Yang and Zhang (2009) and Hou, Peng and Xiong (2013). Recently, Li, Rajgopal and Venkatachalam (2014) argue that the higher idiosyncratic volatility, measured as the variance of the error term from the market model regression, resembles noise. The lower stock return synchronicity is associated with higher price delay, greater insider trading, as well as lower illiquidity levels and higher liquidity risk, if the systematic risk is controlled.

Barberis, Shleifer and Wurgler (2005) find that the comovement of the stock returns increases after the inclusion to S&P 500 index, which cannot be explained by the change of the fundamental values. Deviating from the traditional view of comovement, they attribute their findings to the effect of frictions or noise traders' sentiment. Consistent with their findings, Wahal and Yavuz (2013) argue that the excess comovement of the stock returns to the fundamental correlation can be generated by the style-based investing of investors. In the framework of S&P/Barra categories which divide S&P 500 stocks into Value and Growth indices, Boyer (2011) finds that the economically meaningless index labels can cause excess comovement of the stocks sharing the same label. Green and Hwang (2009) document the price-based category strategy of investors by studying the comovement of the stocks undergoing splits. They find that the price comovement of the stock with the high-priced stocks decreases after the split. While Brealey, Cooper and Kaplanis (2010) find that the comovement of the stock returns decreases with the home market but increases with the acquirer after the cross-border mergers, which could be explained by the investors' trading patterns.

In addition to the commonality of investors' trading behavior, the higher stock return synchronicity is also attributed to other irrational explanations such as the common coverage by particular market participants. Grullon, Underwood and Weston (2014) find an excess price comovement among the firms sharing the same lead underwriter during the equity offerings. The investment banking networks would create segmented information flows to the target investors, thus generating similar trading patterns among the investors. Similarly, Anton and Polk (2014) find that the stocks with common active mutual fund owners intend to display more correlated returns, and this relationship is more pronounced when the mutual funds are experiencing strong net flows. The common ownership of retail investors could also induce excess comovement for the firms with small cap, lower price and lower institutional ownership documented by Kumar and Lee (2006), who highlight the importance of the sentiment to the formation of returns.

While for the psychological effect, Peng and Xiong (2006) demonstrate that the limited attention of investors leads them to possess more market-wide or section-wide information than the firm-specific information when the processing efficiency is low. As a result, the stock return synchronicity should be negatively related to the stock price informativeness when investors are overconfident for their information. The effect of the limited attention is also demonstrated by Peng, Xiong and Bollerslev (2007), who find the stock return synchronicity is higher when the macroeconomic shocks arrive, indicating a shift of the attention from the firm-specific information to the market-wide information. Finally, Eun, Wang, and Xiao (2015) highlight the effect of the culture to the stock return synchronicity. They find the comovement is higher in the countries with tight and collective cultures, and this effect would be weakened by the trade and financial openness.

2.1.3 Efforts to Reconcile the Puzzle

Morck, Yeung and Yu (2013) try to coalesce the seemingly discordant results about the interpretation of the stock return synchronicity into a coherent explanation by characterizing the firm-specific return volatility as the intensity of firm-specific information events. They argue that in an efficient market, the intensity of the firm-specific information events capitalized into the share prices would be reflected in the firm-specific return volatility (French and Roll (1986)), and the firm-specific event intensity would be higher when the arbitrage cost is low or when the creative destruction is more intensive (Chun, Kim, Morck and Yeung (2008)). This reconciliation highlights the effect of the economic dynamism to the stock return synchronicity. The R^2 should vary over time with the information flows capitalized into the stock prices.

This idea is supported by Dasgupta, Gan and Gao (2010) who provide the seemingly inconsistent evidence for the R^2 around a major corporate event. Contrary to the common wisdom, they find that the stock return synchronicity is higher after the issuance of seasonal equity offerings or the cross-listing of ADRs. The reason is that when the information environment is more transparent, stock prices are more informative about the future events, leading to a less intensity of the 'surprise' events in the future. While in a country-level analysis, the countercyclical pattern of the return comovement is confirmed by Brockman, Liebenberg and Schutte (2010). They find that the stock return synchronicity decreases (increases) during the periods of economic expansion (contraction) when the production of information increases (decreases). Based on the endogenously generated information signals from the aggregate economic activity (Veldkamp (2005)), the stock return synchronicity varies with the intensity of the information events when the economic conditions change. In addition, Li, Morck, Yang and Yeung (2004) find that the stock return comovement decreases when the foreign investment barriers are lower in the emerging markets, and the improved disclosure quality would also decrease the stock return synchronicity after the adoption of IFRS (Kim and Shi (2012)). Motivated by this line of literature, this thesis conducts a dynamic approach for the fluctuated R^2, which highlights the interactive mechanism of the information in the price generation process.

Another line of literature attributes the inconsistent empirical results to the disturbance of the systematic volatility. As argued by Dasgupta, Gan and Gao (2010), the positive association between the stock return synchronicity and the S&P additions (Barberis, Shleifer and Wurgler (2005)) and the increased analyst coverage (Piotroski and Roulstone (2004); Chan and Hameed (2006)) is due to the increased β, adding noise for the analysis of information and the firm-specific return variation. They also emphasize the need to control β in the firm-level studies of R^2.

The control for the systematic risk is also recommended by Li, Rajgopal and Venkatachalam (2014) recently. They find that the stock return synchronicity measured by R^2 or its transformed formulas is not equivalent to the inversed idiosyncratic volatility measured by the variance of the residual of the regression model (σ_{ε}^2). Both logarithmic transformation of R^2 and the inversed idiosyncratic volatility (σ_ε^2) are lower in firms with poorer information environment. They argue that although the R^2 is increasing with the inversed idiosyncratic volatility, the R^2 is also increasing with the systematic risk. If the systematic risk is strongly related to the independent variable of interest, contradicting results could be obtained by using different dependent variables of the logarithmic transformation of R^2 versus the inversed σ_ε^2. Consistent with their paper, I construct a model to highlight how the clustered firm-specific information would lower the R^2 by decreasing the systematic volatility, and emphasize the role played by the systematic risk to the puzzle of R^2.

Finally, Lee and Liu (2011) claim that the opposing views about the relationship between the stock return synchronicity and the stock price informativeness can be reconciled by decomposing the idiosyncratic volatility into two parts. One is the noise component caused by the demand of the liquidity traders, and the other is the information component driven by the information regarding to the fundamental values. The noise component decreases with the price informativeness, while the information component follows a U-shaped association with the price informativeness. Therefore, how the stock return synchronicity is associated with the price informativeness depends on the different values of the parameters in the equilibrium. The inversely U-shaped relation between the stock return synchronicity and the informativeness is also documented by Xing and Anderson (2011) who highlight the importance of distinguishing the public and private information that impounded into prices. The relationship between the synchronicity and relative amount of public information is non-linear, which could generate inconsistent evidence for the puzzle in different situations.

2.2 Learning in Financial Markets

2.2.1 Bayesian Updating

The theorem of Bayes' rule is widely used in the financial research to describe how agents would rationally update their prior beliefs according to the new information. In this section, the updating process would be illustrated by a simple example when the signals are unbiased and possess the same level of known variance. Suppose the prior beliefs about the uncertain parameter θ are normally distributed with mean θ_0 and variance σ_θ^2. When the agents receive n signals with respect to the parameter θ as $s_i = \theta + \varepsilon_i, i = 1 \dots n$, where ε_i is normally distributed with mean zero and variance σ_s^2, the posterior beliefs about the parameter would be updated as

$$E(\theta|s_i;\ i = 1 \dots n) = \frac{\sigma_s^2}{\sigma_s^2 + n\sigma_\theta^2}\theta_0 + \frac{\sigma_\theta^2}{\sigma_s^2 + n\sigma_\theta^2}\sum_{i=1}^{n} s_i, \tag{2-4}$$

$$Var(\theta|s_i;\ i = 1 \dots n) = \frac{\sigma_s^2\sigma_\theta^2}{\sigma_s^2 + n\sigma_\theta^2}. \tag{2-5}$$

Compared with the prior uncertainty, the posterior beliefs about the variance of the parameter in Equation (2-5) are lower than the prior beliefs (σ_θ^2), and decrease more when the number of signals increases or when the signals are more precise. In the model of this thesis, I also use the Bayes' rule to illustrate how the variances of the factors vary when investors process new information across assets. Unlike the simple example here, I consider a more complicated case when the signals could only reveal part of other firms' future cash flows by decomposing the cash flows into market factors and firm-specific factors respectively. The signals also follow different distributions since the signals' information qualities would vary across firms.

2.2.2 Learning and Excess Comovement

Many of the parameters characterizing the financial market are uncertain and subject to learning (Pastor and Veronesi (2009)). Timmermann (1993) argues that the learning in financial market could generate excess volatility by fluctuating the expectations of future dividends when the growth rate is unknown. While Pastor and Veronesi (2003) document a negative association between volatility and firm age when the investors could learn more about the fundamentals over time. The effect of learning to the excess comovement of the stock returns has been studied by Veldkamp (2006). Her paper indicates that when the fixed cost for the information production is high, investors price the assets using a common subset of information with higher demand, which elevates the comovement among the stock prices. In her rational model, investors learn the information about the high-demand firms and use the information to price other low-demand firms, which would generate excess comovement among the low-demand firms. Consistent with Veldkamp's (2006) model, Hameed, Morck, Shen and Yeung (2015) provide empirical evidence for this unidirectional spillover effect and find the bellwether firms whose prices are more accurate might exhibit more comovement. However, none of these papers decompose the R^2 and analyze the systematic and idiosyncratic volatilities separately.

Actually, if the cross-assets learning in a multiple-firms setting is one explanation of excess return comovement, the time varying information could move the systematic volatility which is non-diversifiable in a large economy. The effect of the learning behavior to the cost of capital and the systematic risk has been explored in the literature. In the CAPM setting, Lambert, Leuz and Verrecchia (2007) find that the higher disclosure quality would affect the firm's assessed covariance with other firms' cash flows and lower the firm's systematic market risk in the learning process. While Zhang (2013) explores the effect of the improved accounting standards to the prices of all firms in the market. He argues that the improving accounting standards could lower the cost of capital by reducing the systematic component of the measurement error. Furthermore, Patton and Verardo (2012) directly investigate whether stock betas vary with the release of firm-specific news. They find the betas increase on earnings announcement days and explain the results in a learning model when investors use the announcing firms' information to revise the expectations of the aggregate economy. Following the literature, I posit that if investors learn across assets when the firms' fundaments are correlated, the information would affect the systematic variations in addition to the firm-specific variations, which would complicate the analysis of the information interpretation of the stock return synchronicity.

2.3 Information Content in the Earnings Season

2.3.1 Stock Response to the Earnings Announcements

The earnings announcements are important and regular events to provide firm-level information. As the leading paper, Beaver (1968) finds dramatic price and volume reaction in the weeks surrounding the announcement date, indicating that investors do look directly at reported earnings, and that the information content of reported earnings has not been entirely preempt by previous news. After controlling for the risk, Ball and Kothari (1991) also document an increase of the true abnormal returns at the earnings announcement dates by identifying the increased expected returns with the changed variability and co-variability of the stock returns. Recently, Basu, Duong, Markov and Tan (2013) find that the earnings announcements would provide dominant information than other information sources individually. The R^2 which measures the explanation power of the earnings announcement returns to the annual returns is higher than other information sources, which means the earnings announcements could really provide important new information to the market.

The cross-sectional differences of the information content are studied by Freeman (1987), who finds that the abnormal returns surrounding the earnings announcements are higher for the smaller firms whose information content is less likely to be preempted, and Shores (1990) who finds a negative relationship between the information content of the annual earnings announcements and the level of interim information with a sample of OTC firms. The higher information content and greater stock price reactions to the bad news are also documented by Kothari, Shu and Wysocki (2009) when managers withhold the bad news. While in the country-level analysis, DeFond, Hung and Trezevant (2007) find that the annual earnings announcements are more informative in countries with higher quality earnings, better enforced insider trading laws and stronger investor protection institutions.

With the change of the accounting standards and the rapid development of information technologies, the information content of the earnings announcements varies over time. Although the literature concerns the degraded usefulness of the accounting information, Landsman and Maydew (2002) find no evidence for the decline of the information content with respect to the abnormal trading volume and abnormal return volatility. In contract, they find the informativeness of the quarterly earnings increases from 1972 to 1998, which is consistent with the findings of Francis, Schipper and Vincent

(2002) that the market reactions to the earnings announcements have increased due to the increased concurrent disclosures over the decades. Collins, Li, and Xie (2009) also study the reasons for the increased information content of earnings announcements, and provide another explanation of Street earnings to this time trend. In addition, Landsman, Maydew and Thornock (2012) find the recently mandatory adoptions of IFRS in some countries could increase the information content of earnings due to the recued reporting lag and the increased analyst following and foreign investment with the new accounting standards.

However, the earnings announcements may only provide limited incremental information to the market because of the measurement errors contained in the reports and the lagged reporting speed compared with other information sources. Ball and Brown (1968) examine the usefulness of the accounting information and check whether the unexpected income change is associated with the adjustment of stock prices. Although a substantial amount of information is contained in the income numbers, most of the content has been already captured by other timely media, leading to limited information surprise in the earnings. Lev (1989) reconfirms the limited usefulness of the quarterly and annual earnings to the investors. They find the correlation between earnings and stock returns is insufficient and instability. While Bamber, Christensen and Gaver (2000) find that the majority of firms present no significant price reactions to their individual earnings announcements with a different sample selection criteria. Ball and Shivakumar (2008) conclude that the quarterly announcements are only associated with 1% to 2% of total annual information, which can be attributed to the low frequency, less discretionary and backward-looking information content of the earnings reports. Although the earnings announcements do provide incremental information to the market, the amount of the information is only modest.

2.3.2 Information Transfer in the Earnings Season

Earnings announcements are clustered in calendar time and the period of jointly release of annual earnings reports is referred as ‘earnings season’. I consider the earnings season as a period with dramatically changed information environment, not only due to the flood of information released by numerous individual firms, but also because of the great information spillover effect during this time. In this section, I briefly review the papers documenting the information transfer in the earnings season.

Foster (1981) first confirms that a firm’s earnings release can move the stock prices of other firms in the same industry, and this effect of information transfer is stronger for the firms whose revenues are more correlated with the firm who releases the information. Clinch and Sinclair (1987) conduct more powerful tests with the control of the covariance of market model residuals. Their findings confirm the existence of directional intra-industry information transfer during earnings announcements. To address the potential misspecification of the return generating process, Han and Wild (1990) step further to test whether the unexpected earnings rather than the unsystematic returns of the earnings announcement firms could move the stock prices of other firms in the same industry. A positive relationship is found which provides further evidence for the impact of information transfer.

The extent of the information transfer varies across industries and firms. For example, by examining the price reactions of late announcers to the disclosures of early announcers within the industry, Freeman and Tse (1992) find that the extent of the positive information transfer would be more pronounced in the industry with higher earnings comovement. In addition to the fundamental correlations in the industry, Graham and King (1996) find the greater extent of the information transfer is also associated with higher earnings surprise, smaller firm size and lower pre-announcement information.

The investors and analysts may not always be able to appropriately transfer the information contained in early announcers' disclosures to other firms. Ramnath (2002) provides evidence that the investors intend to revise the earnings expectations of related firms using the information of early announcers. They also find predictable stock returns following the first announcement, which indicates an under-reaction of the investors to the public information. Furthermore, Thomas and Zhang (2008) find that the price responses to the earnings reported by early announcers and themselves are negatively correlated, indicating an overreaction to the early announcers' information and a correction process later. However, this anomaly associated with the information transfer has decayed over time with improved efficiency as stated by Chung, Hrazdil and Trottier (2015).

Chapter 3. Theoretical Model and Predictions

In this chapter, I develop a simple rational model to illustrate how the information environment would affect the stock return synchronicity and its two components: the systematic volatility and the idiosyncratic volatility. In the model, investors update their beliefs about the firm's future performance not only based on the news from that particular firm, but also taken reference from other firms' news in the market. In a large economy, this learning behavior across assets would largely reduce the systematic volatility even when the individual news is imperfect, and lower the stock return synchronicity when information environment becomes better.

The chapter is organized as follows. Section 3.1 sets up the model with basic valuation framework and the information structure. Section 3.2 demonstrates the updating process when investors receive signals and describes the model implications. While section 3.3 introduces the empirical testing framework of the earnings season and constructs testable propositions for the empirical analysis.

3.1 Model Setup

3.1.1 Basic Assumptions and Future Cash Flows

I start by considering a single-period economy with N risky assets and one riskless asset. The returns for the risky assets can be expressed as $r = (r_1, r_2 \dots r_n)'$, while the riskless asset has a known rate of return r_f. The random end-of-period cash flow for firm j is represented by a 'single-factor index model' as

$$x_j = \gamma_j f + v_j, \tag{3-1}$$

where f is a market factor, v_j is a firm-specific factor and γ_j captures the importance of the market factor for stock j. Agents have identical prior beliefs about the distributions of the fundamental factors, and since investors cannot infer news across factors and periods, they are identically and independently distributed as

$$f \sim N(\bar{f}, \sigma_f^2); v_j \sim N(\bar{v}_j, \sigma_{v,j}^2), j = 1, \dots n, \tag{3-2}$$

where f is a market factor which follows the normal distribution with the mean of $\bar{f}$ and the variance of σ_f^2 ,and v_j is the firm-specific factor for firm j which follows the normal distribution with mean of $\bar{v}_j$ and the variance of $\sigma_{v,j}^2$. This distribution is assumed for all firms in the market from *1* to *n*.

3.1.2 Information Structure

The prior beliefs about the future cash flows would be updated when investors receive signals which are informative with respect to x_j. The signals are commonly observed by all investors. Consistent with the actual disclosure practice, I model the information as noisy signals of the end-of-period cash flows[7]. Specifically, investors use the information set $\boldsymbol{I}$ to update their prior beliefs where $\boldsymbol{I} = (S_1, S_2 \dots S_n)'$, and the signal for each firm is the sum of the true value of cash flows and an error term as

$$S_j = x_j + \varepsilon_j = (\gamma_j f + v_j) + \varepsilon_j, \tag{3-3}$$

[7] The similar information structure is possessed in the literature such as Lambert, Leuz and Verrecchia (2007), Patton and Verardo (2012) and Zhang (2013).

where S_j is the signal for firm j, and ε_j is the noise contained in the signal which is *i.i.d* normally distributed as $\varepsilon_j \sim N(0, \sigma^2_{\varepsilon,j})$[8]. I regard the magnitude of the error term's variance as an inverse measure of the signal's information quality q_j where

$$q_j = \frac{1}{\sigma^2_{\varepsilon,j}}. \tag{3-4}$$

The precise of the information is negatively related to the error term's volatility, which is associated with the information collecting cost and the investors' efforts to study the news. When $\sigma^2_{\varepsilon,j}$ is large, the information could only imperfectly reveal the true values of the underlying factors.

My model emphasizes two features of the signals in the market. One is the existence of noise in the information, expressed as ε_j in Equation (3-3). Rather than directly observing the true values of the underlying factors, investors are only endowed with partial knowledge about the random factors, and the imperfect discovering process may induce a signal extraction problem for investors. The other is the integrated reporting structure of the signals. In most cases of information discovering process, the news about the market and firm-specific factors is reported together and hard to be perfectly separated, thus making the cross-assets learning an important issue in the price generation process[9].

[8] For simplicity, I suppose the error term is not correlated with each other.
[9] I mainly focus on individual firms' news here. For the macroeconomic news which can be easily learned, I do not consider it for simplicity and it would not affect the implications of the model.

3.1.3 R^2 Expression

In order to analyze how the information quality would affect the stock return synchronicity, I use the standard asset pricing model of conditional CAPM to estimate the R^2. As stated in CAPM, the expected return for firm *j* conditional on the information set is a function of the risk-free rate r_f, the conditional expected return for the market factor $E(r_m|I)$, and the beta coefficient $\beta_j|I$ where $\beta_j|I = \frac{cov(r_j,r_m|I)}{var(r_m|I)}$:

$$E(r_j|I) = r_f + \{\beta_j[E(r_m|I) - r_f]\} = r_f + \frac{cov(r_j,r_m|I)}{var(r_m|I)}[E(r_m|I) - r_f]. \quad (3\text{-}5)$$

Since the stock return equals to the ratio of the end-of-period cash flow x_j to the stock price at the beginning of the period P_j where $r_j \equiv \frac{x_j}{P_j} - 1$, the covariance of the stock return with the market return can be expressed as a function of the future cash flows' covariance that $cov(r_j, r_m) = cov\left(\frac{x_j}{P_j}, \frac{x_m}{P_m}\right) = \frac{1}{P_jP_m}cov(x_j, x_m)$. I define the systematic volatility as the variance of stock *j*'s returns related to the market-wide fluctuations, and the idiosyncratic volatility as the remaining part of the total variance excluding the systematic volatility. Thus the systematic volatility *SYSVOL* and the idiosyncratic volatility *IDIOVOL* can be expressed as

$$SYSVOL|I = \frac{\left[cov(r_j, r_m|I)\right]^2}{var(r_m|I)} = \frac{1}{P_j^2}\frac{\left[cov(x_j, x_m|I)\right]^2}{var(x_m|I)}, \quad (3\text{-}6)$$

$$IDIOVOL|I = var(r_j|I) - RSS|I = \frac{1}{P_j^2}\left\{var(x_j|I) - \frac{\left[cov(x_j, x_m|I)\right]^2}{var(x_m|I)}\right\}. \quad (3\text{-}7)$$

Consistent with Roll (1988) and Morck, Yeung and Yu (2000), the stock return synchronicity or R^2 of the market model regression can be expressed as

$$R^2|I = \frac{SYSVOL|I}{SYSVOL|I+IDIOVOL|I} = \frac{\left[cov\left(x_j, x_m|I\right)\right]^2}{var\left(x_j|I\right)var(x_m|I)}. \tag{3-8}$$

The expressions of R^2 and its two components imply that the information quality would move the stock return synchronicity by affecting investors' inferences about the covariance structure of future cash flows. Based on these formulas, the following sections analyze in details about how the stock return synchronicity would change according to the change of the information quality.

3.2 Information Updating Process

In this section, I illustrate how the information quality could affect the stock return synchronicity as well as its systematic and idiosyncratic volatilities. The updating process is intuitive: based on an information set with respect to the future cash flows, investors update their beliefs about the variance-covariance structure of the market and firm-specific factors. When the updating beliefs about these underlying factors are reflected in the stock returns, the stock return synchronicity would move with the information. I first show a simple case when investors do not learn across assets and update their beliefs only based on the signal for that particular firm. Then I introduce the learning process into the model and illustrate how the information environment of the market, in addition to the information of the particular firm, would move the stock prices and the stock return synchronicity.

3.2.1 Updating Process without Learning

Suppose the information set used by investors to update their beliefs about firm j's future cash flow is $I = S_j$. The covariance structure for firm j's cash flow $x_{j,t}$ with the market-wide cash flow $x_{m,t}$ is updated conditional on the information S_j. As shown in Appendix I, the stock return synchronicity can be expressed as a function of the information quality as

$$R^2|S_j = \frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2+\sigma_{\varepsilon,j}^2} \times \frac{\gamma_j{}^2\sigma_f^2}{\gamma_j{}^2\sigma_f^2+\sigma_{v,j}^2}. \tag{3-9}$$

While the systematic volatility and the idiosyncratic volatility based on the firm's particular information S_j is

$$SYSVOL|S_j = \frac{1}{P_j^2}\left(\frac{1}{\sigma_{v,j}^2 q_j+1} \times \frac{\gamma_j{}^2\sigma_f^2}{(\gamma_j{}^2\sigma_f^2+\sigma_{v,j}^2)q_j+1}\right) \tag{3-10}$$

and

$$IDIOVOL|S_j = \frac{1}{P_j^2}\left(\frac{\sigma_{v,j}^2}{\sigma_{v,j}^2 q_j+1}\right). \tag{3-11}$$

As shown in Equation (3-9), the R^2 is associated with the underlying volatilities of market factor and firm-specific factor (σ_f^2 and $\sigma_{v,j}^2$), the fundamental correlation with the market (γ_j) and the quality of the information (q_j). Furthermore, although the investors only use firm j's signal to update their beliefs, both systematic volatility and idiosyncratic volatility are affected by the updating process. That is because I assume the particular firm j's signal is a noisy measure of the entire future cash flows, and the news for the market and firm-specific factors is not separately reported. As a result, the individual firm's news can update the investors' beliefs about the future cash flows for both market factor and the idiosyncratic factor simultaneously. And the stock return synchronicity is a combined effect of these two components.

3.2.2 Learning and the Quality of Information Environment

I now introduce the cross-assets learning behavior into the updating process and highlight the effect of the information environment which is neglected in the previous studies. According to the information structure, the information set can be separated into two groups: one is the signal for that particular firm which can be used to update the beliefs about the whole cash flows for that firm; the other is a group of other firms' signals in the market, which can be used to update the beliefs about the market factor. When the common component is updated, the conditional variance for all firms in the market would change. Using firm j as an example, I illustrate how the covariance structure for firm j's cash flow x_j with the market-wide cash flow x_m is updated based on the information set $I = (S_1, S_2 \dots S_n)'$ according to the Bayes-Rule. The conditional R^2 is expressed in Theorem 1. See the detailed updating process in Appendix I.

Theorem 1. *When investors update their beliefs about the future cash flows based on all information in the market with the information set $I = (S_1, S_2 \dots S_n)'$, the R^2 for firm j is given by*

$$R^2|(I = S_1, S_2 \dots S_n) = \frac{1}{\sigma_{v,j}^2 q_j + 1} \times \frac{{\gamma_j}^2 \sigma_f^2}{{\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \left(\sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + 1/q_k} + 1\right)}. \qquad (3\text{-}12)$$

As shown in Theorem 1, the R^2 is affected by both the quality of the particular firm's information (q_j) and the general information quality of all other firms' signals in the market ($q_k, k = 1,2..n \;\&\; k \neq j$). Compared with the R^2 derived by using only the particular information in Equation (3-9), the learning process lowers the volatility of the systematic factor (${\gamma_j}^2\sigma_f^2$) by a denominator of ($\sum_{\substack{k=1\\k\neq j}}^{n}\frac{{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2+1/q_k}+1$). This denominator reflects how much information about the market factor can be learned from all the individual firms' signals in the market, including both the extent of learning for each signal and the number of the effective signals in the market.

The logarithm of R^2 can be decomposed into two parts as

$$\ln(R^2|I)=\ln\left(\frac{1}{\sigma_{v,j}^2 q_j+1}\right)+\ln\left[\frac{{\gamma_j}^2\sigma_f^2}{{\gamma_j}^2\sigma_f^2+\sigma_{v,j}^2(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2+1/q_k}+1)}\right]. \qquad (3\text{-}13)$$

The first part illustrates the effect of the firm's own information while the second part reflects the effect of the general information quality of other firms. Both parts would decrease when the information quality improved. Contrary to the common wisdom, I highlight that R^2 would move with the general information quality of other firms, even when the information quality of that particular firm remains the same. The relationship between R^2 and the general information environment is summarized in the following corollary.

Corollary 1. *R^2 is negatively associated with not only the information quality of that particular firm, but also the general information quality of all other firms' signals in the market.*

I then decompose the R^2 into systematic and idiosyncratic volatilities. The conditional systematic and idiosyncratic volatilities are expressed in Theorem 2. See the detailed updating process in the Appendix I.

Theorem 2. *When investors update their beliefs about the future cash flows based on all information in the market with the information set $I = (S_1, S_2 \dots S_n)'$, the systematic volatility and the idiosyncratic volatility for firm j is given by*

$$SYSVOL|(I = S_1, S_2 \dots S_n) = \frac{1}{P_j^2}\left(\frac{\gamma_j}{\sigma_{v,j}^2 q_j + 1}\right)^2 \frac{\sigma_f^2}{\sum_{k=1}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + 1/q_k} + 1} \qquad (3\text{-}14)$$

and

$$IDIOVOL|(I = S_1, S_2 \dots S_n) = \frac{1}{P_j^2}\left(\frac{\sigma_{v,j}^2}{\sigma_{v,j}^2 q_j + 1}\right). \qquad (3\text{-}15)$$

Theorem 2 establishes that both the systematic and the idiosyncratic volatilities are associated with the quality of the information set. However, they do not reflect the information in the same way. The systematic volatility is associated with both the information quality of that particular firm (q_j) and the information qualities for other firms ($q_k, k = 1,2..n$ & $k \neq j$). While the idiosyncratic volatility is only associated with the information quality of that particular firm (q_j).

Unlike the previous literature, the information structure highlights that the news about the market and firm-specific factors in the cash flows is not separately reported. Therefore, the references can be taken across assets since the common component contained in firm *i*'s signal could also provide information for firm *j*'s future cash flows. In Theorem 2, firm *i*'s information quality affects firm *j*'s systematic volatility through the equation of $\frac{{\gamma_i}^2 \sigma_f^2}{\sigma_{v,i}^2 + 1/q_i}$, which reflects how much systematic news can be learned from firm *i*'s signal. If firm *i*'s information quality is improved, investors could learn more about the common component, which would be finally reflected into the systematic volatility of all stocks in the market.

Furthermore, Theorem 2 highlights that, when investors learn the common component from all signals in the market, the effect of learning can be accumulated as $\sum_{k=1}^{n}\frac{{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2+1/q_k}$. That means even when the information quality of each firm's signal only improves slightly, if the number of signals is large, the systematic volatility can still effectively capture the improved quality of the general information environment. On the contrary, the change of the quality of the information environment would not be reflected into the idiosyncratic volatility due to the independence of the firm-specific cash flows. I summarize the effect of the information environment in Corollary 2. Detailed proofs are in the Appendix I.

Corollary 2. *Due to the special information structure and the learning behavior of investors, the systematic volatility decreases when the general information quality of all other firms' signals in the market improved. However, the idiosyncratic volatility would not be affected by the change of the general information environment.*

I then analyze what kinds of firms are more sensitive to the change of the general information environment. Intuitively, the effect of the changing information environment would be more pronounced for the firms with relatively higher systematic uncertainty. If the uncertainty about the firm's future cash flows is fully firm-specific, the quality of the general information environment would play no role to the R^2. Corollary 3 documents this argument and the detailed proofs are in the Appendix I.

Corollary 3. *The effect of the general information environment to the R^2 would be strengthened when the uncertainty about the firm-specific factor is relatively low.*

3.2.3 Other Implications of the Model

3.2.3.1 The Effect of the Particular Firm's Information

Although this model emphasizes the effect of the information environment to the stock return generation process by introducing the learning behavior, it also makes important implications for the studies which explore the effect of the information of the particular firm. For example, Cheng, Leung and Yu (2014) examine the changes of the R^2 and the stock return synchronicity before and after the earnings announcement for one particular firm. They find that upon information arrival, R^2 decreases compared with the one before the earnings announcement, which is consistent with the predictions of Corollary 1 in my model.

However, Dasgupta, Gan and Gao (2010) seem to provide inconsistent evidence to the literature. They argue that in a more transparent information environment, the stock return synchronicity should be higher with less 'surprise' in the future, and find that the stock return synchronicity is higher after seasonal equity offerings and the listing of ADRs. The main difference between their paper and the implications of Corollary 1 is the signal's type: both SEOs and ADRs are important corporate events for a particular firm, but provide limited information for the market. As a result, R^2 should increase with the decrease of idiosyncratic volatility if the systematic volatility remains almost the same.

To address these two types of signals, I extend the model by introducing a dummy variable to the information structure that $S_j = (\gamma_j f \times D_j + v_j) + \varepsilon_j$. When $D_j = 1$, the signals provide the information for the future cash flows of both market and firm-specific factors, such as the earnings announcements; while when $D_j = 0$, the signals mainly provide the information for the firm-specific factors, such as the disclosures for the corporate events. The conditional R^2 is expressed in Theorem 3. See the detailed derivation process in the Appendix I.

Theorem 3. *When investors update their beliefs about the future cash flows based on all information in the market with the information set* $I = (S_1, S_2 \dots S_n)'$ *where* $S_j = (\gamma_j f \times D_j + v_j) + \varepsilon_j$, *the* R^2 *for firms j is given by*

$$R^2|(I = S_1, S_2 \dots S_n) = \frac{[\sigma_{v,j}^2 q_j(1-D_j)+1]^2}{\sigma_{v,j}^2 q_j+1} \times \frac{{\gamma_j}^2 \sigma_f^2}{{\gamma_j}^2 \sigma_f^2\left(\sigma_{v,j}^2 q_j(1-D_j)+1\right)+\sigma_{v,j}^2\left(\sum_{\substack{k=1 \\ k\neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2+\frac{1}{q_k}} D_k+1\right)}. \quad (3\text{-}16)$$

When $D_j = 1 \; for \; \forall j \in n$, R^2 is equal to its expression in Theorem 1, which means the investors can learn the information about the market factor from other firms' signals. While if the information is only about the firm-specific factor for one particular firm, the relationship between R^2 and the information quality is shown in the following corollary:

Corollary 4. *When investors update their beliefs about the future cash flows based on all information in the market with the information set* $I = (S_1, S_2 \dots S_n)'$ *where* $S_j = (\gamma_j f \times D_j + v_j) + \varepsilon_j$,

(a) If $D_k = 0$ *where* $k \in n$ *and* $k \neq j$*, the component learned from firm k's signal for firm j's future cash flow is* $\frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} D_k = 0$;.

(b) If $D_k = 0$ *for* $\forall k \in n$*,* R^2 *is positively associated with the information quality of firm j's signal.*

The intuition for Corollary 4 is straightforward. In an extreme case when all the signals in the market only contain the information for the firm-specific factors, the investors cannot learn across the assets since the common component has not been updated. Therefore, the information about the firm-specific factors would increase the R^2 by decreasing the idiosyncratic volatility, which is consistent with the empirical evidence provided by Dasgupta, Gan and Gao (2010).

3.2.3.2 Implications for the Cross-Sectional Analysis

In addition to the dynamic pattern of the stock return synchronicity, this model also makes important implications for the cross-sectional analysis. As shown in Equation (3-12) in Theorem 1, R^2 is associated with the information quality (q_j), the uncertainty about the market factor and the firm-specific factor (σ_f^2 and $\sigma_{v,j}^2$), the fundamental correlation with the market (γ_j) and the extent of learning across the assets ($\sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}}$).

Corollary 5. *When investors update their beliefs about the future cash flow based on all information in the market with the information set* $I = (S_1, S_2 \ldots S_n)'$*,* R^2 *is lower when*

(a) *The information quality is high;*

(b) *The uncertainty is low for the market factor and high for the firm-specific factor;*

(c) *The fundamental correlation with the market is low;*

(d) *The extent of learning across the assets is high.*

The predictions of Corollary 5 are consistent with the intuition and the evidence provided by the previous literature (Morck, Yeung and Yu (2000); Durnev, Morck, Yeung and Zarowin (2003); Jin and Myers (2006)), stating that R^2 or its logarithmic transformation should be negatively associated with the information quality.

Li, Rajgopal and Venkatachalam (2014) challenge this traditional view by pointing out that the inconsistent empirical results in the literature about the information interpretation of the stock return synchronicity are due to the improper view for the R^2 and the idiosyncratic volatility (σ_ε^2). They argue that the negative relationship between R^2 and the informativeness of the stock price turns to be positive after control for the systematic volatility. My model provides theoretical implications for their findings which are stated in Corollary 6. See the detailed derivation process in the Appendix I.

Corollary 6. *The systematic volatility and the idiosyncratic volatility are both negatively associated with the information quality of that particular firm.*

Corollary 6 implies that the idiosyncratic volatility and the inverse expression of R^2 are not interchangeable with respect to the information quality, which is consistent with Li, Rajgopal and Venkatachalam (2014). Although the R^2 is negatively associated with the information quality, the synchronicity measured by the revised idiosyncratic volatility of σ_ε^2 is positively associated with the information quality. That is because the systematic volatility inherit in the R^2 metric is also correlated with the information quality. However, our conclusions are different. Their paper argues that the idiosyncratic volatility resembles noise rather than information. While in my thesis, I present a direct association between the R^2 and the information quality in the model.

3.3 Empirical Predictions

In this section, I develop the empirical implications which highlight the effect of the information environment to the stock return synchronicity. The earnings season serves as a good setting for this purpose. I first argue that in the earnings season, the quality of the information environment is improved when firms report their earnings announcements simultaneously. Then I state the predictions for the dynamic pattern of stock return synchronicity as well as the systematic and idiosyncratic volatilities in the second part of this section.

3.3.1 The Framework of the Earnings Season

I define the earnings season as the special period when the majority of firms in a market report their earnings announcements in a clustered manner. The general information environment in the earnings season is highly improved for the following reasons. On the one hand, the individual firm's earnings announcement serves as an important and regular event to provide information which can be easily learned by all investors. Thus the information quality of that particular firm is improved when the firm makes its earnings announcement. On the other hand, the earnings announcements are clustered at calendar time. This reporting structure indicates that in the earnings season, the information qualities of all firms in the market would be improved simultaneously, which highlights the importance of cross-sectional learning (Foster (1981); Han and Wild (1990); Ramnath (2002); Thomas and Zhang (2008)) and provides a nature framework to test how the stock return synchronicity would move with the varying general information environment.

Suppose that in the earnings season, the information quality is higher than the one in the normal periods for any firm in the market:

$$q_{j(ES)} > q_{j(NES)}\ , \forall j \in \mathrm{n}, \tag{3-17}$$

where $q_{j(ES)}$ is the information quality of firm *j*'s signal in the earnings season, and $q_{j(NES)}$ is the information quality of firm *j*'s signal in the non-earnings seasons. The general information environment could be highly improved from two perspectives: one is the highly improved information quality of one particular firm ($q_{j(ES)} \gg q_{j(NES)}$), which is associated with the information content in the earnings report compared with the information from other sources; and the other is the increased number of the effective signals in the market (n$\sim\infty$), which is associated with the extent of clustering in the reporting structure.

3.3.2 Hypotheses Development

The dramatically increased information disclosure intensity in the earnings season would improve not only the information quality of each particular firm ($q_{j(ES)} > q_{j(NES)}$), but also the general information environment of the whole market by activating the learning process ($\sum_{k=1}^{n} \frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+1/q_{k(ES)}} > \sum_{k=1}^{n} \frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+1/q_{k(NES)}}$). According to Corollary 1 that the R^2 is negatively associated with both the information quality of that particular firm and the general information quality of all other firms' signals in the market, I propose that there is a dynamic pattern of R^2 around the earnings season.

Proposition 1. *As a special period with intense information disclosures, R^2 is lower in the earnings season than it is in the normal period.*

I then argue that the improvement of the general information environment in the earnings season is the main reason for this dynamic pattern. Actually, if there is no information spillover effect, the incremental information provided by the public news such as the earnings announcements may be too modest to affect the R^2 (Berry and Howe (1994); Ball and Shivakumar (2008)). Roll (1988) also finds that the public firm-specific news can only explain a relatively small portion of the stock price movement in US. It may be true that the earnings announcements could only improve the information quality of one particular firm slightly. However, if investors could learn across assets, the R^2 should be lower when the earnings announcements are simultaneously released in the earnings season.

Suppose that the information quality of any firm is only slightly improved when the firm makes the earnings announcement:

$$q_{j(ES)} > q_{j(NES)}\,, q_{j(ES)} \approx q_{j(NES)}, \forall j \in n. \qquad (3\text{-}18)$$

Recall that the quality of the general information environment would affect the systematic volatility and stock return synchronicity in a sum function of $\sum_{k=1}^{n} \frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+1/q_k}$.

When q_k increases slightly for all firms in the earnings season, the small increase for each component would be accumulated into a large increase of the sum value if n is large. In another word, the quality of the information environment should be improved substantially in the earnings season even though the information quality of a particular firm is only slightly improved in a large economy.

The intuition is straightforward. In the earnings season, investors could update their beliefs about the market-wide factor from all firms' earnings announcements. The large number of signals could compensate for the limitation of inaccurate signal from each firm, and lower the systematic volatility through the learning process. In contrast, the idiosyncratic volatility can only be learned from the signal for that particular firm, so the idiosyncratic volatility would not be reduced if the earnings announcement only provides modest incremental information for that firm.

Proposition 2. *The dominant effect for the pattern of R^2 around the earnings season is coming from the systematic volatility, rather than the idiosyncratic volatility.*

Finally, I explore what kinds of firms are more vulnerable to the varying information environment around the earnings season. I first posit that the investors would possess more uncertainty about the future cash flows for the younger firms. As stated by Pastor and Veronesi (2003), investors attempting to value the newly listed firms are confronted with substantial uncertainty about their future profitability, and this uncertainty can be resolved over time through learning. Similarly, Dasgupta, Gan and Gao (2010) also argue that when a firm becomes older, the market could learn more about its time-invariant characteristics, thus the uncertainty about the fundamentals will be reduced over time. According to Corollary 3, R^2 would be more sensitive to the change of the general information environment with relatively lower firm-specific uncertainty, so I argue that the R^2s of the older firms should change more around the earnings season.

Proposition 3. *The change of R^2 around the earnings season would be more pronounced for older firms.*

Chapter 4. Dynamic Pattern of R^2 around the Earnings Season: Evidence from China

In this chapter, I conduct the empirical analysis for the dynamic pattern of the stock return synchronicity using Chinese listed firms from 2003 to 2015. The model in Chapter 3 proposes that the stock return synchronicity is lower in the earnings season than it is in the non-earnings seasons, which would be carefully examined in this chapter with both univariate analysis and the panel data regressions. Further analysis is also conducted for the driven force of the pattern and the robustness of the findings.

The chapter is organized as follows. Section 4.1 describes the data and sample while section 4.2 constructs the variables. The empirical results are presented in section 4.3.

4.1 Data and Sample

I obtain stock return, trading volume and accounting data from the China Stock Market and Accounting Research (CSMAR) database and the bid-ask price data from DataStream. The initial sample contains all A shares listed in Shanghai and Shenzhen stock exchanges[10]. I also exclude the stocks listed on the Growth Enterprises Market (GEM) Board. I require the accounting data to be quarterly available since I need to match the latest quarterly accounting data to the series of the synchronicity in the earnings season and the non-earnings seasons. Therefore, the sample period covers 13 years from 2003 to 2015 since the quarterly accounting information is first required in 2002 in China.

I exclude two types of abnormal daily returns from the sample: when the stock prices are hitting the daily price limit or when the stocks are under special treatment. In

[10] I exclude B shares and H shares from the sample because they have different trading rules.

1996, Shanghai and Shenzhen Stock Exchanges impose the daily price limit on trading of stocks and mutual funds with a daily price up/down limit of 10%. I exclude the trading days when the stock returns exceed the limit and one day after[11]. In addition, according to the stock listing rules, the stock exchanges would give special treatment to the stocks of the listed companies with abnormal financial conditions, which called 'ST' shares. I require the sample to include non-ST firms only to exclude potential noises caused by ST firms to the analysis.

I then require the sample firms to have at least 30 available trading days for each season which covers three months. I also exclude firm-years that are within 2 years of the IPO year and limit the sample to non-financial and non-utility firms according to the Industry Classifying Index Code of Listed Companies released by the China's Securities Regulatory Commission (CSRC)[12]. The final sample contains 16,810 firm-year observations for 2036 firms.

[Insert Table 4. 1 Here]

Table 4.1 presents the sample distribution across industries and years. As shown in Panel A, the number of firms within each industry ranges from 10 for Other Manufacturing, which posit less than 1% of the sample, to 402 for Machinery, Equipment and Instrument which posit 19.74%. While the number of firms increases monotonically over the sample years as shown in Panel B. In 2003, there are 892 firms in the sample while in 2015 there are 1923 firms, increased more than twice during one decade.

[11] In this screening process, I exclude about 224,000 observations which account for 4.5% of the sample. My empirical results are robust without this filter.
[12] http://www.csrc.gov.cn/pub/csrc_en/

4.2 Construction of Variables

4.2.1 Definition of the Earnings Season

I define the earnings season as the period when the majority of firms jointly make their annual earnings announcements. On the one hand, I consider the effect of the annual earnings announcements rather than the quarterly reports because the annual earnings statements provide relatively more information in China. Quarterly earnings announcements play a minor role as they are of low quality without auditing and attract less attention from the market. On the other hand, I consider a period of clustered information release rather than a single earnings announcement to emphasize the role of information transfer among different firms.

CSRC requires Chinese listed firms to complete and disclose the annual reports within four months from their fiscal year ends. Since the fiscal year ends of all Chinese firms are coincident with the calendar year end, and most of the firms disclose their annual reports within three months before the required deadline, I define the earnings season as the period from February to April when majority of firms release their earnings reports. In order to make the earnings season and the non-earnings seasons comparable, the non-earnings seasons are also defined to cover three months, from November of the last year to January this year, May to July, and August to October respectively. As a result, the analysis year in this thesis is defined from last year's November to this year's October with one earnings season and three non-earnings seasons.

[Insert Table 4. 2 Here]

Table 4.2 shows the time distribution of the annual earnings announcements which clearly present a clustered pattern. 97.89% of the annual earnings statements are announced during the earnings season, with 8.72% in February, 42.11% in March and 47.28% in April. In addition, this clustered pattern of earnings announcements is consistent over years. All in all, this table confirms the rationality of the definition of the earnings season in this thesis.

4.2.2 Measurement of the Synchronicity (Systematic/Idiosyncratic Volatility)

In order to measure the dynamic pattern of the stock return synchronicity, I estimate both the standard market model and the industry-augmented market model using daily returns for each season:

$$RET_{it} = \alpha + \beta_1 MARKET_t + \beta_2 MARKET_{t-1} + \beta_3 MARKET_{t+1} + \varepsilon_{it}, \quad (4\text{-}1)$$

$$RET_{it} = \alpha + \beta_1 MARKET_t + \beta_2 MARKET_{t-1} + \beta_3 MARKET_{t+1} + \beta_4 INDRET_t + \beta_5 INDRET_{t-1} + \beta_6 INDRET_{t+1} + \varepsilon_{it}, \quad (4\text{-}2)$$

where RET_{it} is the daily return for firm *i* on day *t*, $MARKET_t$ is the value-weighted A-share market return on day *t*, and $INDRET_t$ is value-weighted industry return exclude the firm *i*'s return on day *t*. One-day lag and one-day ahead market (industry) returns are also included. When the industry only includes few firms, the industry return may reflect the dominant firm-specific news rather than the industry news, thus leading to extremely high R^2. With this concern, I require at least five firms to be included in each industry. I also require at least 30 available trading days for each season and extract $R^2(1)$ and $R^2(2)$ from the regressions respectively. The returns on the quarterly earnings announcements days are excluded from non-earnings seasons. The systematic and idiosyncratic volatilities are the sum of squares due to regression and the sum of squared errors respectively. Since the R^2 is bounded between zero and one, I follow the common practice (Morck, Yeung and Yu (2000)) to use a logarithmic transformation of R^2, which turns to be a suitable dependent variable for the regression analysis:

$$SYNCH = ln(\frac{R^2}{1-R^2}). \tag{4-3}$$

In addition, I also estimate the R^2 as well as the systematic and idiosyncratic volatilities with the control for the impact of the individual firm's earnings announcement. I first exclude the observations within three days around the individual firm's earnings announcement, and then estimate the R^2 with the standard market model and the industry-augmented market model respectively. The extracted R^2s are denoted as $R^2(3)$ and $R^2(4)$.

4.2.3 Control Variables

I consider several control variables to exclude other potential effects on the dynamic pattern of stock return synchronicity. Four variables are controlled for the fundamental changes which are widely used in the previous literature, including the logarithm of the total assets (SIZE), market to book value calculated as the total market value of equity divided by total shareholder's equity (MTBV), leverage calculated as the total liabilities divided by the total assets (LEV) and the profitability calculated as operating profit divided by total assets (ROA). I use quarterly accounting data to measure all variables and match the latest accounting numbers to each season. All variables are trimmed at top and bottom 1%.

The stock return synchronicity would also be affected by the major corporate events. I control for their effects by adding dummies if there are important corporate events happened during that particular season. Following Dasgupta, Gan and Gao (2010), I first control the extreme changes in total assets (EVENT) since the corporate events are typically associated with major changes in assets. Second, I control for the effect of merger and acquisitions (M&A) as well as the seasonal equity offerings (SEO) which would change the normal speed of information release and affect the pattern of the stock return synchronicity[13]. Finally, in order to exclude the potential effect of liquidity to the dynamic pattern of stock return synchronicity, I control for three seasonal liquidity measures, namely Turnover (TURN), Amihud Illiquidity (AMIL) and Bid-Ask Spread (SPREAD). The Appendix Ⅱ provides more detailed definitions for all variables.

4.3 Empirical Results

4.3.1 Descriptive Statistics

[Insert Table 4. 3 Here]

The descriptive statistics and the correlation matrix of the main variables in this study are shown in Table 4.3. Panel A of Table 4.3 shows the descriptive statistics of main variables for the sample firms. The R^2 and synchronicity as well as systematic volatility and idiosyncratic volatility are estimated either from the standard market model or the industry-augmented market model and their descriptive statistics are listed respectively. The mean and median of the seasonal R^2 estimated from the standard market model ($R^2(1)$) are 0.4187 and 0.4149 respectively, which are significantly lower than the ones estimated

[13] I do not include right issues and seasoned new issues to specific target into the SEO control variables because their disclosures of information would not be as intense as a public offering.

from industry-augmented market model ($R^2(2)$) with the values of 0.5162 and 0.5226. Both R^2s display considerable variations as reflected in the high standard deviations and inter quartile ranges. The systematic and idiosyncratic volatilities also display considerable variations, with the means of 0.0175 and 0.0231 for the standard market model and 0.0216 and 0.0190 for the industry-augmented market model.

The descriptive statistics of the control variables are shown in the bottom part of Panel A in Table 4.3. The average size of the sample firms is 21.812, and the means of the market to book ratio and leverage are 3.3149 and 0.4866 respectively. The mean and median for the quarterly profitability measured as ROA are 0.0105 and 0.0081 respectively. Less than 1% of the firm-seasons is undergoing major corporate events measured as the sufficient change of total assets and the merger and acquisition, while about 13% of firm-seasons are affected by the process of season equity offerings. The descriptive statistics for the stock liquidity are presented in the bottom lines, with the means for TURN, AMIL and SPREAD as 0.0222, 0.1495 and 0.0018, respectively.

Panel B of Table 4.3 presents the Pearson correlation matrix of the variables. Consistent with the previous literature, the stock return synchronicity is positively associated with SIZE and LEV, while negatively associated with MTBV, which means the firms with higher R^2 are larger firms with higher leverage and lower market to book ratios. Consistent with the common wisdom, TURN is negatively associated with AMIL and SPREAD, and the stock return synchronicity is negatively associated with the liquidity measurements.

4.3.2 Dynamic Pattern of Stock Return Synchronicity

My empirical analysis starts from a carefully examination of the dynamic pattern of the stock return synchronicity around the earnings season. Proposition 1 predicts that the stock return synchronicity is lower in the earnings season than it is in the normal period, when the information environment is substantially improved due to the clustered earnings announcements. I first test this pattern by univariate analysis and then present the regression results with proper controls.

4.3.2.1 The Univariate Analysis

[Insert Table 4. 4 Here]

Table 4.4 reports the results of the univariate analysis for R^2s in the earnings season and in the normal period. The descriptive statistics in Panel A clearly display a changing pattern of firm-level R^2 around the earnings season. For the R^2 estimated from the standard market model (R^2 (1)), the equal-weighted mean is 0.3864 in the earning season and 0.4297 in the non-earnings seasons. The difference is 0.0433 and significant at 1% level. While for the value-weighted means of R^2, the difference between the earnings season and the non-earnings seasons (0.0402) is slightly lower than the difference of the equal-weighted means. It means that the larger firms not only have higher R^2s than the smaller firms, but also present weaker patterns than the smaller firms. The pattern is also robust for the medians of R^2 and the R^2 estimated from the industry-augmented market model (R^2 (2))[14].

[14] A detailed discussion about the dynamic pattern of R^2 in US is in Appendix III.

Furthermore, I argue that the dynamic pattern of R^2 around the earnings season is mainly due to the cross-sectional learning effects, rather than the impact of individual firm's earnings announcement. To support this argument, I first exclude the observations within the three days around the individual firm's earnings announcement, and then estimate the R^2 with the standard market model (R^2 (3)) and industry-augmented market model (R^2 (4)) respectively. After excluding the effect of the individual firm's earnings announcement, the R^2 remains unchanged with the equal-weighted mean of 0.4203 and the median of 0.4168 for the standard market model, compared with the R^2 estimated with all observations (the equal-weighted mean and median are 0.4187 and 0.4149 respectively).. My results are consistent with Roll (1988) who finds that the small value of R^2 in US is not due to the impact of individual days with public announcements[15]. As for the dynamic pattern around the earning season, I find the R^2 is lower in the earnings season than it is in the non-earnings seasons. The equal-weighted means of the difference are 0.0373 and 0.0307 for R^2 (3) and R^2 (4) respectively. The dynamic pattern is robust even after excluding the effect of the individual firm's earnings announcement.

The dynamic pattern of R^2 can be easily disturbed by large macro news and abnormal market conditions. I take this concern into consideration and present the seasonal pattern of R^2 in the normal years in Panel B of Table 4.4. There are two special periods in China stock market over the sample years. One is 2005 when the stock market is undergoing share structure reform. The other is 2008 to 2009 when the whole market is

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[15] Boudoukh, Feldman, Kogan and Richardson (2013) find the median of the estimated R^2 is 16% on the 'news days' and 28% on the 'no news days' using the advanced text analysis software. On the contrary, the R^2s with or without the exclusion of the earnings announcement window are similar in this thesis because I only focus on the limited effect of the public annual earnings announcements here.

under financial crisis. After excluding the observations during the special periods, the difference of R^2 between the earnings season and the non-earnings seasons becomes larger: the equal-weighted means for R^2 (1) and R^2 (2) are 0.0682 and 0.0593 respectively; the value-weighted means are 0.0625 and 0.0387 respectively; and the medians are 0.0759 and 0.0707 respectively. All the values of the difference are significant at 1% level. The pattern is also robust after excluding the effect of the individual firm's earnings announcement.

4.3.2.2 The Main Regression Analysis

I then test whether the stock return synchronicity is lower in the earnings season than it is in the non-earnings seasons by estimating the following regression model:

$$SYNCH_{it} = \alpha + \beta_1 ES_{it} + \sum_k \beta_k Control_{it}^k + Year + Industry + \varepsilon_{it}, \quad (4\text{-}4)$$

where $SYNCH_{it}$ is the stock return synchronicity for stock *i* and season *t*, ES_{it} is a dummy variable taking the value of one if the stock *i* at time *t* is in the earnings season, and zero otherwise, *Control* denotes a set of control variables, and *Year* and *Industry* are the year and industry dummies control for year and industry fixed effects. As predicted by Proposition 1, I expect the coefficient of ES_{it} to be significantly negative, which means the stock return synchronicity is lower in the earnings season than the one in the non-earnings seasons.

[Insert Table 4. 5 Here]

Panel A of Table 4.5 presents the results of the main regression analysis in the sample years from 2003 to 2015. The dependent variable for columns (1) and (2) is the stock return synchronicity estimated from the standard market model. In column (2), I add an interaction term of the dummies for the abnormal years and the earnings season (RCD) to control for the noises caused by the special market conditions. The coefficients for *ES* are -0.2055 and -0.3227 respectively, which are significantly negative as the expectation. Columns (3) and (4) show the results using the stock return synchronicity estimated from the industry-augmented market model as the dependent variable. The pattern remains unchanged which confirms that the stock return synchronicity is lower in the earnings season than it is in the normal period no matter which estimation model is used.

I control for both fundamental variables and major corporate effect dummies in the main regression analysis. Consistent with the previous literature, the coefficients of SIZE are significantly positive, indicating that the stock prices of large firms tend to comove with the market to a greater extent in China. The MTBV and LEV coefficients are significantly negative, which suggests that the firms with higher growth potential and higher financial leverage tend to have lower stock return synchronicity. As for the major corporate events dummies, the coefficients for EVENT and M&A are significantly negative, indicating that the stock return synchronicity would decrease when the major corporate events happen. Finally, the stock return synchronicity does not fluctuate with the process of seasonal equity offerings, which means the SEO process may not release enough information to move the R^2 in China.

4.3.2.3 The Abnormal Response to Earnings Announcements

One potential explanation for the dynamic pattern of R^2 is that since there are abnormal stock returns surrounding the earnings announcements (Beaver (1968)), the decreased R^2 in the earnings season may be caused by the short-run response to the information released by the individual firm's earnings announcement. I test this argument by using *SYNCH (3)* and *SYNCH (4)* as the dependent variables. The results are presented in Panel B of Table 4.5. After control for the impact of special market conditions, the coefficients for ES are -0.2982 for the standard market model (column (2)) and -0.2348 for the industry-augmented market model (column (4)), both are significant at 1% level. The results indicate that the effect of the particular firm's earnings announcement is very limited to explain the dynamic pattern of stock return synchronicity around the earnings season.

4.3.2.4 The Effects of Liquidity

The other concern is whether the lowered R^2 in the earnings season is just a reflection of the changing liquidity. Since the R^2 and liquidity are negatively correlated, if the liquidity increases in the earnings season, the stock return synchronicity would decrease as well. Therefore, I add three liquidity measures in the regressions to control for the potential effect of liquidity. It also controls potential effect of noise traders to the dynamic pattern. As shown in Panel C of Table 4.5, the results are robust with significantly negative coefficients for *ES*. As for the stock return synchronicity estimated from standard market model, the coefficients of ES after control for TURN, AMIL and SPREAD are -0.3067, -0.2804 and -0.3075 respectively; while for the stock return synchronicity estimated from industry-augmented model, the coefficients of ES are -0.2548, -0.2306 and -0.2587 respectively. In addition, TURN is negatively associated with the stock return synchronicity while AMIL and SPREAD are positively associated with the stock return synchronicity, indicating that the R^2 is negatively related with the stock liquidity. The results confirm that the dynamic pattern of the stock return synchronicity is not driven by the effect of liquidity.

4.3.3 Systematic Volatility or Idiosyncratic Volatility?

Now I confirm that the stock return synchronicity is lower in the earnings season than it is in the normal period. However, which component, the systematic volatility or the idiosyncratic volatility, is the dominant force for this pattern remains to be an empirical question. Proposition 2 predicts that the systematic volatility would be significantly lower in the earnings season if investors learn the common component across assets. I test this prediction by analyzing the patterns of the systematic and idiosyncratic volatilities separately.

[Insert Table 4. 6 Here]

Table 4.6 presents the results of the univariate analysis for the systematic and idiosyncratic volatilities. Panel A shows the results with all sample years while Panel B excludes the years when the Chinese firms are undergoing share structure reform in 2005 and the years when the stock market is under financial crisis from 2008 to 2009. The systematic volatility is lower in the earnings season than it is in the non-earnings seasons in both Panel A and Panel B. The means and medians for the systematic volatility estimated from standard market model are 0.0.0152 and 0.0110 in the earnings season and 0.0183 and 0.0145 in the non-earnings seasons. The systematic volatility decreases about 17% and 24% in the earnings season and the differences are significant at 1% level. Similarly, the systematic volatility estimated from the industry-augmented market model is also lower in the earnings season than it is in the non-earnings seasons, with the differences of mean and median as 0.0033 and 0.0040 respectively.

In the normal years, the dynamic pattern of the systematic volatility is more pronounced as shown in Panel B. The equal-weighted mean for the systematic volatility estimated from the standard market model is 0.0105 in the earnings season and 0.0163 in the normal period, decreased about 36% in the earnings season. While for the value-weighted mean and median, the differences are 0.0077 and 0.0035 respectively and the decreased ratios are about 44% and 27%. This pattern is also robust for the systematic volatility estimated from the industry-augmented market model.

However, the difference between the earnings season and the non-earnings seasons for the idiosyncratic volatility is vague. In the normal years, the equal-weighted mean for the idiosyncratic volatility estimated from the standard market model is 0.0213 in the earnings season, which is almost the same as 0.0219 in the normal period. While the difference for the median is 0.0003. As for the idiosyncratic volatility estimated from the industry-augmented market model, the mean and median in the earnings season are 0.0177 and 0.0157 compared with 0.0180 and 0.0158 in the non-earnings seasons. However, the difference of the value-weighted means is significantly positive with the value of 0.0024 for the standard market model and 0.0021 for the industry-augmented market model, which means the larger firms may provide more information in the earnings announcements and have lower idiosyncratic volatility in the earnings season.

[Insert Table 4. 7 Here]

The results of the regression analysis are presented in Table 4.7. The first two columns show the regression results using the logarithm of the systematic volatility as the dependent variable. The coefficients for *ES* are both significantly negative no matter which market model is used in the estimation process, indicating that the systematic volatility is lower in the earnings season than it is in the normal period. However, for columns (3) and (4) which use the logarithm of idiosyncratic volatility as the dependent variable, the coefficients for *ES* are both insignificant, which means there is no significant change for the idiosyncratic volatility around the earnings season[16]. In addition, the systematic volatility is only negatively associated with the market to book ratio for the fundamental variables, indicating that the firms with higher growth potential would present lower systematic volatility. While the idiosyncratic volatility is negatively associated with firm size and positively associated with the market to book ratio and leverage, indicating that the smaller firms with higher market to book and leverage ratios would present higher idiosyncratic volatility. The special market conditions would only affect the pattern of the systematic volatility, but play no effect for the idiosyncratic volatility.

The last four columns of Table 4.7 present the results with the control of liquidity. The coefficients for ES are still significantly negative when the dependent variables are the logarithm of systematic volatilities in columns (5) and (6) and not significant for the idiosyncratic volatility. TURN is positively associated with both systematic volatility and idiosyncratic volatility, indicating that the intensive trading would increase the price volatilities no matter they are systematic or idiosyncratic.

4.3.4 Age Effect

In this section, I test whether the R^2 dynamic pattern around the earnings season is more pronounced for older firms. As the uncertainty about the firm-specific factor can be resolved over time, older firms would have relatively higher market-level uncertainty then younger firms. When the information environment is improved in the earnings

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[16] Since volatilities are highly associated with the number of observations, I also test the pattern of the standard deviations. The results remain to be the same.

season, the learning helps to reduce the market-level uncertainty, which would decrease R^2 more for older firms.

[Insert Table 4. 8 Here]

In Table 4.8, I calculate the change of R^2 and the ratio of systematic to idiosyncratic risk (SYS_VOL/IDIO_VOL) using the average value in the non-earnings seasons minus the value in the earnings season. And in each fiscal year, I classify the sample firms into three groups according to the years after IPO. The means of the age for each group are 5, 10 and 15 respectively. Consistent with Proposition 3, the change of R^2 is larger for older firms than the younger firms, and this result is robust for the systematic to idiosyncratic ratio. In normal years, the means of the change of R^2 are 0.0741 for the older firms and 0.0624 for the younger firms for the estimation of standard market model, and 0.0634 and 0.0547 for the estimation of industry-augmented market model respectively.

In addition, the change of R^2 increases at a higher speed when firms are young. The mean of the change of R^2 for the standard market model increases from 0.0624 to 0.0705 with the increased ratio of 13% from younger group to the median group, while only increases about 2% from median group to older group. It is consistent with the previous literature that the uncertainty resolution process is more pronounced for younger firms than older firms.

Table 4.8 also presents the change of fundamentals around the earnings season (denoted as ‘Δ’) as well as the annual values (SIZE, MTBV, LEV and ROA). In China, the older firms would have larger size, higher market to book value and leverage ratio, and lower profitability. I use these variables as controls in the following regression analysis.

[Insert Table 4. 9 Here]

In Table 4.9, I test the effect of age to the change of R^2 and the systematic to idiosyncratic ratio in the following regression models:

$$\Delta R_{it}^2 = \alpha + \beta_1 AGE_{it} + \sum_k \beta_k \Delta Control_{it}^k + \sum_j \beta_j Control_{it}^j + Year + Industry + \varepsilon_{it} \quad (4\text{-}5)$$

and

$$\Delta(\frac{SYS\_VOL}{IDIO\_VOL})_{it} = \alpha + \beta_1 AGE_{it} + \sum_k \beta_k \Delta Control_{it}^k + \sum_j \beta_j Control_{it}^j + Year + Industry + \varepsilon_{it}, \quad (4\text{-}6)$$

where ΔR_{it}^2 is the change of average R^2 in the non-earnings seasons minus the R^2 in the earnings season for firm *i* in year *t*, $\Delta(\frac{SYS\_VOL}{IDIO\_VOL})_{it}$ is the change of systematic to idiosyncratic volatility ratio around the earnings season, AGE is the firm age, $\Delta Control$ and $Control$ are the changes and annual values for fundamental variables and liquidity, and *Year* and *Industry* are the year and industry dummies control for year and industry fixed effects. As shown in Table 4.9, the change of R^2 or the change of systematic to idiosyncratic volatility ratio is positively associated with the firm age, indicating that the R^2 would change more around the earnings season for older firms. The results are robust for different estimation models and with control of the liquidity change.

4.3.5 Robust Tests

I conduct four additional tests to confirm the dynamic pattern of the stock return synchronicity around the earnings season. First, I decompose the systematic volatility of standard market model into loadings on the market factor and the market return volatility. Second, I decompose the systematic risk from industry-augmented model into market risk and industry risk, and test which component is more important for the dynamic pattern. Third, I analyze the size effect to the changing pattern of R^2. Finally, I consider the potential effect of the quarterly earnings announcements to the main findings.

4.3.6.1 Loadings on Market Factor and Market Return Volatility

For the standard market model (without one-day lag and one-day ahead market returns), the systematic volatility can be decomposed into two components: the squared loadings on the market factor, and the market return volatility. Since the dynamic pattern of R^2 around the earnings season is mainly driven by the change of the systematic volatility, I test which component would present more pronounced dynamic pattern around the earnings season in this section.

[Insert Table 4.10 Here]

The regression results are shown in Table 4.10. In column (1) when the dependent variable is the logarithm of the squared beta, the coefficient of ES is -0.0870 and insignificant, while when the dependent variable is the logarithm of the market volatility in column (2), the coefficient of ES is -0.2556 with 5% significance, which means only the market volatility decreases when majority of the firms make their earnings announcements simultaneously. Columns (3) and (4) report the regression results with the control of TURN, and the dynamic patterns are more pronounced for the market return volatility.

4.3.6.2 Market Risk vs Industry Risk

For the industry-augmented market model, the systematic volatility can be decomposed into two components: the volatility which is associated with the market factor and the volatility which is associated with the industry factor. Since the dynamic pattern of R^2 around the earnings season is mainly driven by the change of the systematic volatility, I test which component, the market risk or the industry risk, would present more pronounced dynamic pattern around the earnings season in this section.

[Insert Table 4. 11 Here]

The regression results are shown in Table 4.11. In column (1) when the dependent variable is the logarithm of the market risk, the coefficient of ES is -0.3207 with 5% significance, and when the dependent variable is the logarithm of the industry risk in column (2), the coefficient of ES is -0.2705 with 5% significance as well, which means both components are significantly reduced when majority of the firms make their earnings announcements simultaneously. Columns (3) and (4) report the regression results with the control of TURN, and the dynamic patterns of the market risk and industry risk remain to be the same: the coefficients of *ES* are -0.3477 and -0.3040 for different risk components, which means the change of the information environment would affect both market risk and industry risk simultaneously.

4.3.6.3 The Size Effect

The second test is to document whether the dynamic patterns of the stock return synchronicity are different for the firms with different sizes. According to the total assets at the beginning of the fiscal year, I first classify all sample firms into two groups, and then rerun the regression analysis for these two groups respectively.

[Insert Table 4. 12 Here]

The results are shown in Table 4.12. Both groups are presented with lower synchronicity in the earnings season, and the pattern for the smaller firms is stronger than the larger firms no matter which pricing models are used to estimate the R^2. For the larger firms, the coefficients of *ES* are -0.2800 and -0.2238 for the standard market model and industry-augmented market model respectively, while the coefficients of *ES* are -0.3322 and -0.2857 for the groups of smaller firms.

4.3.6.4 The Effect of Quarterly Earnings Announcements

Although the quarterly earnings announcements present low information quality and attract little market attention in China, someone may argue that the R^2 would also be fluctuated with the clustered quarterly earnings announcements in addition to the effect of annual earnings announcements. I conduct additional test for the effect of quarterly earnings announcements in this section. The results of the robust analysis are shown in Table 4.13.

[Insert Table 4. 13 Here]

Panel A of Table 4.13 shows the distribution of the quarterly earnings announcements over months. The quarterly earnings announcements are also released in a clustered pattern. More than 99% of the earnings announcements in the first quarter and the third quarter are released in April and October respectively, and almost 88% semi-annual earnings announcements are released in August. If the information environment changes with the clustered quarterly earnings announcements, the stock return synchronicity may be lower in the non-earnings seasons as well. I control for the effect of quarterly earnings announcements by deleting the observations in August and

October when R^2 is estimated. With clearer time-varying information environment, the dynamic pattern of the stock return synchronicity is predicted to be stronger.

Panel B of Table 4.13 presents the regression results controlling for the effect of quarterly earnings announcements. The coefficients of *ES* are -0.3517 and -0.2983 for the stock return synchronicity estimated from the standard market model and the industry-augmented market model respectively. After control for the liquidity measured as TURN, the coefficients of *ES* turn to be -0.3379 and -0.2866 with the corresponding t-values estimated as -3.10 and -3.42. Compared with the regression results when the effect of the quarter earnings announcements is not controlled in Table 4.5, the coefficients of *ES* are both with larger absolute value and more significance, indicating that the dynamic pattern of the stock return synchronicity becomes more pronounced with the control of the effect of the quarterly earnings announcements[17].

[17] In Table 4.5, the coefficients of *ES* after control for TURN are -0.3067 and -0.2548 for different estimation models with t-values estimated as -2.53 and -2.53

Chapter 5. Dynamic Pattern of R^2 around the Earnings Season: International Evidence

This chapter presents the empirical results of the dynamic pattern of R^2 around the earnings season using the international data for 40 countries around the world. In Chapter 4, I find that the stock return synchronicity is lower in the earnings season than it is in the non-earnings seasons using the evidence of China, and demonstrate that this pattern is mainly driven by the change of the systematic volatility rather than the idiosyncratic volatility. In this chapter, I examine whether this dynamic pattern could be generalized into the international markets with both country-level and firm-level empirical analyses.

The chapter is organized as follows. Section 5.1 describes the data and sample selection process, while section 5.2 constructs the main variables and describes the research methodology for the regression approach. The empirical results are presented in section 5.3 for both country-level analysis and firm-level analysis respectively.

5.1 Data and Sample

I collect the market and macro data from Thomson Financial DataStream and the accounting and earnings announcements data from WorldScope. The sample period covers 21 years from 1995 to 2015. Although the DataStream and WorldScope cover the return series prior to 1995, my sample starts from 1995 because the coverage for the emerging markets is sparse in the early times. To be part of the sample, the securities need to be covered by both DataStream and WorldScope, and noted as primary security with the instrumental type of Equity in the DataStream. I also require the securities to include 'RI' in their Data-Types to make sure that the data for the return series is available. In addition, DataStream classifies the stock according to the firm's original country rather than the country where the stock is traded or cross listed. For example, the stock with the market of Australia may be traded in the exchange of London where the traded currency is United Kingdom Pound. To ensure the securities are only traded in the home market, I further require the securities to be traded in local currency and in the country's major exchanges[18].

I restrict the sample stocks to the common-original stocks following Ince and Porter (2006) and Griffin, Kelly and Nardari (2010). I first identify the non-common stocks through the industry codes in DataStream which could indicate funds, trusts, REITs or other non-typical common stocks. Panel A of Table A1 lists the industry codes identified in this thesis. The stocks belonging to these industries are eliminated from the sample, and only REITs are identified in this thesis since other types of non-common stocks have already been eliminated in the previous process. I then apply the general filter rules to eliminate non-common stocks by searching the name fields of all securities. The words listed in Panel B of Table A1 are searched in the names of the securities, including preferred stocks, unit and trusts, income funds, depository receipts and interest, venture capital, bonds and certificates, split, yields and participations, and so on. I also double check the full names of the stocks to make sure the identifications are correct. Panel C of Table A1 lists the country-specific identifiers for the non-common stocks, which indicate other preferred or non-voting stocks or the stocks with special trading rules in each country. For US firms, I restrict the sample to the securities whose local codes are ended up with 10 or 11. Finally, I deal with the firms with multiple classes when two or more securities with different DS codes share the same WorldScope identifier (Filed 06035). I

[18] See Table A3 for the list of major exchanges.

first include the stocks which are traded by local residents and noted as major security by DataStream. The stocks which are traded at least three months earlier than other classes are also included in the sample following Griffin, Kelly and Nardari (2010). In other cases, the stocks which are more actively traded are included in the sample.

After eliminating the non-common stocks from the sample, I further restrict the stocks to non-financial industries (SIC 6000-6999) and non-utility industries (SIC 4900-4999) according to the SIC code from WorldScope (WC07021). The screening process for the sample stocks is summarized in Panel A of Table 5.1. The number of securities after the screening process is 41,501. Compared with the initial number of securities, I eliminate about 30% of securities from the sample.

[Insert Table 5. 1 Here]

For the daily returns, I first eliminate the invalid returns when RI is less than 0.1 and then trim the observations by top and bottom 0.5% for the outliers. At least 30 valid non-zero trading returns are required for each season to estimate the extended standard market model. I obtain 1,534,250 firm-season observations as shown in Panel B of Table 5.1. I then eliminate the observations within three years of the initial public offerings to control for the potential noises caused by listing. In order to obtain a relatively clear dynamic pattern of the information environment, I further eliminate the observations when the firms' fiscal year end months are different with the majority of the firms in that country. The fiscal year end month for most of the countries is December, except for Australia, Pakistan and South Africa, whose fiscal year end month is June, and India, Japan and Sri Lanka, whose fiscal year end month is March. The countries with less than 25 firms for each season (including Argentina, Colombia, Czech, Hungary, Ireland, Luxembourg, and Venezuela) and the countries with less than 30 seasons (including Austria, Bulgaria, Cyprus, Jordan, New Zealand and Russia) are excluded from the sample. The final sample contains 830,929 firm-season observations for 40 countries during the sample years from 1995 to 2015.

Following World Bank's classification scheme, the countries are classified into high income countries and middle income countries (including upper middle and lower middle income countries) according to the gross national income (GNI) per capita in 2014 with the threshold of USD 12,736. The final sample includes 25 high income countries and 15 middle income countries[19]. In addition, the number of sample firms is increasing steadily from 4,376 in 1995 to 16,529 in 2015 as shown in Panel C of Table 5.1. The number of the firm-year observations is 231,453 in the final sample.

[Insert Table 5. 2 Here]

Table 5.2 shows the detailed sample distributions across countries. The sample period starts from 1995 for most of the countries except for Brazil, Chile, Egypt, Israel, Pakistan, Peru, Poland, Romania and Sri Lanka, whose starting points are after 2000. The firm-level fiscal year end dates can be obtained from WorldScope (Field 05350), and I define the fiscal year end month for a country as the one of the majority firms in that country. Most of the countries' fiscal year end months are December, except for Australia, Pakistan, and South Africa in June and India, Japan and Sri Lanka in March. The number of firms and the number of the firm-season observations are shown in the next two columns. United States and Japan have the largest number of firms across countries, shown as 3,004 and 2,810 respectively, followed by India and China with the number of

[19] Taiwan is classified into the group of high income countries by the author.

2,116 and 2,099. The number of the firms for these four countries accounts for 38.5% of the total number of firms around the world. To the contrary, five countries have less than 100 firms in the sample, listed as Chile, Egypt, Pakistan, Peru and Portugal. For more details, the distribution of the number of the sample firms by country and year is shown in Table A2.

In the last four columns of Table 5.2, I display the distribution of the number of firms and firm-season observations whose fiscal year ends are not equal to the countries' fiscal year ends. These observations are deleted from the sample and the percentages of the deletions are also shown across countries. The fiscal year ends are exclusively clear for Chile, China, Israel, Mexico, Peru, and Romania, where the fiscal years for all firms in that country end in the same month. To the contrary, South Africa exhibits the most disperse distribution of the fiscal year ends, with more than 60% of firms end their fiscal years other than June. On average, about 25% of the firms end their fiscal years in months different with the majority of the firms, and are excluded from the sample.

5.2 Variable Construction and Methodology

5.2.1 Definition of the Earnings Season

The earnings season is defined as the period when the majority of the firms jointly make their annual earnings announcements. I obtain the data of the earnings announcement dates from WorldScope (Filed 05901). In the early years, most of the countries especially the emerging markets only require the listed firms to disclose the annual reports. Due to limited data coverage and accuracy, annual earnings announcements are analyzed in this study.

In each country, I first identify the months which cover most of the earnings announcements of the sample firms. The period of the clustered earnings announcements usually lasts for three months started immediately after the fiscal year end or one month later. I then define the earnings season as the continues three months which cover most of the earnings reports for that country, and the non-earnings seasons as other periods which also cover three months following the earnings season. For example, the earnings season for the United States is from January to March when majority of annual earnings reports are released after the fiscal year end of December. The non-earnings seasons are defined as April to June, July to September and October to December respectively.

[Insert Table 5. 3 Here]

Table 5.3 shows the definition of the earnings season for each country and the number of the annual earnings announcements released in each season. The period of the defined earnings season is different across countries due to the difference of the fiscal year end dates and the reporting practice. For 34 countries with December as the fiscal year end month, the earnings season for 26 countries is defined from February to April, and the non-earnings seasons for these countries are from May to July, August to October and November to next year's January respectively. The listed firms in Chile, Finland, Mexico and Peru make their earnings announcements earlier and the earnings season is defined from January to March. To the contrary, Philippine, Taiwan and United Kingdom's earnings season is defined later from March to May. For the three countries whose fiscal year end month is June, the earnings season is defined from August to October for Australia, Pakistan and South Africa. While for the three countries whose fiscal year end month is March, India and Japan release the clustered earnings reports from April to June, and Sri Lanka's earnings season is from May to July.

Although the earnings announcements present a cluttering pattern for all of the countries around the world, the extent of the clustering is quite different across countries. The last column of Table 5.3 shows the percentage of the earnings announcements released in the earnings season for each country. On average, about 90.64% of the earnings reports are released in the earnings season, indicating a highly clustered reporting pattern of the earnings announcements and a clear dynamic pattern of the information environment around the earnings season. More than 95% of the earnings announcements are released in the earnings season for the following countries: Australia, Finland, Hong Kong, Israel, Japan, Malaysia, Mexico, Singapore, Taiwan, Thailand and United States. However, there are still five countries whose clustering ratios are less than 80%, listed as France (73.73%), Germany (77.96%), Portugal (69.72%), Romania (68.06%) and United Kingdom (74.01%). The distributions of the earnings announcements for these countries are relatively more disperse than other countries such as the United States (96.67%), Australia (98.46%) and Finland (98.19%).

5.2.2 Measurement of the Synchronicity (Systematic/Idiosyncratic Volatility)

Following Morck, Yeung and Yu (2000) and Jin and Myers (2006), the stock return synchronicity is estimated from the extended market model using daily returns for each season:

$$RET_{it} = \alpha + \beta_1 MARKET_{j,t} + \beta_2(USMARKET_t + EX_{j,t}) + \beta_3 MARKET_{j,t-1} + \beta_4(USMARKET_{t-1} + EX_{j,t-1}) + \beta_5 MARKET_{j,t+1} + \beta_6(USMARKET_{t+1} + EX_{j,t+1}) + \varepsilon_{it}, \quad (5\text{-}1)$$

where RET_{it} is the daily return for firm i on day t, $MARKET_{j,t}$ is the value-weighted market return for country j to which the firm i belongs on day t, $USMARKET_t$ is the value-weighted US market return on day t, and $EX_{j,t}$ is the change of the exchange rate from country j's currency to US dollars. The market return is obtained from the total market index (TOTMK) from DataStream, which is calculated on a representative list of stocks for each market with the minimum coverage rate of 75-80% of total market capitalization. Returns are in local currency, and the expression of $(USMARKET_t + EX_{j,t})$ translates the US market returns to local currency as well. For the Far East countries, I lag US market returns by one day to account for the time zone differences. The Far East countries in my sample are China, Hong Kong, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Taiwan and Thailand.

I use the daily stock returns calculated from the return index of DataStream to estimate the R^2 and the systematic and idiosyncratic volatilities for each season in each country. Although the returns have been adjusted for dividend, splits and other unusual events, I winsorize the data by top and bottom 0.5% to eliminate potential coding errors. Zero returns are deleted from the sample if the trading volumes are zero or missing. The non-trading days are also deleted from the sample if more than 90% of stocks of the country have zero returns on that day. At least 30 available trading days are required to estimate the market model in each season. The R^2 of the regression, which measures to what extent the stock returns can be explained by the market returns, is extracted for each country in each season. While the systematic volatility and the idiosyncratic volatility are the sum of squares due to regression and the sum of squared errors respectively.

For the country level analysis, I calculate two types of R^2 with equal weight and variance weight as followings:

$$R^2_{j,EqualW} = \frac{1}{N_j}\sum_i R^2_{i,j}, \tag{5-2}$$

$$R^2_{j,VarianceW} = \frac{\sum_i R^2_{i,j} \times SST_{i,j}}{\sum_i SST_{i,j}}, \tag{5-3}$$

where $R^2_{j,EqualW}$ is the equal-weighted R^2 for country j, $R^2_{j,VarianceW}$ is the variance-weighted R^2 for country *j*, and $SST_{i,j}$ is the total variance of firm *i* in country *j*. Following the previous literature, the country-level synchronicity is a logarithmic transformation of the country level R^2:

$$SYNCH_{j,EqualW} = \ln\left(\frac{R^2_{j,EqualW}}{1-R^2_{j,EqualW}}\right), \tag{5-4}$$

$$SYNCH_{j,VarianceW} = \ln\left(\frac{R^2_{j,VarianceW}}{1-R^2_{j,VarianceW}}\right), \tag{5-5}$$

where $SYNCH_{j,EqualW}$ and $SYNCH_{j,VarianceW}$ are the equal-weighted and variance-weighted country level measures of stock return synchronicity for country *j* respectively. While the country-level systematic and idiosyncratic volatilities are equal-weighted firm-level volatilities correspondingly.

5.2.3 Research Design

I take the following regression approaches to test whether the stock return synchronicity and the systematic and idiosyncratic volatilities are lower in the earnings season than they are in the normal period. The dependent variable is the stock return synchronicity or the logarithm of the systematic volatility or the idiosyncratic volatility in both country-level and firm-level. The regression analysis is conducted in the following models:

For the country-level analysis:

$$\begin{aligned} SYNCH_{j,t}(SYS/IDIO) &= \alpha + \beta_1 ES_{j,t} + \beta_2 \ln(GDP\ per\ capita)_{j,t-1} \\ &+ \beta_3 \operatorname{Var}(GDP\ per\ capita\ Growth)_{j,t} + \beta_4 \ln(Country\ Size)_{j,t-1} \\ &+ \beta_5 \ln(No.Stocks)_{j,t} + \beta_6 (Industry\ Herfindahl)_{j,t-1} \\ &+ \beta_7 (Firm\ Herfindahl)_{j,t-1} + Country + Year + \varepsilon_{j,t}. \end{aligned} \tag{5-6}$$

For the firm-level analysis:

$$\begin{aligned} SYNCH_{i,t}(SYS/IDIO) &= \alpha + \beta_1 ES_{i,t} + \beta_2 SIZE_{i,t-1} + \beta_3 MTBV_{i,t-1} \\ &+ \beta_4 \ln(GDP\ per\ capita)_{j,t-1} + \beta_5 \operatorname{Var}(GDP\ per\ capita\ Growth)_{j,t} \\ &+ \beta_6 \ln(Country\ Size)_{j,t-1} + \beta_7 (Industry\ Herfindahl)_{j,t-1} \\ &+ \beta_8 (Firm\ Herfindahl)_{j,t-1} + Country(Industry) + Year + \varepsilon_{i,t}, \end{aligned} \tag{5-7}$$

where *ES* is the dummy variable taking the value of one if the country *j* or firm *i* at season *t* is in the earnings season, and zero otherwise. If the stock return synchronicity is lower in the earnings season than it is in the non-earnings seasons, the coefficient of *ES* (β_1) is predicted to be negative.

$ln(GDP\ per\ capita)$ is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars. Morck, Yeung and Yu (2000) and Jin and Myers (2006) find the significantly negative relationship between the country-level synchronicity and the GDP per capita. I include this variable into the regression to control for the effect of the quarterly economic condition to the dynamic pattern of the synchronicity. The series of the quarterly GDP per capita is obtained from Oxford Economics and other local sources through DataStream. Some countries' GDP per capita are seasonal adjusted while others are not. If the seasonal adjustment has not been performed in the original quarterly dataset, I apply the X12-ARIMA model (the US Census Bureau) to adjust the series. See Table A3 for more detailed description of the GDP series across countries.

$GDP\ per\ capita\ Growth$ is the quarterly growth rates of the GDP per capita. Following Brockman, Liebenberg and Schutte (2009), this variable is used to control potential effect of the business cycle to the dynamic pattern of R^2.

$Var(GDP\ per\ capita\ Growth)$ is the variance of the quarterly growth rates of the GDP per capita in the last three years. This variable is used to measure the macroeconomic instability and the unstable of the market fundamentals. I predict the stock return synchronicity is positively related with the variance of the GDP per capita growth: when the uncertainty about the market factors dominants the variation of the firm-level factors, the stock return synchronicity would be higher in these countries.

$ln(Country\ Size)$ is the logarithm of the land area in square kilometers from World Development Index. The smaller countries are more likely to have higher fundamental correlations and localized economic activities. I include this variable into the regression to control for any potential relationship between the country size and the stock return synchronicity.

$ln(No.Stocks)$ is the logarithm of the number of the listed stocks in the sample. The number of stocks is controlled in the country-level regression analysis since the market with fewer traded stocks may present higher synchronicity by nature.

$Industry/Firm\ Herfindahl$ is the sum of the squared ratio of the industry (firm) sales to the total sales within the country. This variable is used to measure the country's economic specification that whether the economy is dominated by few industries (few large firms) or not. The data for the firm-level sales in US dollars is from WorldScope (Field 01001) which represent gross sales and other operating revenue less discounts, returns and allowances. Two digit Standard Industry Classification (SIC) codes are used for the industry classification. The industry Herfindahl index for country j can be expressed as $Herfindahl_{Ind,j} = \sum_k h_{k,j}^2$ where $h_{k,j}$ is the percentage of industry k's sales to the country j's total sales. While the firm Herfindahl index can be expressed as $Herfindahl_{Firm,j} = \sum_i h_{i,j}^2$ where $h_{i,j}$ is the percentage of firm i's sales to the country j's total sales.

SIZE is the logarithm of the quarterly market capitalization in thousand US dollars. *SIZE* is controlled in the firm-level analysis and the data is obtained from WorldScope (Field 07210). According to the previous literature, the stock return synchronicity is predicted to be positively associated with the firm size.

MTBV is the quarterly market capitalization to common equity ratio. It is controlled in the firm-level analysis and the data is obtained from WorldScope (Filed 09704). I restrict the market to book ratio to be positive and less than 20.

Country, Industry and Year are dummy variables control for country, industry and year fixed effects in the two way fixed effects models. Industry is classified according to the two digit SIC codes.

5.3 Empirical Results

5.3.1 Descriptive Statistics

[Insert Table 5. 4 Here]

Table 5.4 shows the descriptive statistics and the correlation matrix of the variables in this chapter. Panel A shows the descriptive statistics of the country-level variables including both equal-weighted and variance-weighted R^2s, the stock return synchronicity, systematic volatility, idiosyncratic volatility and other control variables in the regression analysis. The countries are classified into high income countries and middle income countries according to World Bank, and the statistics are shown for these two groups of countries respectively. The mean and median for the equal-weighted R^2 in the country-level are 0.2330 and 0.2139 respectively, while the values are 0.2166 and 0.1934 for the variance-weighted R^2. Consistent with Morck, Yeung and Yu (2000) and Jin and Myers (2006), the mean and median of the R^2 in high income countries are lower than the ones in middle income countries. The means of the equal-weighted R^2 are 0.2208 for high income countries and 0.2585 for middle income countries. Similarly, the means of the variance-weighted R^2 are 0.2038 for high income countries and 0.2433 for middle income countries.

The descriptive statistics of the stock return synchronicity, which is a logarithmic transformation of the R^2, are also shown in Panel A of Table 5.4. The mean and median for the equal-weighted synchronicity are -1.2371 and -1.3014 respectively, and -1.3411 and -1.4283 for the variance-weighted synchronicity. As for the systematic volatility, the mean is 0.0128 for high income countries, which is much lower than the mean for middle income countries as 0.0180. The statistics for the idiosyncratic volatility do not present too much difference for high income and middle income countries. The means of the idiosyncratic volatility are 0.0492 and 0.0534 for high income countries and middle income countries respectively. The descriptive statistics for the control variables are also shown at the end of Panel A. All of the control variables are at country-level.

Panel B of Table 5.4 shows the descriptive statistics of the firm-level variables. I only include the observations with valid market capitalization and MTBV ratio in the firm-level sample, which induces 636,727 firm-season observations. The mean and median of the R^2 for the entire sample are 0.2426 and 0.2044 respectively. R^2 is much higher in middle income countries, with the mean of 0.2871, than it is in high income countries, with the mean of 0.2279. The systematic volatility is higher in middle income countries than high income countries. The means of the systematic volatility for these two groups are 0.0176 and 0.0134 respectively. While for the idiosyncratic volatility, the mean and median are similar for high income countries and middle income countries. The mean and median are 0.0524 and 0.0278 for high income countries and 0.0437 and 0.0297 for middle income countries. The average size is 12.0404 and the mean of MTBV is

2.1487. All variables display considerable variations as reflected in the inter quartile ranges.

Panel C of Table 5.4 shows the correlation matrix of the country-level variables and firm-level variables respectively. In the country-level analysis, both equal-weighted and variance-weighted R^2s are negatively related to the GDP per capita and positively related to the variance of the GDP per capita growth. Furthermore, both systematic volatility and idiosyncratic volatility are negatively correlated with the GDP per capita, and positively correlated with the economic instability as measured by the variance of the GDP per capita growth. The correlation coefficient for the logarithm of GDP per capita and the variance of the GDP per capita growth is -0.2119, indicating a higher economic stability for the developed countries. Finally, the firm-level R^2 and the stock return synchronicity is positively correlated with the firm size, which is consistent with the previous literature.

[Insert Table 5. 5 Here]

The summary statistics for some main variables across countries are shown in Table 5.5. The mean and median of the R^2 for each country are listed for high income countries and middle income countries respectively. Australia, Canada, Poland, South Korea and United Kingdom present lowest average R^2s around the world, with the mean values lower than 0.19. All these countries belong to the group of high income countries with relatively higher GDP per capita. China shows the highest average R^2 with the mean and median of 0.3967 and 0.3896 respectively, followed by Egypt, Turkey and Mexico. The average value of the logarithm of GDP per capita for these middle income countries is 6.898, which is lower than high income countries as 9.051. In addition, the variance of the

GDP per capita growth is higher for middle income countries with the mean of 0.233, than high income countries with the mean value of 0.104, indicating that the economic conditions are more stable in high income countries than in middle income countries. The average firm size measured in US dollars presents considerable variations across countries, with the highest mean of 5,688 in Brazil and the lowest mean of 62 in Sri Lanka. Industry Herfindahl index is higher in middle income countries than high income countries, which means the industry concentration is more serious in middle income countries. While the firm Herfindahl indexes are highest in Netherlands and Romania, which means the economies are more likely to be dominated by few firms in these countries.

5.3.2 Country Level Analysis

In this section, I test whether the country-level R^2 and the systematic and idiosyncratic volatilities are lower in the earnings season than they are in the non-earning seasons. The variables are either equal-weighted or variance-weighted for each country in each season. I first present the empirical results of the univariate analysis, and then conduct the regression analysis with proper controls and different estimation techniques. The separate analyses for high income countries and middle income countries are shown at the end of this section.

5.3.2.1 The Univariate Analysis

[Insert Table 5. 6 Here]

The empirical results for the univariate analysis are shown in Table 5.6. The mean and median for the country-level R^2 as well as the systematic volatility and idiosyncratic volatility are presented for the earnings season and non-earnings seasons respectively. Both equal-weighted and variance-weighted R^2s display clear dynamic patterns around the earning season. The mean and median for the equal-weighted R^2 are 0.2351 and 0.2140 in the non-earnings seasons respectively, and decrease to 0.2268 and 0.2139 in the earnings season. The mean of the difference between the non-earnings seasons and the earnings season is 0.0083 and significant at 5% level. The dynamic pattern remains to be robust for the variance-weighted R^2, with the mean of the difference as 0.0084.

The dynamic pattern of R^2 around the earnings season is persistent for both high income countries and middle income countries. The means for the difference of R^2 between the non-earnings seasons and the earnings season are 0.0069 for the equal-weighted R^2 and 0.0073 for the variance-weighted R^2. The pattern is more pronounced for middle income countries. The average differences are 0.0112 and 0.0106 for the equal-weighted and variance-weighted R^2 respectively. The larger difference for middle income countries is not only due to the higher value of R^2. The average R^2 decreases about 3.1% with equal weight and 3.6% with variance weight for high income countries, and decreases about 4.3% with equal weight and 4.3% with variance weight for middle income countries.

I then analyze whether the systematic volatility and the idiosyncratic volatility present similar patterns as R^2 around the earnings season. Since the variance-weighted R^2 is the difference between of the equal-weighted systematic volatility and the equal-weighted idiosyncratic volatility, the lower value of R^2 in the earnings season comes from either decreased systematic volatility or increased idiosyncratic volatility or both. The mean for the systematic volatility is 0.0148 in the non-earnings seasons and

0.0136 in the earnings season, decreased 0.0012 with 5% significance. However, the idiosyncratic volatility presents similar average values for the earnings season as 0.0502 and the non-earnings seasons as 0.0507. As shown in the univariate analysis, the dynamic pattern of the country-level R^2 is mainly driven by the change of the systematic volatility rather than the idiosyncratic volatility.

[Insert Table 5. 7 Here]

Table 5.7 shows the results of the univariate analysis across countries. The equal-weighted and variance-weighted R^2s in the country level are averaged for the earnings season and non-earnings seasons respectively for each country. The differences between the non-earnings seasons and the earnings season are listed in the last two columns, which are predicted to be positive. For high income countries, the average values of the differences are 0.0068 for the equal-weighted R^2 and 0.0074 for the variance-weighted R^2. About 84% of the countries (21 of 25 countries) present lower R^2s in the earnings season than the ones in the non-earnings seasons. The most pronounced patterns for both equal-weighted R^2 and variance-weighted R^2 are presented for United States, South Korea and Finland.

For middle income countries, the average value of the differences is higher than the one of high income countries. The highest differences are for China and Egypt, and followed by Indonesia, Romania and Sri Lanka. Because of the instabilities of the economics and widespread risk and rumors in middle income countries, five countries present negative differences between the non-earnings seasons and the earnings season, listed as India, Malaysia, Pakistan, South Africa and Turkey. All in all, Table 5.7 shows that the dynamic pattern of R^2 around the earnings season is robust for most of countries in the sample.

5.3.2.2 The Regression Analysis

[Insert Table 5. 8 Here]

Table 5.8 shows the regression results using the country-level stock return synchronicity as the dependent variable. In columns (1) and (2), the equal-weighted synchronicity is regressed on the earnings season dummy and other control variables. The coefficients for *ES* are -0.0397 and -0.0348 for the pooled OLS approach and two way fixed effects approach respectively, and are significant at 1% level. This dynamic pattern is also robust for the variance-weighted synchronicity. The coefficients of *ES* are significantly negative with the values of -0.0389 and -0.0317 in columns (3) and (4) respectively. The results confirm my prediction that the stock return synchronicity is lower in the earnings season than it is in the non-earnings seasons around the world. For the control variables, the coefficients of the logarithm of quarterly GDP per capita are significantly negative, which means the stock return synchronicity is lower in the countries with higher GDP per capita. While the coefficients for the variance of the GDP per capita growth are significantly positive, which means the stock return synchronicity is higher in the countries with less economic stabilities.

[Insert Table 5. 9 Here]

The decreased stock return synchronicity in the earnings season is due to either decreased systematic volatility or increased idiosyncratic volatility or both. To confirm which component dominates the dynamic pattern around the earnings season, the regression analysis is conducted for the systematic volatility and idiosyncratic volatility respectively. The regression results using the logarithm of the systematic volatility as the dependent variable are shown in columns (1) and (2) in Table 5.9 with different estimation techniques. The coefficients of *ES* are -0.0498 and -0.0523 respectively and significant at 1% level, which means the systematic volatility is lower in the earnings season than it is in the non-earnings seasons. In addition, the logarithm of GDP per capita is negatively associated with the systematic volatility, which means the systematic risk is higher in the countries with lower GDP per capita. Furthermore, the coefficients for the variance of the GDP per capita growth are 0.5933 and 0.2824 with 1% significant level respectively, indicating that the systematic volatilities are higher in the countries with instable economies.

In contract, the idiosyncratic volatility does not present significant dynamic pattern around the earnings season. As shown in column (3) in Table 5.9, the coefficient for *ES* is -0.0108 and insignificant, which means the idiosyncratic volatility remains the same between earnings season and non-earnings seasons. The dynamic pattern is still vague with the results using two way fixed effects of country and year dummies in column (4). Consistent with Dasgupta, Gan and Gao (2010) and Li, Rajgopal and Venkatachalam (2014), the idiosyncratic volatility is negatively associated with the logarithm of GDP per capita, which means high income countries may present lower idiosyncratic volatilities. While both the variance of the GDP per capita growth and the number of listed stocks are positively associated with the idiosyncratic volatility, indicating that the countries with instable economies and more listed stocks would present higher idiosyncratic volatilities.

[Insert Table 5. 10 Here]

I then examine whether high income countries and middle income countries both present dynamic patterns around the earnings season. The countries are classified into high income countries and middle income countries according to the World Bank, and the regressions are conducted for these two groups of countries respectively. Table 5.10 reports the empirical results with the dependent variables of the equal-weighted synchronicity (columns (1) and (2)), variance-weighted synchronicity (columns (3) and (4)) and the logarithm of systematic volatility (columns (5) and (6)) respectively. In columns (1) and (2), the coefficients of *ES* is -0.0307 for high income countries and -0.0565 for middle income countries. Similarly, the variance-weighted synchronicity also decreases in the earnings season for both middle income countries and high income countries. The last two columns report the results using the systematic volatility as the dependent variable.

5.3.3 Firm Level Analysis

This section examines whether the stock return synchronicity and the systematic and idiosyncratic volatilities are lower in the earnings season than they are in the non-earnings seasons using firm-level variables. I first report the empirical results of the univariate analysis, and then conduct the regression analysis for all the sample countries and the countries with different income levels.

5.3.3.1 The Univariate Analysis

[Insert Table 5. 11 Here]

Table 5.11 shows the results of the univariate analysis of R^2, systematic volatility and idiosyncratic volatility around the earnings season. Both mean and median values are reported for the earnings season and non-earnings seasons respectively and the means are both equal-weighted and value-weighted. The difference between the non-earnings seasons and the earnings season is shown in the last column of this table. As shown in Panel A of Table 5.11, R^2 is lower in the earnings season than it is in the non-earnings seasons: the equal-weighted means are 0.2321 and 0.2461 for the earnings season and non-earnings seasons respectively, and the value-weighted mean is 0.3741 in the earnings season and 0.3823 in the non-earnings seasons. The pattern is also robust for the medians, with the difference of 0.0106 at 1% significant level.

The dynamic pattern of R^2 is presented for both middle income countries and high income countries. For the equal-weighted means, the R^2 decreases from 0.2307 in the non-earnings seasons to 0.2200 in the earnings season, decreased 0.0106 with the ratio of 4.6% for high income countries; while for middle income countries, the difference between the non-earnings seasons and the earnings season is 0.0228 with the decreased ratio of 7.8%. For the value-weighted means, the decreased ratio of R^2 is 1.6% for high income countries and 4.8% for middle income countries, which means the firms with larger market capitalizations may present less pronounced dynamic patterns as the smaller firms. Similarly, the differences of the medians are 0.0073 and 0.0213 for high income and middle income countries respectively.

Panel B of Table 5.11 shows the univariate analysis for the systematic volatility. The equal-weighted and value-weighted means of the systematic volatility are 0.0149 and 0.0123 in the non-earning seasons, and decreased to 0.0132 and 0.0098 in the earnings season. The differences are 0.0017 and 0.0025 with the significant level of 1% respectively. For high income countries, the equal-weighted mean of the systematic volatility decreases from 0.0137 to 0.0126 with the decreased ratio of 8%; while the mean of middle income countries decreases from 0.0185 to 0.0150 with the decreased ratio of 19%. While for the idiosyncratic volatility shown in Panel C of Table 5.11, the differences between the non-earnings seasons and the earnings season are not significant for both the equal-weighted means and medians. To sum up, Panel B and C show that the systematic volatility, rather than the idiosyncratic volatility, is lower in the earnings season than it is in the non-earnings seasons.

5.3.3.2 The Regression Analysis

[Insert Table 5. 12 Here]

Table 5.12 shows the regression results of the firm-level synchronicity around the earnings season. The firm-level synchronicity, measured as the logarithmic transformation of R^2, is regressed on the earnings season dummy and other control variables. As the predictions, the stock return synchronicity is lower in the earnings season than it is in the non-earnings seasons. The coefficients of *ES* are significantly negative with the values of -0.0636 in column (1) with pooled OLS and -0.0772 and -0.0718 in columns (2) and (3) with two way fixed effects models. Consistent with the previous literature, the coefficients of SIZE is significantly positive, indicating that the larger firms would present higher stock return synchronicity than the smaller firms. In addition, MTBV is negatively associated with the stock return synchronicity, which means the firms with higher growth potential may present lower stock return synchronicity. The coefficients for the logarithm of GDP per capita are significantly negative, indicating a lower stock return synchronicity in the countries with higher values of the GDP per capita.

[Insert Table 5. 13 Here]

In Table 5.13, the systematic volatility and idiosyncratic volatility are regressed on the earnings season dummy and other control variables respectively. For the systematic volatility, although the coefficient of *ES* is insignificant in column (1) with pooled OLS, the coefficients are -0.0716 and -0.0700 at 10% and 1% level of significance in columns (2) and (3) with the two way fixed effects models. MTBV is positively associated with the systematic volatility, indicating that the firm-level systematic volatility is higher for the firms with larger size and higher growth potential. To the contrary, the coefficients of *ES* using the idiosyncratic volatility as the dependent variable are all insignificant in columns (4), (5) and (6), which means the idiosyncratic volatility dose not significantly change around the earnings season.

[Insert Table 5. 14 Here]

[Insert Table 5. 15 Here]

The regression analysis of the stock return synchronicity is conducted for high income countries and middle income countries respectively in Table 5.14. Using the two way fixed effects model with country and year dummies, the coefficients of *ES* are -0.0638 for high income countries and -0.1155 for middle income countries. In addition, the regression analysis is also conducted for the large firms and small firms respectively as a robust test. The sample firms are classified into two groups according to the market capitalizations for each country in each year. As shown in Table 5.15, there is no much difference for the dynamic pattern of R^2 between these two types of firms. In the two way fixed effect model with country and year dummies, the coefficients of *ES* are -0.0784 for the large firms and -0.0768 of the small firms respectively.

Chapter 6. Conclusion

6.1 Concluding Remarks

The stock return synchronicity decreases (increases) when the general information environment becomes better (worse). This thesis joins the R^2 debate by emphasizing the time varying nature of the R^2, and provides new evidence for the information interpretation of stock return synchronicity. In a multi-firms setting, I demonstrate a dynamic pattern of the systematic volatility with individual firms' earnings announcements if investors could learn across assets. The learning is possible with two special assumptions: the firms' fundamentals are correlated and the information can be characterized as noisy signals for the integrated cash flows. When investors update their beliefs about one firm's future cash flows based on other firms' information in the market, the large number of signals can compensate for the insufficient information content of each signal and reduce the systematic volatility. Therefore, a lower stock return synchronicity is presented when the information environment becomes better.

I then provide empirical evidence for the varying R^2s with the change of the information environment. With dramatically increased disclosure intensity, I consider the earnings season as a special period with improved information environment, and explore whether the stock return synchronicity is lower in the earnings season than it is in the normal period. I first conduct the analysis in the framework of China. Consistent with the hypothesis, I find the stock return synchronicity decreases about 18% in the earnings season than in the non-earnings seasons. Furthermore, this dynamic pattern of R^2 is mainly driven by the changes of the systematic volatility rather than the idiosyncratic volatility. In addition, this dynamic pattern is more pronounced for the older firms.

The dynamic pattern of R^2 around the earnings season can be generalized to other countries around the world. With a sample of 40 countries from 1995 to 2015, I find the stock return synchronicity is lower in the earnings season than it is in the non-earnings seasons in both country-level and firm-level analyses. The dominant force is the reduced systematic volatility rather than the idiosyncratic volatility, and the pattern is more pronounced for the middle-income countries than the high-income countries.

6.2 Limitations and Future Research

In this thesis, I provide a rational explanation for the decreased R^2 with the improved information environment: the cross-assets learning by investors. However, there are other explanations for the underlying mechanism as well. For example, Morck, Yeung and Yu (2000) use the noise trader risk to explain the large systematic component of the returns variation in the emerging markets. As argued by DeLong, Shleifer, Summers and Waldmann (1990), the noise traders can create their own space in the stock market with irrational optimism or pessimism which would affect all stocks simultaneously. The elevated systematic risk as well as the raised cost of capital would in turn drive away the informed arbitrageurs, thus left the market with even higher noise trader risk. Inspired by these arguments, it would be possible that the dynamic pattern of R^2 is caused by the changed sentiment of noise traders around the earnings season.

In addition, the elevated systematic volatility can also be caused by the category trading of market participants such as mutual funds and institutional investors. The simultaneously trading for a group of stocks would induce higher return comovement within the category (Barberis, Shleifer and Wurgler (2005); Anton and Polk (2014)). Thus the dynamic pattern of R^2 around the earnings season could also be caused by the systematically change of the trading strategy because of some unknown reasons. All in all, although the rational model in this thesis provides the most possible explanation, I do not exclude other irrational explanations and leave them for further studies.

Appendix I. Model Deviations

Proof for section 3.2.1

Construct vector $\boldsymbol{Z} = \begin{pmatrix} x_j \\ x_m \\ S_j \end{pmatrix} = \begin{pmatrix} \gamma_j f + v_j \\ f \\ \gamma_j f + v_j + \varepsilon_j \end{pmatrix} \sim N(M, \Sigma),$

where x_j is the random cash flow for firm j and x_m is the market-wide cash flow. In a large economy, I assume the market cash flow equals to the common factor f when the idiosyncratic cash flows are fully diversified.

Then the variance-covariance matrix of **Z** is given by

$$\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix},$$

where $\Sigma_{11} = \begin{pmatrix} {\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 & \gamma_j \sigma_f^2 \\ \gamma_j \sigma_f^2 & \sigma_f^2 \end{pmatrix}$, $\Sigma_{12} = \Sigma_{21}' = \begin{pmatrix} {\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \\ \gamma_j \sigma_f^2 \end{pmatrix}$

$$and\ \Sigma_{22} = {\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2.$$

In this part, I suppose that the investors update their beliefs about firm j's future performance only based on the information released from that particular firm and do not learn across assets. Then the posterior variance-covariance matrix conditional on the information set S_j is

$$\Sigma_{(x_j,x_m)'|S_j} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$$

$$= \begin{pmatrix} {\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 & \gamma_j\sigma_f^2 \\ \gamma_j\sigma_f^2 & \sigma_f^2 \end{pmatrix}$$

$$- \frac{1}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\begin{pmatrix} \left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right)^2 & \gamma_j\sigma_f^2\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right) \\ \gamma_j\sigma_f^2\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right) & \left(\gamma_j\sigma_f^2\right)^2 \end{pmatrix}$$

$$= \begin{pmatrix} \dfrac{\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} & \dfrac{\sigma_{\varepsilon,j}^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\gamma_j\sigma_f^2 \\ \dfrac{\sigma_{\varepsilon,j}^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\gamma_j\sigma_f^2 & \dfrac{\left(\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2\right)}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\sigma_f^2 \end{pmatrix}.$$

(A. 1)

The conditional R^2, given the firm's particular information S_j and Equation (3-4), is

$$R^2|S_j = \frac{\left[cov\left(x_j, x_m|S_j\right)\right]^2}{var\left(x_j|S_j\right)var\left(x_m|S_j\right)} = \frac{\left(\dfrac{\sigma_{\varepsilon,j}^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\gamma_j\sigma_f^2\right)^2}{\left[\dfrac{\left(\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2\right)}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\sigma_f^2\right]\left[\dfrac{\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\right]}$$

$$= \frac{\left(\gamma_j\sigma_f^2\sigma_{\varepsilon,j}^2\right)^2}{\left[\left(\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2\right)\sigma_f^2\right]\left[\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2\right]}$$

$$= \frac{1}{\sigma_{v,j}^2 q_j + 1} \times \frac{{\gamma_j}^2\sigma_f^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2}.$$

(A. 2)

While according to the definition of the systematic and idiosyncratic volatilities, the conditional volatilities, given signal S_j, are

$$SYSVOL|S_j = \frac{1}{P_j^2}\frac{\left[cov\left(x_j, x_m\middle|S_j\right)\right]^2}{var\left(x_m\middle|S_j\right)} = \frac{1}{P_j^2}\frac{\left(\frac{\sigma_{\varepsilon,j}^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\gamma_j\sigma_f^2\right)^2}{\frac{\left(\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2\right)}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\sigma_f^2}$$

$$= \frac{1}{P_j^2} \times \frac{1}{\sigma_{v,j}^2 q_j + 1} \times \frac{{\gamma_j}^2\sigma_f^2}{({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2)q_j + \sigma_{\varepsilon,j}^2},$$

(A. 3)

and

$$IDIOVOL|S_j = \frac{1}{P_j^2}\left\{\frac{\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} - \frac{{\gamma_j}^2\sigma_{\varepsilon,j}^4}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{\sigma_f^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\right\}$$

$$= \frac{1}{P_j^2}\left[\frac{\left(\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2\right)\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2 - {\gamma_j}^2\sigma_{\varepsilon,j}^4\sigma_f^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{1}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\right]$$

$$= \frac{1}{P_j^2}\left\{\frac{\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{v,j}^2\sigma_{\varepsilon,j}^2 + \sigma_{\varepsilon,j}^4\sigma_{v,j}^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{1}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\right\}$$

$$= \frac{1}{P_j^2}\frac{\sigma_{v,j}^2\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} = \frac{1}{P_j^2}\frac{\sigma_{v,j}^2}{\sigma_{v,j}^2 q_j + 1}.$$

(A. 4)

Proof for section 3.2.2

Proof of Theorem 1

In this section, investors learn across assets and update the common component using the information from other firms' signals in the market. Since the sequence of updating process does not affect the final results, I extend the formulas derived from section 3.2.1 and consider the effect of other signals using Bayes' rule.

I first consider the situation when investors use one additional signal S_k to update their beliefs about firm *j*'s performance. Since the information contained in S_k can only be used to update the common component *f*, I substitute the volatility of the common component with the newly updated one. The posterior belief about the variance of the market factor conditional on firm *k*'s information is

$$var(f|S_k) = \sigma_f^2 - \frac{{\gamma_k}^2\sigma_f^2\sigma_f^2}{{\gamma_k}^2\sigma_f^2 + \sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} = \frac{(\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2)\sigma_f^2}{{\gamma_k}^2\sigma_f^2 + \sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2}. \tag{A. 5}$$

According to Equation (A.2) and the Bayes-Rule, the R^2 given TWO signals is

$$R^2|(S_j, S_k) = \frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{{\gamma_j}^2 var(f|S_k)}{{\gamma_j}^2 var(f|S_k) + \sigma_{v,j}^2}$$

$$= \frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{\dfrac{(\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2){\gamma_j}^2\sigma_f^2}{{\gamma_k}^2\sigma_f^2 + \sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2}}{\dfrac{(\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2){\gamma_j}^2\sigma_f^2}{{\gamma_k}^2\sigma_f^2 + \sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + \sigma_{v,j}^2}$$

$$= \frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{{\gamma_j}^2\sigma_f^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\left(\dfrac{{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + 1\right)}.$$

Similarly, the conditional R^2 based on the third signal S_l is given by

$$R^2|(S_j, S_k, S_l) = \frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{{\gamma_j}^2 var(f|S_l)}{{\gamma_j}^2 var(f|S_l) + \sigma_{v,j}^2 \left(\frac{{\gamma_k}^2 var(f|S_l)}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + 1 \right)}$$

$$= \frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}$$

$$\times \frac{\frac{(\sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2){\gamma_j}^2 \sigma_f^2}{{\gamma_l}^2 \sigma_f^2 + \sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2}}{\frac{(\sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2){\gamma_j}^2 \sigma_f^2}{{\gamma_l}^2 \sigma_f^2 + \sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2} + \sigma_{v,j}^2 \left(\frac{(\sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2){\gamma_k}^2 \sigma_f^2}{({\gamma_l}^2 \sigma_f^2 + \sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2)(\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2)} + 1 \right)}$$

$$= \frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{{\gamma_j}^2 \sigma_f^2}{{\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \left(\frac{{\gamma_k}^2 \sigma_f^2}{(\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2)} + \frac{{\gamma_l}^2 \sigma_f^2}{(\sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2)} + 1 \right)}.$$

Repeating the process N-1 times yields the conditional R^2 as

$$R^2|(I = S_1, S_2 \dots S_n) = \frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{{\gamma_j}^2 \sigma_f^2}{{\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \left(\sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + 1 \right)}. \tag{A. 6}$$

According to Equation (3-4), the R^2 can be expressed as

$$R^2|(I = S_1, S_2 \dots S_n) = \frac{1}{\sigma_{v,j}^2 q_j + 1} \times \frac{{\gamma_j}^2 \sigma_f^2}{{\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \left(\sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} + 1 \right)}. \tag{A. 7}$$

Theorem 1 is proved.

Proof of Corollary 1

The relationship between the stock return synchronicity and the information quality can be easily proved by taking derivatives of R^2 with respect to the information quality q_j of firm *j* and the information quality $q_k (k \neq j)$ of other firms in the market.

For the information quality of the particular firm *j*,

$$\frac{\partial R^2|(I = S_1, S_2 \dots S_n)}{\partial q_j} = -\frac{\sigma_{v,j}^2}{\left(\sigma_{v,j}^2 q_j + 1\right)^2} \times \frac{{\gamma_j}^2 \sigma_f^2}{{\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \left(\sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} + 1 \right)} < 0.$$

(A. 8)

For the information quality of other firms' signals,

$$\frac{\partial R^2|(I = S_1, S_2 \dots S_n)}{\partial q_k}$$

$$= -\frac{{\gamma_j}^2 {\gamma_k}^2 \sigma_f^4 \sigma_{v,j}^2}{\left(\sigma_{v,j}^2 q_j + 1\right)\left(\sigma_{v,k}^2 q_k + 1\right)^2} \times \frac{1}{\left({\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \left(\sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} + 1 \right) \right)^2} < 0.$$

(A. 9)

Corollary 1 is proved.

Proof of Theorem 2

I then decompose the R^2 into systematic and idiosyncratic volatilities and explore whether they exhibit the same pattern when the information environment changes. Similarly, when investors update their beliefs about the common component as Equation (A.5), the systematic volatility given TWO signals is

$$SYSVOL|(S_j, S_k) = \frac{1}{P_j^2} \times \frac{\gamma_j{}^2 \sigma_{\varepsilon,j}^4}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{var(f|S_k)}{\gamma_j{}^2 var(f|S_k) + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}$$

$$= \frac{1}{P_j^2} \times \frac{\gamma_j{}^2 \sigma_{\varepsilon,j}^4}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{\frac{(\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2)\sigma_f^2}{\gamma_k{}^2 \sigma_f^2 + \sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2}}{\gamma_j{}^2 \frac{(\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2)\sigma_f^2}{\gamma_k{}^2 \sigma_f^2 + \sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}$$

$$= \frac{1}{P_j^2} \left(\frac{\gamma_j \sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \right)^2 \times \frac{\sigma_f^2}{\frac{\gamma_j{}^2 \sigma_f^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} + \frac{\gamma_k{}^2 \sigma_f^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + 1}.$$

(A. 10)

Similarly, the conditional systematic volatility based on the third signal S_l is

$$SYSVOL|S_j, S_k, S_l = \frac{1}{P_j^2} \left(\frac{\gamma_j \sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \right)^2 \times \frac{var(f|S_l)}{\frac{\gamma_j{}^2 var(f|S_l)}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} + \frac{\gamma_k{}^2 var(f|S_l)}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + 1}$$

$$= \frac{1}{P_j^2} \left(\frac{\gamma_j \sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \right)^2 \times \frac{\frac{(\sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2)\sigma_f^2}{\gamma_l{}^2 \sigma_f^2 + \sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2}}{\left(\frac{\gamma_j{}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} + \frac{\gamma_k{}^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} \right) \frac{(\sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2)\sigma_f^2}{\gamma_l{}^2 \sigma_f^2 + \sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2} + 1}$$

$$= \frac{1}{P_j^2} \left(\frac{\gamma_j \sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \right)^2 \times \frac{\sigma_f^2}{\frac{\gamma_j{}^2 \sigma_f^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} + \frac{\gamma_k{}^2 \sigma_f^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + \frac{\gamma_l{}^2 \sigma_f^2}{\sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2} + 1}.$$

(A. 11)

Repeating the process N-1 times yields the conditional systematic volatility as

$$SYSVOL|(I = S_1, S_2 \dots S_n) = \frac{1}{P_j^2}\left(\frac{\sigma_{\varepsilon,j}^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\right)^2 \times \frac{{\gamma_j}^2\sigma_f^2}{\sigma_f^2 \sum_{k=1}^{n} \frac{{\gamma_k}^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + 1}.$$

(A. 12)

According to Equation (3-4), the systematic volatility can be expressed as

$$SYSVOL|(I = S_1, S_2 \dots S_n) = \frac{1}{P_j^2}\left(\frac{\gamma_j}{\sigma_{v,j}^2 q_j + 1}\right)^2 \frac{\sigma_f^2}{\sum_{k=1}^{n} \frac{{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} + 1}.$$

(A. 13)

For the idiosyncratic volatility, since investors cannot infer additional information from other firms' signals for the firm-specific component, the idiosyncratic volatility remains the same as Equation (A.4).

Theorem 2 is proved.

Proof of Corollary 2

For any firm $k \in n$ and $k \neq j$, I take the derivatives of the systematic volatility to the information quality of firm k:

$$\frac{\partial SYSVOL|(I = S_1, S_2 \dots S_n)}{\partial q_k (k \neq j)} = -\frac{1}{P_j^2}\frac{(\gamma_j\gamma_k\sigma_f^2)^2}{(\sigma_{v,j}^2 q_j + 1)^2(\sigma_{v,k}^2 q_k + 1)^2(\sum_{k=1}^{n} \frac{{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} + 1)^2}$$

$$< 0.$$

(A. 14)

The value of the derivative is negative, which means the systematic volatility of firm j is negatively associated with any other firm's information quality in the market. While in Equation (A.4), q_k is not included in the expression of the idiosyncratic volatility, so the general information environment would not affect the idiosyncratic volatility.

Corollary 2 is proved.

Proof of Corollary 3

According to Equation (3-13), the information environment changes the R^2 through the component of

$$R^2_{Info\_environment} = \frac{{\gamma_j}^2\sigma_f^2}{{\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2+\frac{1}{q_k}}+1\right)}$$

$$= \frac{{\gamma_j}^2}{{\gamma_j}^2 + \sigma_{v,j}^2\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{{\gamma_k}^2}{\sigma_{v,k}^2+\frac{1}{q_k}}+1/\sigma_f^2\right)}. \tag{A. 15}$$

I further suppose $\varphi = \sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{\gamma_k{}^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} + 1/\sigma_f^2$, and φ is almost the same for all firms in the market. As φ is positively associate with q_k, I consider it to be a proper measure of the quality of the general information environment. Then I take the derivative of $R^2_{Info\_environment}$ to the information environment quality φ as

$$\frac{\partial(R^2_{Info\_environment})}{\partial\varphi} = -\frac{\gamma_j{}^2\sigma_{v,j}^2}{\left(\gamma_j{}^2 + \sigma_{v,j}^2\varphi\right)^2} < 0$$

and

$$\frac{\partial^2(R^2_{Info\_environment})}{\partial\varphi\partial\sigma_{v,j}^2} = \gamma_j{}^4 \frac{(\sigma_{v,j}^2\varphi - \gamma_j{}^2)}{(\gamma_j{}^2 + \sigma_{v,j}^2\varphi)^3}. \tag{A. 16}$$

Since $\varphi > \gamma_j{}^2/\sigma_{v,j}^2$ when n is large, $\frac{\partial^2(R^2_{Info\_environment})}{\partial\varphi\partial\sigma_{v,j}^2} > 0$.

Corollary 3 is proved.

Proof for section 3.2.3

Proof of Theorem 3

With the information structure of $S_j = \gamma_j f \times D_j + v_j + \varepsilon_j$, the variance-covariance matrix of **Z** is given by

$$\Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix},$$

$$\text{where } \Sigma_{11} = \begin{pmatrix} {\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 & \gamma_j\sigma_f^2 \\ \gamma_j\sigma_f^2 & \sigma_f^2 \end{pmatrix},\ \Sigma_{12} = \Sigma_{21}' = \begin{pmatrix} {\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 \\ \gamma_j\sigma_f^2 \times D_j \end{pmatrix},$$

$$and\ \Sigma_{22} = {\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2.$$

Suppose the investors first update their beliefs about the firm's future performance according to the information from that particular firm S_j, and then update the common component using the information from other firms' signals. The posterior variance-covariance matrix conditional on the information set S_j is

$$\Sigma_{(x_j,x_m)'|S_j} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$$

$$= \begin{pmatrix} {\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2 & \gamma_j\sigma_f^2 \\ \gamma_j\sigma_f^2 & \sigma_f^2 \end{pmatrix}$$

$$- \frac{1}{{\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \begin{pmatrix} \left({\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2\right)^2 & \gamma_j\sigma_f^2 \times D_j\left({\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2\right) \\ \gamma_j\sigma_f^2 \times D_j\left({\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2\right) & \left(\gamma_j\sigma_f^2 \times D_j\right)^2 \end{pmatrix}$$

$$= \begin{pmatrix} \dfrac{\left({\gamma_j}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2 + {\gamma_j}^2\sigma_f^2\sigma_{v,j}^2\left(1 - D_j\right)}{{\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} & \dfrac{\sigma_{\varepsilon,j}^2 + \left(1 - D_j\right)\sigma_{v,j}^2}{{\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\gamma_j\sigma_f^2 \\ \dfrac{\sigma_{\varepsilon,j}^2 + \left(1 - D_j\right)\sigma_{v,j}^2}{{\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\gamma_j\sigma_f^2 & \dfrac{\left(\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2\right)}{{\gamma_j}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\sigma_f^2 \end{pmatrix}.$$

(A. 17)

The conditional R^2 given the firm's particular information is

$$R^2|S_j = \frac{\left[cov\left(x_j, x_m|S_j\right)\right]^2}{var\left(x_j|S_j\right)var\left(x_m|S_j\right)}$$

$$= \frac{\left(\frac{\sigma_{\varepsilon,j}^2 + \left(1 - D_j\right)\sigma_{v,j}^2}{\gamma_j{}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\gamma_j\sigma_f^2\right)^2}{\left[\frac{\left(\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2\right)}{\gamma_j{}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\sigma_f^2\right]\left[\frac{\left(\gamma_j{}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2 + \gamma_j{}^2\sigma_f^2\sigma_{v,j}^2\left(1 - D_j\right)}{\gamma_j{}^2\sigma_f^2 \times D_j + \sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}\right]}$$

$$= \frac{\left(\sigma_{\varepsilon,j}^2 + \left(1 - D_j\right)\sigma_{v,j}^2\right)^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2} \times \frac{\gamma_j{}^2\sigma_f^2}{\left(\gamma_j{}^2\sigma_f^2 + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2 + \gamma_j{}^2\sigma_f^2\sigma_{v,j}^2\left(1 - D_j\right)}.$$

(A. 18)

The posterior belief about the variance of the market factor conditional on firm k's information is

$$var(f|S_k) = \sigma_f^2 - \frac{\gamma_k{}^2\sigma_f^2\sigma_f^2 \times D_j}{\gamma_k{}^2\sigma_f^2 \times D_k + \sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} = \frac{\left(\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2\right)\sigma_f^2}{\gamma_k{}^2\sigma_f^2 \times D_k + \sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2}.$$

(A. 19)

According to the Bayes-Rule, the R^2 given TWO signals is

$$R^2|(S_j, S_k) = \frac{\left(\sigma_{\varepsilon,j}^2 + \left(1 - D_j\right)\sigma_{v,j}^2\right)^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}$$

$$\times \frac{\gamma_j{}^2 var(f|S_k)}{\left(\gamma_j{}^2 var(f|S_k) + \sigma_{v,j}^2\right)\sigma_{\varepsilon,j}^2 + \gamma_j{}^2 var(f|S_k)\sigma_{v,j}^2\left(1 - D_j\right)}$$

$$= \frac{\left(\sigma_{\varepsilon,j}^2 + \left(1 - D_j\right)\sigma_{v,j}^2\right)^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}$$

$$\times \frac{\gamma_j{}^2\sigma_f^2}{\gamma_j{}^2\sigma_f^2\left(\sigma_{v,j}^2\left(1 - D_j\right) + \sigma_{\varepsilon,j}^2\right) + \sigma_{v,j}^2\sigma_{\varepsilon,j}^2\left(\frac{D_k\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + 1\right)}.$$

(A. 20)

Similarly, the conditional R^2 based on the third signal S_l is given by

$$R^2|(S_j,S_k,S_l) = \frac{\left(\sigma_{\varepsilon,j}^2 + (1-D_j)\sigma_{v,j}^2\right)^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}$$

$$\times \frac{{\gamma_j}^2\sigma_f^2}{{\gamma_j}^2\sigma_f^2\left(\sigma_{v,j}^2(1-D_j) + \sigma_{\varepsilon,j}^2\right) + \sigma_{v,j}^2\sigma_{\varepsilon,j}^2\left(\frac{D_k{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + \frac{D_l{\gamma_l}^2\sigma_f^2}{\sigma_{v,l}^2 + \sigma_{\varepsilon,l}^2} + 1\right)}.$$

(A. 21)

Repeating the process N-1 times yields the conditional R^2 as

$$R^2|(I = S_1, S_2 \dots S_n)$$

$$= \frac{\left(\sigma_{\varepsilon,j}^2 + (1-D_j)\sigma_{v,j}^2\right)^2}{\sigma_{v,j}^2 + \sigma_{\varepsilon,j}^2}$$

$$\times \frac{{\gamma_j}^2\sigma_f^2}{{\gamma_j}^2\sigma_f^2\left(\sigma_{v,j}^2(1-D_j) + \sigma_{\varepsilon,j}^2\right) + \sigma_{v,j}^2\sigma_{\varepsilon,j}^2\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{D_k{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2 + \sigma_{\varepsilon,k}^2} + 1\right)}$$

$$= \frac{\left[\sigma_{v,j}^2 q_j(1-D_j) + 1\right]^2}{\sigma_{v,j}^2 q_j + 1}$$

$$\times \frac{{\gamma_j}^2\sigma_f^2}{{\gamma_j}^2\sigma_f^2\left(\sigma_{v,j}^2 q_j(1-D_j) + 1\right) + \sigma_{v,j}^2\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{{\gamma_k}^2\sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}}D_k + 1\right)}.$$

(A. 22)

Proof of Corollary 4

According to Equation (A.22), if $\mathrm{D_k} = 0$ for $\forall \mathrm{k} \in \mathrm{n}$, which means all the signals in the market are only about the firm-specific factors, then the R^2 is

$$R^2|(I = S_1, S_2 \ldots S_n) = (\sigma_{v,j}^2 q_j + 1) \times \frac{{\gamma_j}^2 \sigma_f^2}{{\gamma_j}^2 \sigma_f^2 \left(\sigma_{v,j}^2 q_j + 1\right) + \sigma_{v,j}^2}.$$

(A. 23)

Taking the derivatives of the R^2 to the information quality q_j of firm *j* yields

$$\frac{\partial R^2|(I = S_1, S_2 \ldots S_n)}{\partial q_j} = \frac{{\gamma_j}^2 \sigma_f^2 \sigma_{v,j}^4}{\left[{\gamma_j}^2 \sigma_f^2 \left(\sigma_{v,j}^2 q_j + 1\right) + \sigma_{v,j}^2\right]^2} > 0.$$

(A. 24)

Corollary 4 is proved.

Proof of Corollary 5

According to Equation (3-12) in Theorem 1, the derivatives of R^2 respect to the information quality, uncertainty for the underlying factors, fundamental correlation with the market and the extent of learning are as follows:

(a) $\frac{\partial R^2|(I=S_1,S_2 \ldots S_n)}{\partial q_j} = -\frac{\sigma_{v,j}^2}{\left(\sigma_{v,j}^2 q_j+1\right)^2} \times \frac{{\gamma_j}^2 \sigma_f^2}{{\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \left(\sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} + 1\right)} < 0;$

(b) $\frac{\partial R^2|(I=S_1,S_2 \ldots S_n)}{\partial \sigma_f^2} = \frac{{\gamma_j}^2 \sigma_{v,j}^2}{\left[{\gamma_j}^2 \sigma_f^2 + \sigma_{v,j}^2 \left(\sum_{\substack{k=1 \\ k \neq j}}^{n} \frac{{\gamma_k}^2 \sigma_f^2}{\sigma_{v,k}^2 + \frac{1}{q_k}} + 1\right)\right]^2 (\sigma_{v,j}^2 q_j + 1)} > 0;$

(c) $\frac{\partial R^2|(I=S_1,S_2 \dots S_n)}{\partial \sigma_v^2} = -\frac{\gamma_j{}^2\sigma_f^2\left[\gamma_j{}^2\sigma_f^2 q_j+\left(2\sigma_{v,j}^2 q_j+1\right)\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+\frac{1}{q_k}}+1\right)\right]}{\left(\gamma_j{}^2\sigma_f^2+\sigma_{v,j}^2\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+\frac{1}{q_k}}+1\right)\right)^2\left(\sigma_{v,j}^2 q_j+1\right)^2} < 0;$

(d) $\frac{\partial R^2|(I=S_1,S_2 \dots S_n)}{\partial \gamma_j^2} = \frac{\sigma_f^2\sigma_{v,j}^2\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+1/q_k}+1\right)}{\left[\gamma_j{}^2\sigma_f^2+\sigma_{v,j}^2\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+\frac{1}{q_k}}+1\right)\right]^2\left(\sigma_{v,j}^2 q_j+1\right)} > 0;$

(e) $\frac{\partial R^2|(I=S_1,S_2 \dots S_n)}{\partial \sum_{\substack{k=1\\k\neq j}}^{n}\frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+1/q_k}} = -\frac{\gamma_j{}^2\sigma_f^2\sigma_{v,j}^2}{\left[\gamma_j{}^2\sigma_f^2+\sigma_{v,j}^2\left(\sum_{\substack{k=1\\k\neq j}}^{n}\frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+\frac{1}{q_k}}+1\right)\right]^2\left(\sigma_{v,j}^2 q_j+1\right)} < 0.$

(A. 25)

Corollary 5 is proved.

Proof of Corollary 6

According to Theorem 2, the derivative of the systematic volatility to the information quality of firm *j* is

$$\frac{\partial SYSVOL|(I=S_1,S_2 \dots S_n)}{\partial q_j}$$

$$= -\frac{\gamma_j{}^2\sigma_f^2}{P_j^2}\left(\frac{\sigma_{v,j}^2}{\left(\sigma_{v,j}^2 q_j+1\right)^2}+\frac{\gamma_j{}^2\sigma_f^2+\sigma_{v,j}^2 A}{\left(\gamma_j{}^2\sigma_f^2 q_j+A\left(1+\sigma_{v,j}^2 q_j\right)\right)^2}\right) < 0,$$

(A. 26)

where A=$\sum_{\substack{k=1\\k\neq j}}^{n}\frac{\gamma_k{}^2\sigma_f^2}{\sigma_{v,k}^2+\frac{1}{q_k}}+1$.

While the derivative of the idiosyncratic volatility to the information quality of firm j is

$$\frac{\partial IDIOVOL|(I = S_1, S_2 \ldots S_n)}{\partial q_j} = -\frac{1}{P_j^2}\frac{\sigma_{v,j}^4}{\left(\sigma_{v,j}^2 q_j + 1\right)^2} < 0. \tag{A. 27}$$

Corollary 6 is proved.

Appendix II. Variable Definitions for Chapter 4

R^2	The R-square value estimated from the standard market model ($R^2(1)$) and the industry-augmented market model ($R^2(2)$) for each season using the daily returns.
SYNCH	Logarithmic transformation of R^2, computed as $\ln\left(\frac{R^2}{1-R^2}\right)$.
SYS_VOL	The systematic volatility estimated from the standard market model (SYS_VOL(1)) and the industry-augmented market model (SYS_VOL(2)) respectively.
IDIO_VOL	The idiosyncratic volatility estimated from the standard market model (IDIO_VOL(1)) and the industry-augmented market model (IDIO_VOL(2)) respectively.
ES	A dummy variable for the earnings season, which equals to one in the earnings season (February to April) and zero otherwise.
SIZE	Firm size calculated as the log of total assets in the previous quarter (in the previous fiscal year for annual values).
MTBV	Market to book ratio calculated as the total market value of equity divided by total shareholders' equity in the previous quarter (in the previous fiscal year for annual values).
LEV	Leverage calculated as the total liabilities divided by the total assets in the previous quarter (in the previous fiscal year for annual values).
ROA	Profitability calculated as operating profit divided by total assets in the previous quarter (in the previous fiscal year for annual values).
EVENT	A dummy variable for major corporate changes which equals to one if the total assets increase or decrease more than 50% compared to the previous season, and zero otherwise (Annual value equals to one if any of the quarterly dummies equals to one during that year).
M&A	A dummy variable equals to one if there is merger and acquisition in the current season (in the current year for annual values).
SEO	A dummy variable equals to one if there are seasonal equity offerings

	in the current season (SEO; in the current year for annual values) or within four seasons before (SEO_1) and after (SEO_2) the seasonal equity offering, and zero otherwise. Right issues and seasoned new issues to specific target are not included.
TURN	Turnover calculated as the log of one plus the percentage of trading volume to the number of total tradable shares outstanding and averaged using daily observations over the season.
AMIL	Amihud illiquidity measure (Amihud (2002)) computed as $10^8 \times \ln(1 + \frac{\lvert R_{i,d} \rvert}{P_{i,d} VO_{i,d}})$ where $R_{i,d}$ is daily return, $P_{i,d}$ is price and $VO_{i,d}$ is trading volume for stock *i* on day d. Daily observations are averaged over the season.
SPREAD	Bid-Ask Spread computed as the difference between ask and bid prices divided by their average and averaged using daily observations over the season.
RCD	Interaction term of ES and a dummy variable equals to one if the observations are during the period of share structure reform in 2005 and financial crisis from 2008 to 2009, and zero otherwise.
AGE	Firm age computed as the log of firm years since IPO.

Appendix III. Does US Present Similar R^2 Pattern?

In this Appendix, I examine whether there is a dynamic pattern of R^2 around the earnings season in US. The challenge comes from the indistinct change of the information environment in US. The earnings reports have dispersed fiscal year ends for US firms. In addition, the uncertainty about the market factor is lower in the developed countries than in the developing countries, which means the effect of the cross-sectional learning about the market factor may be less pronounced in US than in China. Therefore, I predict that the dynamic pattern of R2 in US is much weaker than it is in China.

I obtain the daily stock return and trading volume data from CRSP and accounting data from COMPUSTAT from 1975 to 2015. I only include the stocks listed on the NYSE, AMEX, or NASDAQ with the CRSP share code of 10 or 11, and exclude the firms in the industries of finance and banking (SIC 6000-6999) and regulated utilities (SIC 4900-4999). I require at least 30 available trading days to calculate the seasonal R2 from a standard market model, and the final sample contains 13,952 firms with 454,283 firm-season observations.

[Insert Table A1 Here]

The clustering period for the annual earnings announcements in US starts from January 15th. As shown in Panel A of Table 4.10, around 66% of the sample firms make their annual earnings announcements from January 15th to April 15th, which I defined as the earnings season in US. The low percentage of earnings announcements in the earnings season is mainly due to the firms whose fiscal year ends are not December. In addition, the US firms release their earnings reports earlier than China. Almost 30% of the sample firms make the earnings announcements within 45 days after the fiscal year end and 25%

of firms within 75 days. The clustering pattern of the earnings announcements is consistent over decades.

I then estimate the R^2 from a standard market model from January 15th to April 15th as the earnings season, and April 15th to July 15th, July 15th to October 15th and October 15th to Jan 15th the next year as the non-earnings seasons. The dynamic pattern of R^2 is shown in Panel B of Table 4.10. Consistent with the previous literature, the equal-weighted mean of the R^2 is only 0.1259 in US, which is much lower than the value in China as 0.3907. The average R^2 is 0.1286 in the non-earnings seasons, which is higher than 0.1181 in the earnings season. The systematic volatility also presents similar pattern as the R^2. I then control for the effects of the financial crisis in 1987, the crash of internet bubble from 2000 to 2001 and the subprime crisis from 2008 to 2009. The equal-weighted mean of the systematic volatility decreases a lot from 0.0091 to 0.0065 in the earnings season, and the dynamic pattern of R^2 as well as the systematic volatility remains to be robust. All in all, I confirm that the R^2 in US also presents similar dynamic pattern around the earnings season, but the pattern is much weaker than the one in China.

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Table 4. 1 Sample distribution

Panel A shows the distribution of sample firms across industries according to the Industry Classifying Index Code of Listed Companies released by the China's Security Regulatory Commission (CSRC). Panel B shows the distribution of firm-year observations across years.

Panel A: Industry distribution

Industry	Number of Firms	Percentage
Agriculture, forestry, livestock farming, fishery	37	1.82%
Mining	71	3.49%
Food and beverage	88	4.32%
Textile, clothes and fur	69	3.39%
Timber and furniture	12	0.59%
Paper making and printing	41	2.01%
Petroleum, chemistry, rubber and plastic	232	11.39%
Electronic	101	4.96%
Metal and non-metal	191	9.38%
Machinery, equipment and instrument	402	19.74%
Medicine and biological products	117	5.75%
Other manufacturing	10	0.49%
Construction	65	3.19%
Transport and storage	80	3.93%
Information technology	119	5.84%
Wholesale and retail trade	146	7.17%
Real estate	134	6.58%
Social service	60	2.95%
Communication and Culture industry	31	1.52%
Comprehensive	30	1.47%
Total	2036	100.00%

Panel B: Yearly distribution

Year	Number of firm-year observations	Percentage
2003	892	5.31%
2004	934	5.56%
2005	1002	5.96%
2006	1047	6.23%
2007	1094	6.51%
2008	1106	6.58%
2009	1175	6.99%
2010	1274	7.58%
2011	1335	7.94%
2012	1435	8.54%
2013	1715	10.20%
2014	1878	11.17%
2015	1923	11.44%
Total	16810	100.00%

Table 4. 2 Distribution of earnings announcements

This table shows the number of annual earnings announcements in each month across years. '% in the earnings season' shows the percentage of the annual earnings announcements released during the earnings season, from February to April, to the total number of announcements in that year. The bottom row '%' shows the percentage of earnings announcements in that month to the total number of the annual reports.

Year	Jan	Feb	Mar	Apr	Others	% in the earnings season
2003	49	87	335	416	5	93.95%
2004	18	124	383	408	1	97.97%
2005	27	97	411	464	3	97.01%
2006	20	111	386	525	5	97.61%
2007	26	102	420	546	0	97.62%
2008	27	150	422	506	1	97.47%
2009	8	109	483	575	0	99.32%
2010	23	144	557	550	0	98.19%
2011	35	99	670	531	0	97.38%
2012	6	130	686	613	0	99.58%
2013	16	100	722	877	0	99.07%
2014	24	111	798	943	2	98.62%
2015	23	101	805	993	1	98.75%
Total	302	1465	7078	7947	18	97.89%
%	1.80%	8.72%	42.11%	47.28%	0.11%	

Table 4. 3 Descriptive statistics and correlation matrix

Panel A shows the descriptive statistics of the variables while Panel B shows the correlation matrix and reports Pearson correlations below the diagonal. R-squares are estimated based on the standard market model (1) and the industry-augmented market model (2) respectively; SYNCH is the logarithmic transformation of R-square; SYS_VOL and IDIO_VOL are the systematic and idiosyncratic volatilities respectively. ***, **and* indicate the significance at 1%, 5% and 10% levels respectively. See Appendix Ⅱ for detailed variable definitions.

Panel A: Descriptive statistics

Variables	Mean	Std.dev	5th Pctl.	25th Pctl.	Median	75th Pctl.	95th Pctl.
Standard Market Model							
$R^2(1)$	0.4187	0.1722	0.1417	0.2852	0.4149	0.5497	0.7060
SYNCH(1)	-0.3840	0.8046	-1.8012	-0.9188	-0.3438	0.1995	0.8761
SYS_VOL(1)	0.0175	0.0135	0.0036	0.0079	0.0134	0.0227	0.0466
IDIO_VOL(1)	0.0231	0.0130	0.0060	0.0130	0.0210	0.0309	0.0476
Industry-Augmented Market Model							
$R^2(2)$	0.5162	0.1658	0.2320	0.3963	0.5226	0.6423	0.0466
SYNCH(2)	0.0683	0.7403	-1.1969	-0.4211	0.0905	0.5852	0.0476
SYS_VOL(2)	0.0216	0.0152	0.0050	0.0106	0.0173	0.0284	0.7775
IDIO_VOL(2)	0.0190	0.0110	0.0050	0.0106	0.0169	0.0251	1.2514
Control Variables							
SIZE	21.812	1.215	20.160	20.966	21.661	22.465	24.063
MTBV	3.3149	2.5220	0.9685	1.6926	2.5685	4.0304	8.3560
LEV	0.4866	0.1927	0.1479	0.3475	0.4969	0.6319	0.7863
ROA	0.0105	0.0188	-0.0153	0.0015	0.0081	0.0185	0.0439
EVENT	0.0098	0.0986	0	0	0	0	0
M&A	0.1314	0.3378	0	0	0	0	1
SEO	0.0058	0.0762	0	0	0	0	0
TURN	0.0222	0.0166	0.0041	0.0095	0.0176	0.0307	0.0569
AMIL	0.1495	0.2423	0.0077	0.0237	0.0544	0.1451	0.6879
SPREAD	0.0018	0.0010	0.0006	0.0011	0.0016	0.0023	0.0038

(Cont.)

Table 4.3 (Cont.)

Panel B: Correlation Matrix

	R^2(1)	SYNCH(1)	SYS_VOL(1)	IDIO_VOL(1)	R^2(2)	SYNCH(2)	SYS_VOL(2)	IDIO_VOL(2)
SYNCH(1)	0.9926***							
SYS_VOL(1)	0.6238***	0.6132***						
IDIO_VOL(1)	-0.4265***	-0.4249***	0.2868***					
R^2(2)	0.8706***	0.8659***	0.5871***	-0.3065***				
SYNCH(2)	0.8661***	0.8654***	0.5877***	-0.3037***	0.9971***			
SYS_VOL(2)	0.4950***	0.4864***	0.9565***	0.4297***	0.5883***	0.5901***		
IDIO_VOL(2)	-0.4236***	-0.4228***	0.2446***	0.9417***	-0.4554***	-0.4539***	0.3003***	
SIZE	0.1421***	0.1407***	0.0126***	-0.1565***	0.1630***	0.1648***	0.0058	-0.1777***
MTBV	-0.1373***	-0.1445***	0.0760***	0.2152***	-0.1026***	-0.1023***	0.1059***	0.2003***
LEV	0.0194***	0.0200***	0.0345***	0.0275***	0.0081*	0.0088*	0.0310***	0.0324***
ROA	0.0001	0.0007	-0.0057	-0.0178***	0.0360***	0.0367***	0.0077*	-0.0382***
TURN	-0.1674***	-0.1639***	0.2554***	0.5430***	-0.1081***	-0.1059***	0.3180***	0.5156***
AMIL	0.1283***	0.1281***	-0.0370***	-0.1800***	0.0707***	0.0677***	-0.0760***	-0.1533***
SPREAD	0.1084***	0.1079***	-0.0651***	-0.2015***	0.0296***	0.0268***	-0.1126***	-0.1621***

	SIZE	MTBV	LEV	ROA	TURN	AMIL
MTBV	-0.3296***					
LEV	0.3559***	0.0223***				
ROA	0.0923***	0.1126***	-0.2646***			
TURN	-0.1619***	0.0784***	-0.0016	-0.0887***		
AMIL	-0.3214***	-0.1301***	0.0047	-0.1240***	-0.3133***	
SPREAD	-0.1786***	-0.2529***	0.1098***	-0.2281***	-0.3134***	0.6137***

Table 4. 4 Univariate analysis of R^2

This table shows the descriptive statistics of R^2 in the earnings season (From February to April) and the non-earnings seasons. Panel A reports the statistics with all observations while Panel B excludes the observations in special years when the Chinese firms are undergoing share structure reform in 2005 and when the stock market is under financial crisis during 2008 to 2009. R-squares are estimated based on the standard market model (1) and the industry-augmented market model (2) respectively. $R^2(3)$ and $R^2(4)$ are the R^2s estimated without the three days' observations around the earnings announcement date. Both mean and median values are reported and the means are both equal-weighted and market-value weighted. I calculate the differences of average R^2s between the non-earnings seasons and the earnings season, and the significance of the differences is based on 2-tailed tests (t-test for mean and rank sum test for median). ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

	All Seasons			Earnings Season			Non-Earnings Seasons			Difference (NES-ES)		
	Mean		Median	Mean		Median	Mean		Median	Mean		Median
	Equal-W	MV-W		Equal-W	MV-W		Equal-W	MV-W		Equal-W	MV-W	
Panel A: All Years												
All observations												
$R^2(1)$	0.4187	0.4533	0.4149	0.3864	0.4231	0.3754	0.4297	0.4633	0.4292	0.0433***	0.0402***	0.0538***
$R^2(2)$	0.5162	0.5602	0.5226	0.4874	0.5426	0.4862	0.5260	0.5660	0.5349	0.0385***	0.0234***	0.0487***
Exclude earnings announcements effect												
$R^2(3)$	0.4203	0.4554	0.4168	0.3925	0.4311	0.3824	0.4298	0.4633	0.4292	0.0373***	0.0322***	0.0469***
$R^2(4)$	0.5183	0.5622	0.5253	0.4953	0.5507	0.4964	0.5260	0.5660	0.5350	0.0307***	0.0153***	0.0385***
Panel B: Normal Years												
All observations												
$R^2(1)$	0.4037	0.4428	0.3943	0.3528	0.3957	0.3408	0.4210	0.4583	0.4167	0.0682***	0.0625***	0.0759***
$R^2(2)$	0.5019	0.5510	0.5062	0.4577	0.5218	0.4547	0.5171	0.5606	0.5254	0.0593***	0.0387***	0.0707***
Exclude earnings announcements effect												
$R^2(3)$	0.4052	0.4449	0.3966	0.3585	0.4043	0.3479	0.4211	0.4583	0.4167	0.0626***	0.0540***	0.0687***
$R^2(4)$	0.5040	0.5531	0.5087	0.4655	0.5303	0.4635	0.5171	0.5606	0.5255	0.0516***	0.0303***	0.0620***

Table 4. 5 Regression analysis of stock return synchronicity around earnings season

Panel A shows the results of the regression analysis of seasonal stock return synchronicity on earnings season dummy and other control variables. The stock return synchronicity is a logarithmic transformation of R^2 from standard market model or industry-augmented market model. The effects of share structure reform and financial crisis are controlled in columns (2) and (4). In Panel B, R^2 are estimated by excluding the three days' observations around the earnings announcement date. Panel C reports the results with control for the liquidity. Year and industry dummies are included to control for the fixed effects. T-statistics reported in the parentheses are calculated using standard errors clustered by both firm and season. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively. See Appendix Ⅱ for variable definitions.

Panel A: Main Regression Analysis

	Standard Market Model		Industry-Augmented Market Model	
	SYNCH(1)	SYNCH(1)	SYNCH(2)	SYNCH(2)
	(1)	(2)	(3)	(4)
ES	-0.2055*	-0.3227***	-0.1705*	-0.2678***
	(-1.85)	(-2.70)	(-1.86)	(-2.69)
SIZE	0.0864***	0.0836***	0.1062***	0.1038***
	(5.90)	(5.67)	(9.34)	(9.04)
MTBV	-0.0382***	-0.0400***	-0.0311***	-0.0326***
	(-3.77)	(-4.03)	(-4.04)	(-4.31)
LEV	-0.2063***	-0.1900***	-0.2284***	-0.2149***
	(-4.09)	(-3.81)	(-5.52)	(-5.27)
ROA	-0.8621*	-0.5894	0.1173	0.3435
	(-1.82)	(-1.30)	(0.27)	(0.86)
EVENT	-0.1456***	-0.1484***	-0.1634***	-0.1658***
	(-4.29)	(-4.31)	(-5.52)	(-5.48)
M&A	-0.0874***	-0.0887***	-0.0547***	-0.0557***
	(-3.46)	(-3.57)	(-3.02)	(-3.13)
SEO_1	-0.0526	-0.0556	0.0108	0.0083
	(-0.97)	(-0.99)	(0.21)	(0.16)
SEO	-0.1122**	-0.1211**	-0.0768	-0.0841
	(-2.10)	(-2.22)	(-1.46)	(-1.59)
SEO_2	0.0086	0.0208	0.0145	0.0246
	(0.22)	(0.52)	(0.36)	(0.60)
RCD		0.5911***		0.4903***
		(2.95)		(2.98)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
_cons	-2.0868***	-2.0041***	-2.2490***	-2.1806***
	(-5.71)	(-5.49)	(-8.33)	(-8.15)
R-squared	0.153	0.169	0.163	0.176
No. of obs	61168	61168	61150	61150

(Cont.)

Table 4.5 (Cont.)

Panel B: Regression Analysis - Exclude earnings announcements effect

	Standard Market Model		Industry-Augmented Market Model	
	SYNCH(3)	SYNCH(3)	SYNCH(4)	SYNCH(4)
	(1)	(2)	(3)	(4)
ES	-0.1790	-0.2982**	-0.1361	-0.2348**
	(-1.61)	(-2.49)	(-1.48)	(-2.35)
SIZE	0.0868***	0.0839***	0.1063***	0.1039***
	(5.91)	(5.69)	(9.35)	(9.05)
MTBV	-0.0381***	-0.0400***	-0.0313***	-0.0328***
	(-3.74)	(-4.02)	(-4.06)	(-4.34)
LEV	-0.2119***	-0.1953***	-0.2328***	-0.2190***
	(-4.20)	(-3.92)	(-5.61)	(-5.36)
ROA	-0.7944*	-0.5190	0.2153	0.4433
	(-1.71)	(-1.16)	(0.50)	(1.11)
EVENT	-0.1388***	-0.1417***	-0.1602***	-0.1626***
	(-4.04)	(-4.08)	(-5.37)	(-5.35)
M&A	-0.0845***	-0.0858***	-0.0518***	-0.0528***
	(-3.35)	(-3.45)	(-2.85)	(-2.95)
SEO_1	-0.0404	-0.0434	0.0189	0.0164
	(-0.72)	(-0.75)	(0.37)	(0.32)
SEO	-0.1120**	-0.1210**	-0.0714	-0.0789
	(-2.10)	(-2.22)	(-1.35)	(-1.48)
SEO_2	0.0140	0.0264	0.0200	0.0302
	(0.36)	(0.66)	(0.50)	(0.74)
RCD		0.6004***		0.4969***
		(3.00)		(3.02)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
_cons	-2.0864***	-2.0025***	-2.1829***	-2.1110***
	(-5.72)	(-5.50)	(-7.20)	(-6.75)
R-squared	0.149	0.166	0.159	0.172
No. of obs	61124	61124	61106	61106

(Cont.)

Table 4.5 (Cont.)

Panel C: Control for Liquidity

	SYNCH(1)	SYNCH(2)	SYNCH(1)	SYNCH(2)	SYNCH(1)	SYNCH(2)
	(1)	(2)	(3)	(4)	(5)	(6)
ES	-0.3067**	-0.2548**	-0.2804**	-0.2306**	-0.3075***	-0.2587***
	(-2.53)	(-2.53)	(-2.38)	(-2.36)	(-2.59)	(-2.62)
TURN	-6.7542***	-5.7684***				
	(-2.89)	(-3.82)				
AMIL			0.5948***	0.5387***		
			(5.85)	(6.55)		
SPREAD					70.1696***	41.9533**
					(2.99)	(2.44)
SIZE	0.0575***	0.0818***	0.1262***	0.1400***	0.0938***	0.1100***
	(2.66)	(5.68)	(8.09)	(11.87)	(6.20)	(9.18)
MTBV	-0.0433***	-0.0355***	-0.0306***	-0.0248***	-0.0352***	-0.0297***
	(-4.04)	(-4.40)	(-3.14)	(-3.36)	(-3.57)	(-3.88)
LEV	-0.1486**	-0.1805***	-0.2756***	-0.2892***	-0.2363***	-0.2425***
	(-2.55)	(-4.01)	(-5.35)	(-6.72)	(-4.74)	(-5.79)
ROA	-0.7724*	0.1889	-0.1420	0.7255*	-0.0327	0.6769
	(-1.71)	(0.46)	(-0.31)	(1.76)	(-0.06)	(1.50)
EVENT	-0.1368***	-0.1545***	-0.1658***	-0.1787***	-0.1503***	-0.1670***
	(-3.97)	(-5.07)	(-4.82)	(-5.88)	(-4.44)	(-5.53)
M&A	-0.0868***	-0.0539***	-0.0887***	-0.0545***	-0.0855***	-0.0538***
	(-3.36)	(-2.90)	(-3.64)	(-3.15)	(-3.50)	(-3.08)
SEO_1	-0.0598	0.0063	-0.0468	0.0230	-0.0487	0.0124
	(-1.13)	(0.12)	(-0.88)	(0.45)	(-0.85)	(0.23)
SEO	-0.1173**	-0.0823	-0.0804	-0.0462	-0.1031*	-0.0734
	(-2.21)	(-1.62)	(-1.58)	(-0.95)	(-1.86)	(-1.36)
SEO_2	0.0190	0.0228	0.0756*	0.0737*	0.0273	0.0284
	(0.49)	(0.57)	(1.83)	(1.84)	(0.67)	(0.68)
RCD	0.6006***	0.4976***	0.5637***	0.4684***	0.5888***	0.4887***
	(3.03)	(3.11)	(2.80)	(2.86)	(3.00)	(3.02)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-1.1893**	-1.4139***	-3.1245***	-2.9510***	-2.2376***	-2.2448***
	(-2.25)	(-3.65)	(-7.85)	(-9.11)	(-5.81)	(-7.39)
R-squared	0.179	0.186	0.184	0.191	0.173	0.178
No. of obs	60143	60126	59857	59839	61143	61125

Table 4. 6 Univariate analysis of systematic volatility and idiosyncratic volatility

This table shows the descriptive statistics of systematic and idiosyncratic volatilities in the earnings season (From February to April) and the non-earnings seasons. Panel A reports the statistics with all observations while Panel B excludes the observations in special years when the Chinese firms are undergoing share structure reform in 2005 and when the stock market is under financial crisis during 2008 to 2009. The systematic and idiosyncratic volatilities are estimated based on the standard market model and the industry-augmented market model respectively. Both mean and median values are reported and the means are both equal-weighted and market-value weighted. I calculate the differences of average volatilities between the non-earnings seasons and the earnings season, and the significance of the differences is based on 2-tailed tests (t-test for mean and rank sum test for median). ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

	All Seasons			Earnings Season			Non-Earnings Seasons			Difference (NES-ES)		
	Mean		Median	Mean		Median	Mean		Median	Mean		Median
	Equal-W	MV-W		Equal-W	MV-W		Equal-W	MV-W		Equal-W	MV-W	
Panel A: All Years												
<u>*Systematic Volatility*</u>												
Standard Market Model	0.0175	0.0180	0.0134	0.0152	0.0144	0.0110	0.0183	0.0192	0.0145	0.0031***	0.0048***	0.0035***
Industry-Augmented Market Model	0.0216	0.0221	0.0173	0.0191	0.0183	0.0145	0.0224	0.0234	0.0186	0.0033***	0.0051***	0.0040***
<u>*Idiosyncratic Volatility*</u>												
Standard Market Model	0.0231	0.0205	0.0210	0.0229	0.0190	0.0208	0.0232	0.0210	0.0210	0.0003**	0.0020***	0.0002
Industry-Augmented Market Model	0.0190	0.0164	0.0169	0.0189	0.0151	0.0170	0.0190	0.0168	0.0169	0.0001	0.0017***	-0.0001
Panel B: Normal Years												
<u>*Systematic Volatility*</u>												
Standard Market Model	0.0148	0.0156	0.0117	0.0105	0.0098	0.0095	0.0163	0.0175	0.0130	0.0058***	0.0077***	0.0035***
Industry-Augmented Market Model	0.0186	0.0194	0.0153	0.0140	0.0134	0.0126	0.0202	0.0214	0.0167	0.0061***	0.0080***	0.0041***
<u>*Idiosyncratic Volatility*</u>												
Standard Market Model	0.0217	0.0192	0.0194	0.0213	0.0174	0.0191	0.0219	0.0198	0.0195	0.0006***	0.0024***	0.0003**
Industry-Augmented Market Model	0.0180	0.0154	0.0158	0.0177	0.0138	0.0157	0.0180	0.0159	0.0158	0.0003**	0.0021***	0.0001

Table 4. 7 Regression analysis of systematic and idiosyncratic volatilities around earnings season

This table shows the results of the regression analysis of systematic and idiosyncratic volatilities on earnings season dummy and other control variables. Both volatilities are estimated from standard market model (1) or industry-augmented market model (2). In columns (5)-(8), the regression analysis are controlled for the effect of liquidity. Year and industry dummies are included to control for the fixed effects. T-statistics reported in the parentheses are calculated using standard errors clustered by both firm and season. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively. See Appendix Ⅱ for variable definitions.

					Control for the liquidity			
	Systematic Volatility		Idiosyncratic Volatility		Systematic Volatility		Idiosyncratic Volatility	
	SYS_VOL(1)	SYS_VOL(2)	IDIO_VOL(1)	IDIO_VOL(2)	SYS_VOL(1)	SYS_VOL(2)	IDIO_VOL(1)	IDIO_VOL(2)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ES	-0.3288**	-0.2703**	-0.0061	-0.0025	-0.3517***	-0.2961***	-0.0450	-0.0412
	(-2.53)	(-2.48)	(-0.14)	(-0.06)	(-2.74)	(-2.75)	(-1.14)	(-1.16)
SIZE	-0.0207	-0.0195	-0.1043***	-0.1233***	0.0211	0.0260	-0.0364***	-0.0558***
	(-1.08)	(-1.25)	(-10.57)	(-11.78)	(0.98)	(1.64)	(-4.10)	(-6.29)
MTBV	-0.0225***	-0.0142**	0.0174***	0.0184***	-0.0174**	-0.0086	0.0258***	0.0269***
	(-2.59)	(-2.09)	(4.05)	(4.36)	(-2.02)	(-1.31)	(5.23)	(5.59)
LEV	0.0722	0.0756	0.2622***	0.2905***	-0.0057	-0.0084	0.1429***	0.1721***
	(1.35)	(1.59)	(6.32)	(7.16)	(-0.11)	(-0.19)	(4.04)	(4.93)
ROA	-0.6215	-0.0591	-0.0321	-0.4026	-0.5477	0.0453	0.2247	-0.1437
	(-1.19)	(-0.12)	(-0.09)	(-1.20)	(-1.09)	(0.10)	(0.65)	(-0.43)
EVENT	-0.0441*	-0.0349	0.1043***	0.1309***	-0.0512*	-0.0425**	0.0856***	0.1120***
	(-1.68)	(-1.61)	(5.04)	(6.11)	(-1.89)	(-2.14)	(5.44)	(6.15)

(Cont.)

Table 4.7 (Cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M&A	-0.0373*	-0.0129	0.0515***	0.0428***	-0.0430*	-0.0188	0.0439***	0.0350***
	(-1.65)	(-0.78)	(5.00)	(4.40)	(-1.92)	(-1.19)	(5.18)	(4.41)
SEO_1	-0.0048	0.0263	0.0508	0.0180	-0.0020	0.0302	0.0578*	0.0240
	(-0.11)	(0.65)	(1.57)	(0.53)	(-0.04)	(0.70)	(1.84)	(0.70)
SEO	-0.0541	-0.0293	0.0670**	0.0548	-0.0730	-0.0496	0.0444	0.0327
	(-1.23)	(-0.74)	(2.11)	(1.64)	(-1.56)	(-1.13)	(1.53)	(1.20)
SEO_2	0.0244	0.0168	0.0036	-0.0078	0.0093	0.0021	-0.0097	-0.0207
	(0.58)	(0.42)	(0.12)	(-0.26)	(0.21)	(0.05)	(-0.31)	(-0.69)
RCD	0.6504***	0.5385***	0.0593	0.0482	0.6501***	0.5363***	0.0495	0.0388
	(3.24)	(3.36)	(0.78)	(0.57)	(3.19)	(3.26)	(0.79)	(0.59)
TURN					7.8132***	8.7767***	14.5674***	14.5451***
					(4.42)	(6.49)	(8.80)	(9.26)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	-4.0178***	-3.9073***	-2.0137***	-1.7267***	-4.9054***	-5.3837***	-3.7160***	-3.9698***
	(-9.43)	(-11.55)	(-9.05)	(-7.39)	(-10.05)	(-13.66)	(-16.58)	(-19.37)
R-squared	0.327	0.390	0.369	0.319	0.344	0.414	0.445	0.392
No. of obs	61168	61150	61168	61150	60143	60126	60143	60126

Table 4. 8 Univariate analysis of age and the change of R^2

This table shows the descriptive statistics of the change of R^2 as well as the systematic to idiosyncratic ratio according to the firm age. Each year, I group all firms into three categories according to the firm age. 'Δ' means the difference of the average values in the non-earnings seasons minus the one in the earnings season, while SIZE, MTBV, LEV and ROA in this table are annual fundamental variables. I calculate the differences of change R^2 and other variables between older firms and younger firms. The significance of the differences is based on 2-tailed tests (t-test for mean and rank sum test for median). ***, ** and * indicate significance at 1%, 5% and 10% levels respectively. See Appendix Ⅱ for variable definitions.

	Younger Firms		Median Firms		Older Firms		Difference (Older-Younger)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
AGE	5.0331	5.0000	10.5791	11.0000	15.1208	15.0000	10.0877***	10.0000***
ΔR^2								
All Years								
Standard Model	0.0375	0.0360	0.0451	0.0454	0.0449	0.0437	0.0074**	0.0077**
Industry-Augmented Model	0.0339	0.0272	0.0384	0.0344	0.0408	0.0348	0.0069**	0.0076**
Normal Years								
Standard Model	0.0624	0.0633	0.0705	0.0755	0.0720	0.0741	0.0096***	0.0108***
Industry-Augmented Model	0.0547	0.0527	0.0596	0.0579	0.0634	0.0610	0.0087**	0.0083**
Δ(SYS_VOL/IDIO_VOL)								
All Years								
Standard Model	0.1465	0.1783	0.1837	0.2103	0.1818	0.2060	0.0353***	0.0277***
Industry-Augmented Model	0.1807	0.2359	0.2190	0.2678	0.2280	0.2579	0.0472**	0.0220**
Normal Years								
Standard Model	0.2480	0.2440	0.2821	0.2778	0.2909	0.2818	0.0429***	0.0378***
Industry-Augmented Model	0.3192	0.3103	0.3513	0.3434	0.3740	0.3480	0.0548***	0.0377**
Control Variables								
ΔSIZE	0.0197	0.0146	0.0232	0.0166	0.0198	0.0131	0.0001	-0.0015
ΔMTBV	0.1459	0.1089	0.1267	0.0841	0.1751	0.0977	0.0292	-0.0113
ΔLEV	0.0023	0.0027	0.0016	0.0027	0.0009	0.0014	-0.0015**	-0.0013***
ΔROA	0.0018	0.0015	0.0020	0.0016	0.0016	0.0011	-0.0003	-0.0004**
ΔTURN	-0.0030	-0.0017	-0.0028	-0.0016	-0.0028	-0.0016	0.0003	0.0001
SIZE	21.6236	21.4041	21.9885	21.8495	21.8443	21.7516	0.2207***	0.3475***
MTBV	3.1251	2.4681	2.9840	2.2658	3.2426	2.4309	0.1175**	-0.0372
LEV	0.4291	0.4342	0.5030	0.5162	0.5191	0.5321	0.0900***	0.0980***
ROA	0.0509	0.0448	0.0379	0.0307	0.0356	0.0317	-0.0153***	-0.0131***

Table 4. 9 Regression analysis of age and the change of R^2

This table shows the results of the regression analysis of the change R^2 and systematic to idiosyncratic volatility ratio on firm age and other control variables. 'Δ' means the difference of the average values in the non-earnings seasons minus the one in the earnings season, while SIZE, MTBV, LEV and ROA in this table are annual fundamental variables. Year and industry dummies are included to control for the fixed effects. T-statistics reported in the parentheses are calculated using standard errors clustered by both firm and season. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively. See Appendix Ⅱ for variable definitions.

					Control for Liquidity			
	Standard Market Model		Industry-Augmented Market Model		Standard Market Model		Industry-Augmented Market Model	
	$\Delta R^2(1)$	$\Delta\left(\frac{SYS\_VOL(1)}{IDIO\_VOL(1)}\right)$	$\Delta R^2(2)$	$\Delta\left(\frac{SYS\_VOL(2)}{IDIO\_VOL(2)}\right)$	$\Delta R^2(1)$	$\Delta\left(\frac{SYS\_VOL(1)}{IDIO\_VOL(1)}\right)$	$\Delta R^2(2)$	$\Delta\left(\frac{SYS\_VOL(2)}{IDIO\_VOL(2)}\right)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AGE	0.0066**	0.0343***	0.0078**	0.0464***	0.0078**	0.0376***	0.0089**	0.0511***
	(2.07)	(3.62)	(2.38)	(3.85)	(2.07)	(3.19)	(2.33)	(3.65)
ΔSIZE	0.0547***	0.1536***	0.0419***	0.1841**	0.0366***	0.0988*	0.0266**	0.1155
	(4.59)	(2.84)	(3.57)	(2.14)	(3.03)	(1.77)	(2.41)	(1.40)
ΔMTBV	0.0183***	0.0377*	0.0195***	0.0724**	0.0120***	0.0175	0.0141***	0.0481**
	(3.61)	(1.68)	(4.00)	(2.44)	(3.45)	(0.96)	(4.78)	(2.09)
ΔLEV	-0.2387***	-0.5882***	-0.1865***	-0.7388***	-0.2228***	-0.5390***	-0.1768***	-0.6873***
	(-6.66)	(-4.68)	(-4.45)	(-3.71)	(-6.61)	(-4.49)	(-5.56)	(-4.27)
ΔROA	0.1443**	0.4113**	0.1443**	0.7068**	0.1826***	0.5205**	0.1784***	0.8532**
	(2.24)	(2.18)	(2.49)	(2.44)	(2.74)	(2.46)	(2.69)	(2.39)

(Cont.)

Table 4.9 (Cont.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SIZE	-0.0057	-0.0285**	-0.0085**	-0.0429***	-0.0037	-0.0206**	-0.0068*	-0.0346**
	(-1.46)	(-2.23)	(-2.37)	(-2.68)	(-1.10)	(-2.10)	(-1.80)	(-2.29)
MTBV	-0.0012	-0.0199***	-0.0008	-0.0238**	-0.0002	-0.0161**	0.0001	-0.0192**
	(-0.82)	(-2.88)	(-0.73)	(-2.40)	(-0.13)	(-2.45)	(0.07)	(-2.00)
LEV	0.0159	0.0763	0.0126	0.0943	0.0113	0.0582	0.0073	0.0722
	(1.17)	(1.55)	(1.19)	(1.60)	(0.92)	(1.43)	(0.73)	(1.28)
ROA	-0.0184	0.0855	-0.0405	0.0446	-0.0229	0.0572	-0.0448	0.0184
	(-0.29)	(0.46)	(-0.62)	(0.19)	(-0.32)	(0.27)	(-0.63)	(0.07)
EVENT	0.0014	-0.0163	-0.0033	-0.0276	0.0045	-0.0061	0.0002	-0.0125
	(0.22)	(-0.70)	(-0.50)	(-0.74)	(0.56)	(-0.22)	(0.03)	(-0.29)
M&A	0.0044	0.0067	0.0026	-0.0061	0.0036	0.0038	0.0018	-0.0110
	(1.63)	(0.64)	(1.55)	(-0.46)	(1.29)	(0.36)	(0.97)	(-0.80)
SEO	-0.0099	-0.0336	-0.0062	-0.0061	-0.0082	-0.0287	-0.0044	0.0012
	(-0.97)	(-0.65)	(-0.40)	(-0.07)	(-0.76)	(-0.49)	(-0.25)	(0.01)
ΔTURN					-4.4349***	-14.6768***	-3.8069***	-18.0437***
					(-5.50)	(-6.21)	(-5.43)	(-7.41)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	0.1905**	0.7754***	0.2286***	1.0037***	0.1199*	0.4935**	0.1846***	0.7788***
	(2.17)	(2.98)	(3.23)	(3.48)	(1.71)	(2.29)	(2.68)	(2.80)
R-squared	0.244	0.229	0.234	0.218	0.296	0.272	0.273	0.247
No. of obs	11755	11755	11755	11755	11582	11582	11582	11582

Table 4. 10 Loadings on market factor and market volatility

I decompose the systematic volatility estimated from the standard market model (without one-day lag and one-day ahead market returns in the regression) into two components: the squared loadings on market returns and the volatility of market returns. I regress the log values of these two components on the earnings season dummy and other control variables. Year and industry dummies are included to control for the fixed effects. T-statistics reported in the parentheses are calculated using standard errors clustered by both firm and season. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively. See Appendix Ⅱ for variable definitions.

			Control for Liquidity	
	$\ln(\beta^2)$	$\ln(\sigma_m^2)$	$\ln(\beta^2)$	$\ln(\sigma_m^2)$
	(1)	(2)	(3)	(4)
ES	-0.0870	-0.2556**	-0.1071*	-0.2557**
	(-1.40)	(-2.16)	(-1.87)	(-2.15)
	-0.0333*	0.0195***	0.0117	0.0143
SIZE	(-1.66)	(2.82)	(0.51)	(1.46)
	-0.0311***	0.0029	-0.0257***	0.0021
MTBV	(-3.46)	(0.77)	(-2.92)	(0.56)
	0.1350***	-0.0707***	0.0542	-0.0616**
LEV	(2.70)	(-3.20)	(1.08)	(-2.37)
	-0.9966*	0.4734*	-0.8637*	0.4248*
ROA	(-1.78)	(1.96)	(-1.67)	(1.82)
	-0.0451	-0.0245*	-0.0530*	-0.0232*
EVENT	(-1.62)	(-1.82)	(-1.85)	(-1.72)
	-0.0190	-0.0304***	-0.0240	-0.0300***
M&A	(-0.90)	(-2.74)	(-1.14)	(-2.65)
	-0.0298	0.0357**	-0.0240	0.0309*
SEO_1	(-0.64)	(2.04)	(-0.49)	(1.91)
	-0.0755*	0.0299**	-0.0912**	0.0268*
SEO	(-1.73)	(2.09)	(-2.04)	(1.96)
	0.0057	0.0247	-0.0044	0.0193
SEO_2	(0.15)	(1.26)	(-0.11)	(1.03)
	0.1987**	0.4859***	0.1929**	0.4903***
RCD	(2.18)	(2.84)	(2.05)	(2.88)
			8.5782***	-1.2067
TURN			(5.73)	(-0.86)
			(3.22)	(5.00)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
_cons	0.7401*	-4.8866***	-0.3674	-5.1876***
	(1.68)	(-28.46)	(-0.71)	(-16.50)
R-squared	0.119	0.702	0.153	0.703
No. of obs	61228	61228	60163	60163

Table 4. 11 Market risk and Industry risk

I decompose the systematic volatility estimated from the industry-augmented market model into two components: the risk associated with the market factor and the risk associated with the industry factor. I regress the log values of these two components on the earnings season dummy and other control variables. Year and industry dummies are included to control for the fixed effects. T-statistics reported in the parentheses are calculated using standard errors clustered by both firm and season. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively. See Appendix Ⅱ for variable definitions.

			Control for Liquidity	
	Market Risk	Industry Risk	Market Risk	Industry Risk
	(1)	(2)	(3)	(4)
ES	-0.3207**	-0.2705**	-0.3477**	-0.3040**
	(-2.04)	(-2.10)	(-2.23)	(-2.37)
SIZE	-0.0486	0.0384	0.0114	0.0930***
	(-1.40)	(1.35)	(0.30)	(2.96)
MTBV	0.0218	0.0055	0.0292**	0.0112
	(1.53)	(0.53)	(2.05)	(1.08)
LEV	-0.0636	0.0048	-0.1765	-0.0914
	(-0.52)	(0.04)	(-1.42)	(-0.78)
ROA	-1.7112*	1.6592	-1.7391*	2.0022*
	(-1.84)	(1.41)	(-1.92)	(1.72)
EVENT	-0.0136	-0.1701**	-0.0232	-0.1724**
	(-0.15)	(-1.99)	(-0.28)	(-2.08)
M&A	-0.0356	0.0273	-0.0501	0.0191
	(-0.97)	(0.74)	(-1.37)	(0.53)
SEO_1	-0.1298	0.1070	-0.1252	0.1188
	(-0.75)	(0.86)	(-0.72)	(0.97)
SEO	-0.1566	0.0633	-0.1850	0.0370
	(-1.28)	(0.66)	(-1.53)	(0.37)
SEO_2	0.0059	-0.0193	-0.0203	-0.0403
	(0.05)	(-0.17)	(-0.17)	(-0.34)
RCD	0.5025**	0.5397***	0.4951**	0.5342***
	(2.23)	(3.29)	(2.16)	(3.08)
TURN			8.8130***	12.6923***
			(3.22)	(5.00)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
_cons	-4.5713***	-7.1160***	-6.1639***	-8.8206***
	(-5.71)	(-10.47)	(-6.83)	(-11.24)
R-squared	0.054	0.130	0.057	0.135
No. of obs	61228	61228	60163	60163

Table 4. 12 Size effects

This table shows the regression analysis of the seasonal stock return synchronicity on the earnings season dummy and other control variables for large firms and small firms respectively. I classify the sample firms into two groups according to the firm size each year. The stock return synchronicity is a logarithmic transformation of R^2 from standard market model and industry-augmented market model respectively. Year and industry dummies are included to control for the fixed effects. T-statistics reported in the parentheses are calculated using standard errors clustered by both firm and season. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively. See Appendix Ⅱ for variable definitions.

	Standard Market Model		Industry-Augmented Market Model	
	Large Firms	Small Firms	Large Firms	Small Firms
	(1)	(2)	(3)	(4)
ES	-0.2800**	-0.3322***	-0.2238**	-0.2857***
	(-2.38)	(-2.65)	(-2.30)	(-2.75)
SIZE	0.0446**	0.0464	0.0722***	0.0718**
	(2.13)	(1.23)	(4.42)	(2.54)
MTBV	-0.0546***	-0.0367***	-0.0435***	-0.0320***
	(-4.34)	(-3.04)	(-4.65)	(-3.59)
LEV	-0.2406***	-0.1175*	-0.2208***	-0.1570***
	(-3.12)	(-1.67)	(-3.42)	(-2.89)
ROA	-1.6648**	0.0730	-0.1383	0.5293
	(-2.36)	(0.16)	(-0.21)	(1.39)
EVENT	-0.1153**	-0.1601***	-0.1426***	-0.1650***
	(-2.54)	(-4.24)	(-3.76)	(-4.21)
M&A	-0.0779***	-0.0961***	-0.0414**	-0.0789***
	(-3.09)	(-3.18)	(-2.15)	(-3.52)
SEO_1	-0.0233	-0.1324*	0.0198	-0.0402
	(-0.33)	(-1.74)	(0.28)	(-0.49)
SEO	-0.0922	-0.1718***	-0.0482	-0.1760***
	(-1.34)	(-2.82)	(-0.68)	(-2.71)
SEO_2	0.0338	-0.0454	0.0582	-0.1059
	(0.75)	(-0.61)	(1.16)	(-1.35)
RCD	0.5465***	0.6550***	0.4390***	0.5575***
	(2.87)	(3.17)	(2.95)	(3.24)
TURN	-8.1437***	-5.6939**	-6.6223***	-5.1908***
	(-3.43)	(-2.33)	(-4.18)	(-3.31)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
_cons	-0.8793*	-1.0742	-1.1921***	-1.2109*
	(-1.72)	(-1.25)	(-3.00)	(-1.83)
R-squared	0.179	0.165	0.191	0.166
No. of obs	29861	30112	29853	30103

Table 4. 13 The effect of quarterly earnings announcements

This table shows the results of the robust test by controlling the effect of the quarterly earnings announcements. Panel A presents the distribution for the number of the quarterly earnings announcements across months. '% in April/August/October' shows the percentage of the quarterly earnings announcements released in April, August and October respectively. Panel B shows the regression results of the seasonal stock return synchronicity on earnings season dummy and other control variables. The dependent variables SYNCH (1) and SYNCH (2) are logarithmic transformations of R^2s estimated using the daily returns without the observations in August and October. Year and industry dummies are included to control for the fixed effects. T-statistics reported in the parentheses are calculated using standard errors clustered by both firm and season. Coefficients marked ***, ** and * are significant at 1%, 5% and 10% levels respectively. See Appendix Ⅱ for variable definitions.

Panel A: Distribution of quarterly earnings announcement dates

First Quarter	April	Other Months	% in April
	16785	20	99.88%
Semi-Annual	August	Other Months	% in August
	14841	1956	88.36%
Third Quarter	October	Other Months	% in October
	16794	0	100.00%

Panel B: Regression Analysis

			Control for Liquidity	
	Standard Market Model	Industry-Augmented Market Model	Standard Market Model	Industry-Augmented Market Model
	SYNCH(1)	SYNCH(2)	SYNCH(1)	SYNCH(2)
	(1)	(2)	(3)	(4)
ES	-0.3517***	-0.2983***	-0.3379***	-0.2866***
	(-3.41)	(-3.74)	(-3.10)	(-3.42)
SIZE	0.0783***	0.0979***	0.0581**	0.0797***
	(5.09)	(8.13)	(2.40)	(5.03)
MTBV	-0.0476***	-0.0401***	-0.0504***	-0.0428***
	(-5.54)	(-6.87)	(-5.16)	(-6.55)
LEV	-0.1549***	-0.1795***	-0.1242**	-0.1522***
	(-2.99)	(-4.32)	(-1.96)	(-3.20)
ROA	-0.1769	0.6904	-0.2859	0.5948
	(-0.35)	(1.53)	(-0.58)	(1.29)
EVENT	-0.1412***	-0.1559***	-0.1328***	-0.1482***
	(-3.42)	(-4.34)	(-3.18)	(-4.09)
M&A	-0.0799***	-0.0478***	-0.0803***	-0.0478***
	(-4.46)	(-3.79)	(-4.17)	(-3.48)
SEO_1	-0.0513	0.0015	-0.0574	-0.0021
	(-0.91)	(0.03)	(-1.08)	(-0.04)
SEO	-0.1016	-0.0768	-0.0970	-0.0723
	(-1.47)	(-1.22)	(-1.52)	(-1.23)
SEO_2	0.0595	0.0534	0.0552	0.0460
	(1.37)	(1.11)	(1.34)	(0.99)
RCD	0.7152***	0.5843***	0.7217***	0.5898***
	(3.27)	(3.53)	(3.35)	(3.67)
TURN			-5.3934*	-4.8672***
			(-1.86)	(-2.70)
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
_cons	-1.8203***	-1.9389***	-1.0209*	-1.7264***
	(-4.97)	(-7.13)	(-1.71)	(-4.74)
R-squared	0.203	0.195	0.211	0.203
No. of obs	46127	46124	45394	45391

Table 5. 1 Sample selection process and yearly distribution

Panel A and Panel B show the sample selection process for the securities and the firm-season observations respectively. The initial sample is covered by DataStream and WorldScope from 1995 to 2015. Panel C shows the yearly distribution of the number of firms in the final sample. The column 'Sub Total' shows the sum number of firms for each period. See Appendix Table A1 and Table A3 for the listing of country's major exchanges and the selection process for non-common equities.

Panel A: Selection Process For Securities

Description	No. of Securities
All security listings covered by DataStream and WorldScope	57479
- Securities not traded in local currency	-1214
- Securities not traded on country's major exchange	-1151
- Non-Common equity (e.g. REITS, Unit Trusts, Warrants, duplicates)	-5848
- Financial and Utility Industry (SIC 6000-6999; 4900-4999)	-7765
Final Sample	41501

Panel B: Selection Process For Observations

Description	No. of Firm-Season Obs.
Firm-Season observations with valid R-Square	1534250
- Observations within three years after IPO	-309758
- Fiscal Year End is not December (June for Australia, Pakistan and South Africa; March for India, Japan and Sri Lanka)	-373641
- Observations in Countries with less than 25 firms	-14880
- Observations in Countries with less than 30 seasons	-5042
Final Sample	830929

Panel C: Yearly Distribution

Time Periods							Sub Total
1995-2000	*1995*	*1996*	*1997*	*1998*	*1999*	*2000*	
No. of Firms	4,376	4,895	5,395	5,879	6,453	7,442	34,440
2001-2005	*2001*	*2002*	*2003*	*2004*	*2005*	-	
No. of Firms	8,293	8,842	9,830	10,838	11,274	-	49,077
2006-2010	*2006*	*2007*	*2008*	*2009*	*2010*	-	
No. of Firms	12,652	13,005	13,021	13,554	15,211	-	67,443
2011-2015	*2011*	*2012*	*2013*	*2014*	*2015*	-	
No. of Firms	15,777	15,823	15,781	16,583	16,529	-	80,493
Total							231,453

Table 5. 2 Sample distribution across countries

This table shows the sample distribution for 40 countries and the distribution of fiscal year end months. *Series Start Season* denotes the series beginning of the R^2 and other variables. *Fiscal Year End* is the fiscal year end month for the majority of the firms in that country. *No. of Firms* is the total number of the sample firms. *No. of Obs.* is the number of firm-season observations. *Fiscal Year End≠12 (3/6)* denotes the firms or the observations whose fiscal year end month is not the month for majority firms of that country. Most countries' fiscal year end month is December except for Australia, Pakistan and South Africa for June and India, Japan and Sri Lanka for March. *Delete %* denotes the percentage of firms or observations deleted from the initial sample whose fiscal year end month is not the month for majority firms of that country.

Country	Series Start Season	Fiscal Year End	No. of Firms	No. of Obs.	Fiscal Year End≠12 (3/6)		Delete %	
					No. of Firms	No. of Obs.	% of Firms	% of Obs.
Australia	1995/01	Jun	1,543	35,436	363	7,513	19.05%	17.49%
Belgium	1996/01	Dec	105	3,736	12	229	10.26%	5.78%
Brazil	2002/01	Dec	177	3,615	5	85	2.75%	2.30%
Canada	1995/01	Dec	1,645	37,074	1,228	23,755	42.74%	39.05%
Chile	2001/01	Dec	90	2,119	0	0	0.00%	0.00%
China	1997/01	Dec	2,099	63,240	0	0	0.00%	0.00%
Denmark	1995/01	Dec	120	4,292	59	1,478	32.96%	25.62%
Egypt	2006/01	Dec	58	1,430	35	1,202	37.63%	45.67%
Finland	1996/01	Dec	136	5,822	9	276	6.21%	4.53%
France	1995/01	Dec	704	21,492	187	5,356	20.99%	19.95%
Germany	1995/01	Dec	668	21,619	149	3,580	18.24%	14.21%
Greece	1995/01	Dec	303	11,707	15	459	4.72%	3.77%
Hong Kong	1995/01	Dec	727	20,579	427	14,148	37.00%	40.74%
India	1995/01	Mar	2,116	52,096	380	6,858	15.22%	11.63%
Indonesia	1995/01	Dec	320	9,236	9	48	2.74%	0.52%
Israel	2002/01	Dec	311	7,504	0	0	0.00%	0.00%
Italy	1995/01	Dec	253	9,307	26	587	9.32%	5.93%
Japan	1995/01	Mar	2,810	142,060	1,302	46,552	31.66%	24.68%
Malaysia	1995/01	Dec	612	19,741	484	14,855	44.16%	42.94%
Mexico	1997/01	Dec	102	2,912	0	0	0.00%	0.00%
Netherlands	1995/01	Dec	161	6,587	26	553	13.90%	7.75%
Norway	1995/01	Dec	263	6,285	3	116	1.13%	1.81%
Pakistan	2001/01	Jun	95	2,716	55	1,585	36.67%	36.85%
Peru	2004/01	Dec	66	1,412	0	0	0.00%	0.00%
Philippines	1999/01	Dec	119	3,371	19	301	13.77%	8.20%
Poland	2000/01	Dec	367	8,554	17	271	4.43%	3.07%
Portugal	1996/01	Dec	74	2,056	4	120	5.13%	5.51%
Romania	2006/01	Dec	103	1,741	0	0	0.00%	0.00%
Singapore	1995/01	Dec	450	11,431	286	7,091	38.86%	38.28%
South Africa	1995/01	Jun	168	4,064	300	7,017	64.10%	63.32%
South Korea	1995/01	Dec	1,850	64,415	144	3,872	7.22%	5.67%
Spain	1995/01	Dec	138	5,423	13	308	8.61%	5.37%
Sri Lanka	2005/01	Mar	131	3,309	32	866	19.63%	20.74%
Sweden	1995/01	Dec	472	13,643	45	1,139	8.70%	7.71%
Switzerland	1995/01	Dec	193	7,802	34	926	14.98%	10.61%
Taiwan	1995/01	Dec	1,655	56,099	7	132	0.42%	0.23%
Thailand	1995/01	Dec	452	15,973	37	1,184	7.57%	6.90%
Turkey	1995/01	Dec	273	12,370	12	268	4.21%	2.12%
United Kingdom	1995/01	Dec	1,100	26,140	1,440	32,231	56.69%	55.22%
United States	1995/01	Dec	3,004	102,521	1,758	63,218	36.92%	38.14%
Total			26,033	830,929	8,922	248,179	25.52%	23.00%

Table 5. 3 Distribution of annual earnings announcements

This table shows the definition of the earnings season and distribution of the annual earnings announcements dates across different seasons. The dates of the annual earnings announcements are from WorldScope. *ES Definition* denotes the months covered by the earnings season when the majority of firms simultaneously release their annual earnings reports. *No. of Annual earnings announcements* denotes the number of the annual earnings announcements released in the earnings season (*Earnings Season*) and in the non-earnings seasons (*Non-Earnings Seasons 1/2/3; Total* for the sum number of reports in the non-earnings seasons). *% of Announcements in Earnings Season* is the percentage of earnings reports released in the earnings season to the total number of reports for that country.

Country	ES Definition	No. of Annual Earnings Announcements					% of Announcements in Earnings Season
		Earnings Season	Non-Earnings Seasons				
			1	2	3	Total	
Australia	Aug-Oct	32,727	159	17	337	513	98.46%
Belgium	Feb-Apr	3,078	285	27	136	448	87.29%
Brazil	Feb-Apr	3,308	70	29	76	175	94.98%
Canada	Feb-Apr	30,500	2461	143	1200	3804	88.91%
Chile	Jan-Mar	1,868	192	7	4	203	90.20%
China	Feb-Apr	53,119	3522	413	3102	7037	88.30%
Denmark	Feb-Apr	3,975	92	2	146	240	94.31%
Egypt	Feb-Apr	1,267	40	22	70	132	90.56%
Finland	Jan-Mar	5,684	78	10	17	105	98.19%
France	Feb-Apr	14,803	3285	246	1743	5274	73.73%
Germany	Feb-Apr	16,480	3492	295	871	4658	77.96%
Greece	Feb-Apr	8,411	1009	654	207	1870	81.81%
Hong Kong	Feb-Apr	19,223	647	35	85	767	96.16%
India	Apr-Jun	38,124	8173	947	244	9364	80.28%
Indonesia	Feb-Apr	7,167	1168	75	148	1391	83.75%
Israel	Feb-Apr	6,751	178	8	48	234	96.65%
Italy	Feb-Apr	7,878	954	8	104	1066	88.08%
Japan	Apr-Jun	138,571	1620	82	1550	3252	97.71%
Malaysia	Feb-Apr	18,527	345	21	99	465	97.55%
Mexico	Jan-Mar	2,775	74	17	9	100	96.52%
Netherlands	Feb-Apr	5,965	197	10	385	592	90.97%
Norway	Feb-Apr	5,740	145	4	263	412	93.30%
Pakistan	Aug-Oct	2,125	354	35	72	461	82.17%
Peru	Jan-Mar	1,294	84	12	0	96	93.09%
Philippines	Mar-May	2,752	51	105	170	326	89.41%
Poland	Feb-Apr	7,211	839	79	88	1006	87.76%
Portugal	Feb-Apr	1,241	473	38	28	539	69.72%
Romania	Feb-Apr	1,159	484	37	23	544	68.06%
Singapore	Feb-Apr	10,609	97	12	442	551	95.06%
South Africa	Aug-Oct	3,570	187	4	83	274	92.87%
South Korea	Feb-Apr	50,445	8921	1258	1048	11227	81.80%
Spain	Feb-Apr	4,711	312	0	55	367	92.77%
Sri Lanka	May-Jul	2,482	338	84	96	518	82.73%
Sweden	Feb-Apr	11,950	274	17	1057	1348	89.86%
Switzerland	Feb-Apr	6,359	719	34	633	1386	82.10%
Taiwan	Mar-May	48,993	134	17	1605	1756	96.54%
Thailand	Feb-Apr	14,345	122	9	457	588	96.06%
Turkey	Feb-Apr	10,816	654	89	530	1273	89.47%
United Kingdom	Mar-May	19,059	2136	15	4541	6692	74.01%
United States	Jan-Mar	95,113	2478	136	666	3280	96.67%
Total		720,175	46,843	5,053	22,438	74334	90.64%

Table 5. 4 Descriptive statistics and correlation matrix

Panel A shows the descriptive statistics of the country level variables while Panel B shows the descriptive statistics for the firm level variables. Panel C shows the correlation matrix for both the country level and firm level variables and reports Pearson correlations below the diagonal. The countries are classified into high income countries (*High Income*) and upper and lower middle income countries (*Middle Income*) according to the World Bank, and the descriptive statistics are presented for these two types of countries respectively. R^2 is the R-Square value estimated from the extended standard market model using daily returns for each season. Both equal-weighted and variance-weighted country level R^2s are shown in Panel A. *Synchronicity* is the logarithmic transformation of R^2. *Systematic volatility* and *idiosyncratic volatility* are the systematic and idiosyncratic volatilities estimated from the extended market model respectively. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. *Ln(Country Size)* is logarithm of the land area in square kilometers from WDI. *Ln(No. of Stocks)* is the logarithm of the number of listed stocks in the sample. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *SIZE* is the logarithm of the quarterly market capitalization in thousand US dollars. *MTBV* is quarterly market capitalization to common equity ratio. ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

Panel A: Country Level Variables

Variable	N	Mean	Std. Dev.	5th Pctl.	25th Pctl.	Median	75th Pctl.	95th Pctl.
R^2								
- All Sample								
Equal Weighted	2925	0.2330	0.0799	0.1408	0.1754	0.2139	0.2701	0.3914
Variance Weighted	2925	0.2166	0.0826	0.1286	0.1581	0.1934	0.2506	0.3901
- High Income								
Equal Weighted	1976	0.2208	0.0693	0.1365	0.1704	0.2042	0.2561	0.3546
Variance Weighted	1976	0.2038	0.0707	0.1266	0.1533	0.1848	0.2336	0.3483
- Middle Income								
Equal Weighted	949	0.2585	0.0934	0.1498	0.1875	0.2357	0.3045	0.4508
Variance Weighted	949	0.2433	0.0978	0.1359	0.1709	0.2151	0.2896	0.4577
Synchronicity								
Equal Weighted	2925	-1.2371	0.4255	-1.8086	-1.5478	-1.3014	-0.9941	-0.4414
Variance Weighted	2925	-1.3411	0.4537	-1.9133	-1.6724	-1.4283	-1.0954	-0.4470
Systematic Volatility								
- *All Sample*	2925	0.0145	0.0129	0.0035	0.0066	0.0106	0.0179	0.0388
- *High Income*	1976	0.0128	0.0110	0.0033	0.0058	0.0095	0.0161	0.0321
- *Middle Income*	949	0.0180	0.0155	0.0050	0.0088	0.0130	0.0208	0.0497
Idiosyncratic Volatility								
- *All Sample*	2925	0.0506	0.0338	0.0160	0.0270	0.0422	0.0629	0.1219
- *High Income*	1976	0.0492	0.0346	0.0156	0.0251	0.0384	0.0607	0.1273
- *Middle Income*	949	0.0534	0.0319	0.0180	0.0337	0.0472	0.0662	0.1051

(Cont.)

Table 5.4 (Cont.)

Panel A: Country Level Variables (Cont.)

Variable	N	Mean	Std. Dev.	5th Pctl.	25th Pctl.	Median	75th Pctl.	95th Pctl.
Control Variables								
Ln(GDP Per Capita)	2925	8.3780	1.1896	5.9720	7.6695	8.8776	9.2927	9.6933
GDP Per Capita Growth	2925	0.0057	0.0126	-0.0133	0.0002	0.0056	0.0118	0.0239
Var(GDP Per Capita Growth)	2925	0.1466	0.2457	0.0093	0.0264	0.0580	0.1386	0.6609
Ln(Country Size)	2925	12.616	2.200	6.957	11.425	12.763	14.009	16.029
Ln(No. of Stocks)	2925	4.9564	1.1098	3.4965	4.0604	4.7185	5.6630	7.1770
Industry Herfindahl	2925	0.1170	0.0560	0.0530	0.0780	0.1088	0.1412	0.2097
Firm Herfindahl	2925	0.0594	0.0481	0.0074	0.0256	0.0461	0.0795	0.1586

Panel B :Firm Level Variables

Variable	N	Mean	Std. Dev.	5th Pctl.	25th Pctl.	Median	75th Pctl.	95th Pctl.
R-Square								
- All Sample	636727	0.2426	0.1570	0.0517	0.1193	0.2044	0.3359	0.5592
- High Income	479082	0.2279	0.1495	0.0482	0.1118	0.1908	0.3136	0.5325
- Middle Income	157645	0.2871	0.1704	0.0685	0.1491	0.2519	0.4011	0.6157
Synchronicity	636727	-1.3471	0.9524	-2.9087	-1.9988	-1.3589	-0.6814	0.2378
Systematic Volatility								
- All Sample	636727	0.0145	0.0204	0.0010	0.0035	0.0078	0.0169	0.0508
- High Income	479082	0.0134	0.0197	0.0010	0.0032	0.0071	0.0156	0.0472
- Middle Income	157645	0.0176	0.0220	0.0014	0.0051	0.0104	0.0207	0.0624
Idiosyncratic Volatility								
- All Sample	636727	0.0503	0.0661	0.0056	0.0143	0.0283	0.0574	0.1727
- High Income	479082	0.0524	0.0710	0.0054	0.0137	0.0278	0.0589	0.1905
- Middle Income	157645	0.0437	0.0476	0.0066	0.0159	0.0297	0.0541	0.1248
Control Variables								
SIZE	636727	12.0404	2.0189	8.9755	10.5915	11.9180	13.3528	15.5662
MTBV	636727	2.1487	2.3220	0.3700	0.8000	1.4100	2.5700	6.4900

(Cont.)

Table 5.4 (Cont.)

Panel C. Correlation Matrix

<u>*Country Level Variables*</u>

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	R-Square (Equal-W)	-											
(2)	R-Square (Variance-W)	0.9681^{***}											
(3)	Synchronicity (Equal-W)	0.9916^{***}	0.9524^{***}										
(4)	Synchronicity (Variance-W)	0.9614^{***}	0.99^{***}	0.9624^{***}									
(5)	Systematic Volatility	0.5314^{***}	0.5629^{***}	0.5112^{***}	0.5432^{***}								
(6)	Idiosyncratic Volatility	-0.0919^{***}	-0.0781^{***}	-0.0986^{***}	-0.0841^{***}	0.6824^{***}							
	Ln(GDP Per Capita)	-0.2139^{***}	-0.2345^{***}	-0.2114^{***}	-0.2341^{***}	-0.1798^{***}	-0.0471^{***}						
(8)	GDP Per Capita Growth	0.0432^{**}	0.0422^{**}	0.0323^{*}	0.0328^{*}	-0.0903^{***}	-0.1265^{***}	-0.2125^{***}					
(9)	Var(GDP Per Capita Growth)	0.1998^{***}	0.1979^{***}	0.2017^{***}	0.1999^{***}	0.2308^{***}	0.1373^{***}	-0.2119^{***}	0.0204^{***}				
(10)	Ln(Country Size)	0.0645^{***}	0.0512^{***}	0.0451^{**}	0.0302	0.0802^{***}	0.1372^{***}	-0.3059^{***}	0.0435^{**}	-0.1074^{***}			
(11)	Ln(No. Stocks)	-0.0508^{***}	-0.0738^{***}	-0.0688^{***}	-0.0936^{***}	0.0796^{***}	0.2093^{***}	0.1475^{***}	0.0584^{***}	-0.0447^{**}	0.1876^{***}		
(12)	Industry Herfindahl	0.1173^{***}	0.1161^{***}	0.123^{***}	0.1236^{***}	-0.0289	-0.1514^{***}	-0.0525^{***}	-0.0119	0.0796^{***}	-0.1161^{***}	-0.3785^{***}	
(13)	Firm Herfindahl	0.0725^{***}	0.0623^{***}	0.0829^{***}	0.0728^{***}	-0.0766^{***}	-0.1841^{***}	0.1482^{***}	-0.0745^{***}	0.0261	-0.1535^{***}	-0.4885^{***}	0.8179^{***}

(Cont.)

Table 5.4 (Cont.)

Panel C. Correlation Matrix (Cont.)

Firm-Level Variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	R-Square	-										
(2)	Synchronicity	0.9622***										
(3)	Systematic Volatility	0.4095***	0.3909***									
(4)	Idiosyncratic Volatility	-0.2434***	-0.2547***	0.5195***								
(5)	SIZE	0.4149***	0.3927***	-0.0601***	-0.3919***							
(6)	MTBV	0.0757***	0.0674***	0.0883***	0.0256***	0.2942***						
(7)	Ln(GDP Per Capita)	-0.1292***	-0.137***	-0.0552***	0.0776***	0.1188***	-0.0315***					
(8)	GDP Per Capita Growth	0.0811***	0.0793***	-0.0126***	-0.0729***	0.0066***	0.0945***	-0.3979***				
(9)	Var(GDP Per Capita Growth)	0.0326***	0.0476***	-0.0356***	-0.0576***	-0.1162***	-0.1155***	-0.1443***	0.0667***			
(11)	Ln(Country Size)	0.0934***	0.0586***	0.1242***	0.1057***	0.1468***	0.2180***	-0.1771***	0.0846***	-0.3216***		
(12)	Industry Herfindahl	0.0111***	0.0280***	-0.0316***	-0.0647***	-0.0830***	-0.0151***	-0.1895***	0.0830***	0.2388***	-0.3383***	
(13)	Firm Herfindahl	-0.0193***	-0.0116***	-0.0135***	-0.0159***	-0.0029**	0.0476***	-0.0636***	-0.0041***	0.0780***	-0.1613***	0.6356***

Table 5. 5 Summary statistics across countries

This table shows the summary statistics for the market information across 40 countries in the sample. Data is from DataStream and WorldScope and both mean and median values are reported. The countries are classified into high income countries (*High Income*) and upper and lower middle income countries (*Middle Income*) according to the World Bank. R^2 is the R-Square value estimated from the extended standard market model using daily returns for each season. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. Market Cap (Million $) is the market capitalization in million US dollars. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. The summary statistics for all countries and for high income countries and middle income countries are reported in *Total* and *Sub-Total* respectively.

	R^2		Ln(GDP Per Capita)		Var (GDP Per Capita Growth)		Market Cap. (Million $)		Industry Herfindahl		Firm Herfindahl	
Country	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
High Income Countries												
Australia	0.1626	0.1387	9.459	9.489	0.033	0.028	518	32	0.083	0.084	0.035	0.034
Belgium	0.2030	0.1714	9.256	9.290	0.029	0.019	1451	292	0.123	0.119	0.092	0.091
Canada	0.1752	0.1481	9.330	9.363	0.035	0.022	833	88	0.078	0.075	0.019	0.019
Chile	0.2564	0.2168	8.010	8.024	0.144	0.141	1989	571	0.097	0.099	0.060	0.052
Denmark	0.2162	0.1821	9.550	9.565	0.081	0.072	2168	203	0.136	0.145	0.098	0.111
Finland	0.2238	0.1804	9.280	9.331	0.140	0.058	1285	253	0.128	0.132	0.076	0.077
France	0.2212	0.1739	9.191	9.215	0.021	0.013	3632	191	0.079	0.080	0.027	0.028
Germany	0.1985	0.1591	9.215	9.197	0.073	0.043	2231	109	0.132	0.133	0.042	0.043
Greece	0.2745	0.2456	8.725	8.702	0.142	0.095	369	62	0.105	0.091	0.051	0.044
Hong Kong	0.2151	0.1854	8.821	8.803	0.217	0.139	1390	158	0.064	0.063	0.024	0.023
Israel	0.2360	0.2115	8.906	8.923	0.146	0.118	596	72	0.113	0.114	0.046	0.047
Italy	0.2399	0.2058	9.093	9.099	0.047	0.036	1969	233	0.186	0.189	0.100	0.100

(Cont.)

Table 5.5 (Cont.)

	R^2		Ln(GDP Per Capita)		Var (GDP Per Capita Growth)		Market Cap. (Million $)		Industry Herfindahl		Firm Herfindahl	
Country	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Japan	0.2779	0.2470	9.259	9.262	0.115	0.084	1114	143	0.056	0.056	0.006	0.006
Netherlands	0.2588	0.2154	9.371	9.383	0.037	0.021	5612	481	0.206	0.205	0.196	0.196
Norway	0.2273	0.1914	9.952	9.987	0.169	0.140	1326	209	0.160	0.163	0.141	0.143
Poland	0.1892	0.1632	7.926	7.958	0.047	0.039	265	47	0.127	0.124	0.084	0.082
Portugal	0.2399	0.1891	8.587	8.601	0.061	0.050	1449	276	0.153	0.144	0.103	0.093
Singapore	0.2012	0.1765	9.169	9.179	0.426	0.392	512	74	0.089	0.070	0.042	0.033
South Korea	0.1840	0.1568	8.412	8.433	0.198	0.089	558	66	0.096	0.094	0.026	0.026
Spain	0.2620	0.2181	8.889	8.913	0.019	0.011	2750	560	0.117	0.124	0.091	0.095
Sweden	0.2151	0.1718	9.381	9.421	0.092	0.047	1210	91	0.095	0.095	0.045	0.043
Switzerland	0.2377	0.1942	9.759	9.754	0.034	0.026	5389	517	0.140	0.144	0.072	0.071
Taiwan	0.2435	0.2141	8.256	8.261	0.234	0.154	467	84	0.162	0.168	0.017	0.016
United Kingdom	0.1896	0.1532	9.121	9.161	0.027	0.014	3368	150	0.067	0.069	0.041	0.046
United States	0.2390	0.2053	9.357	9.386	0.031	0.018	5301	680	0.052	0.052	0.009	0.007
Sub-Total	0.2235	0.1886	9.051	9.068	0.104	0.075	1910	226	0.114	0.113	0.062	0.061

(Cont.)

Table 5.5 (Cont.)

Country	R^2 Mean	R^2 Median	Ln(GDP Per Capita) Mean	Ln(GDP Per Capita) Median	Var (GDP Per Capita Growth) Mean	Var (GDP Per Capita Growth) Median	Market Cap. (Million $) Mean	Market Cap. (Million $) Median	Industry Herfindahl Mean	Industry Herfindahl Median	Firm Herfindahl Mean	Firm Herfindahl Median
Middle Income Countries												
Brazil	0.2399	0.2058	7.854	7.857	0.128	0.083	5688	1194	0.109	0.111	0.072	0.074
China	0.3967	0.3896	6.598	6.593	0.044	0.042	1238	483	0.125	0.108	0.054	0.036
Egypt	0.3873	0.3744	6.551	6.599	0.666	0.179	683	183	0.135	0.132	0.061	0.065
India	0.2146	0.1896	5.482	5.446	0.141	0.115	639	38	0.105	0.107	0.032	0.029
Indonesia	0.2247	0.1921	6.481	6.417	0.301	0.058	760	82	0.081	0.080	0.030	0.027
Malaysia	0.1998	0.1730	7.588	7.582	0.270	0.149	274	40	0.049	0.048	0.014	0.013
Mexico	0.2802	0.2487	7.686	7.680	0.128	0.051	5048	1312	0.142	0.153	0.053	0.046
Pakistan	0.2774	0.2408	7.891	7.863	0.040	0.031	269	43	0.152	0.156	0.066	0.070
Peru	0.2241	0.1851	5.361	5.354	0.204	0.164	815	237	0.137	0.124	0.054	0.048
Philippines	0.2073	0.1780	6.197	6.206	0.094	0.062	704	76	0.194	0.202	0.080	0.082
Romania	0.2115	0.1785	7.647	7.649	0.266	0.112	137	20	0.372	0.366	0.209	0.192
South Africa	0.1864	0.1520	7.393	7.374	0.033	0.021	1301	242	0.066	0.062	0.022	0.023
Sri Lanka	0.2201	0.1975	6.052	6.037	0.071	0.068	62	16	0.116	0.112	0.032	0.028
Thailand	0.2158	0.1840	6.972	6.971	0.459	0.339	419	54	0.107	0.095	0.064	0.059
Turkey	0.3154	0.2901	7.709	7.704	0.657	0.677	591	104	0.148	0.125	0.082	0.066
Sub-Total	0.2534	0.2253	6.898	6.889	0.233	0.143	1242	275	0.136	0.132	0.062	0.057
Total	0.2347	0.2024	8.243	8.251	0.152	0.100	1659	244	0.122	0.120	0.062	0.060

Table 5. 6 Univariate analysis of country-level R^2 and systematic and idiosyncratic volatilities

This table shows the descriptive statistics in the earnings season and non-earnings seasons for the country level R^2, systematic volatility and idiosyncratic volatility respectively. R^2 is the R-Square value estimated from the extended standard market model using daily returns for each season. Both equal-weighted and variance-weighted country level R^2s are shown in this table. *Systematic volatility* and *idiosyncratic volatility* are the systematic and idiosyncratic volatilities estimated from the extended market model respectively. The countries are classified into high income countries (*High Income*) and upper and lower middle income countries (*Middle Income*) according to the World Bank. Both mean and median values are reported for all the countries and high/middle income groups respectively. I calculate the differences of the average R^2s as well as the systematic and idiosyncratic volatilities between the non-earnings seasons and the earnings season, and the significance of the differences is based on 2-tailed tests (t-test for mean and rank sum test for median). ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

	Earnings Season		Non-Earnings seasons		Difference (NES-ES)	
Variable	Mean	Median	Mean	Median	Mean	Median
R^2						
- All Sample						
Equal Weighted	0.2268	0.2139	0.2351	0.2140	0.0083**	0.0001
Variance Weighted	0.2103	0.1920	0.2187	0.1943	0.0084**	0.0023
- High Income						
Equal Weighted	0.2156	0.2086	0.2225	0.2032	0.0069**	-0.0054
Variance Weighted	0.1983	0.1849	0.2056	0.1848	0.0073**	-0.0001
- Middle Income						
Equal Weighted	0.2501	0.2300	0.2613	0.2386	0.0112*	0.0085*
Variance Weighted	0.2354	0.2067	0.2459	0.2176	0.0106	0.0109
Systematic Volatility						
- All Sample	0.0136	0.0101	0.0148	0.0108	0.0012**	0.0007**
- High Income	0.0120	0.0090	0.0130	0.0096	0.0010*	0.0006
- Middle Income	0.0168	0.0125	0.0184	0.0132	0.0015	0.0007
Idiosyncratic Volatility						
- All Sample	0.0502	0.0420	0.0507	0.0422	0.0006	0.0002
- High Income	0.0490	0.0377	0.0493	0.0386	0.0003	0.0010
- Middle Income	0.0525	0.0469	0.0537	0.0474	0.0012	0.0005

Table 5. 7 Univariate analysis of country-level R^2 across countries

This table shows the means of the country level R^2 in the earnings season and non-earnings seasons across the countries. R^2 is the R-Square value estimated from the extended standard market model using daily returns for each season. Both equal-weighted and variance-weighted country level R^2s are shown in this table. The countries are classified into high income countries (*High Income*) and upper and lower middle income countries (*Middle Income*) according to the World Bank. I calculate the differences of the average R^2s between the non-earnings seasons and the earnings season. The summary statistics for all countries and for high income countries and middle income countries are reported in *Total* and *Sub-Total* respectively.

	All		Earning Season		Non-Earnings Seasons		Difference (NES-ES)	
Country	Equal-W	Variance-W	Equal-W	Variance-W	Equal-W	Variance-W	Equal-W	Variance-W
High Income Countries								
Australia	0.1615	0.1535	0.1727	0.1652	0.1576	0.1494	-0.0151	-0.0158
Belgium	0.2030	0.1952	0.1984	0.1909	0.2046	0.1967	0.0062	0.0057
Canada	0.1655	0.1489	0.1592	0.1451	0.1677	0.1502	0.0085	0.0051
Chile	0.2579	0.2323	0.2536	0.2287	0.2592	0.2335	0.0056	0.0048
Denmark	0.2055	0.1873	0.1975	0.1807	0.2082	0.1896	0.0107	0.0088
Finland	0.2189	0.2101	0.2019	0.1895	0.2246	0.2170	0.0227	0.0275
France	0.2079	0.1924	0.1991	0.1829	0.2109	0.1956	0.0119	0.0128
Germany	0.1872	0.1676	0.1889	0.1678	0.1866	0.1675	-0.0024	-0.0003
Greece	0.2869	0.2680	0.3032	0.2820	0.2814	0.2632	-0.0218	-0.0189
Hong Kong	0.2208	0.2019	0.2184	0.1982	0.2216	0.2032	0.0032	0.0050
Israel	0.2574	0.2361	0.2479	0.2227	0.2606	0.2407	0.0127	0.0180
Italy	0.2364	0.2305	0.2355	0.2309	0.2367	0.2303	0.0012	-0.0006
Japan	0.2607	0.2416	0.2541	0.2328	0.2630	0.2446	0.0088	0.0118
Netherlands	0.2423	0.2268	0.2362	0.2215	0.2443	0.2287	0.0081	0.0072
Norway	0.2254	0.2047	0.2168	0.1942	0.2283	0.2082	0.0115	0.0140
Poland	0.1908	0.1761	0.1906	0.1744	0.1909	0.1767	0.0003	0.0023
Portugal	0.2224	0.1959	0.2168	0.1865	0.2241	0.1988	0.0074	0.0123
Singapore	0.2121	0.1991	0.2071	0.1975	0.2138	0.1996	0.0067	0.0021
South Korea	0.2101	0.1908	0.1936	0.1752	0.2156	0.1960	0.0220	0.0208
Spain	0.2523	0.2440	0.2526	0.2418	0.2522	0.2447	-0.0005	0.0029
Sweden	0.2140	0.1858	0.2054	0.1814	0.2169	0.1873	0.0115	0.0058
Switzerland	0.2232	0.2073	0.2093	0.1924	0.2278	0.2124	0.0185	0.0200
Taiwan	0.2756	0.2649	0.2724	0.2605	0.2767	0.2664	0.0044	0.0059
United Kingdom	0.1805	0.1603	0.1772	0.1576	0.1816	0.1613	0.0044	0.0037
United States	0.2153	0.1832	0.1980	0.1660	0.2211	0.1890	0.0231	0.0230
Sub Total	0.2213	0.2042	0.2163	0.1987	0.2230	0.2060	0.0068	0.0074

(Cont.)

Table 5.7 (Cont.)

	All		Earning Season		Non-Earnings Seasons		Difference (NES-ES)	
Country	Equal-W	Variance-W	Equal-W	Variance-W	Equal-W	Variance-W	Equal-W	Variance-W
Middle Income Countries								
Brazil	0.2363	0.2030	0.2337	0.2009	0.2372	0.2037	0.0035	0.0029
China	0.3994	0.3841	0.3657	0.3494	0.4109	0.3959	0.0451	0.0465
Egypt	0.3875	0.3846	0.3225	0.3229	0.4065	0.4026	0.0840	0.0797
India	0.2371	0.2241	0.2454	0.2330	0.2343	0.2211	-0.0112	-0.0120
Indonesia	0.2308	0.2087	0.2115	0.1898	0.2374	0.2151	0.0259	0.0252
Malaysia	0.2338	0.2265	0.2409	0.2354	0.2314	0.2235	-0.0095	-0.0119
Mexico	0.2856	0.2700	0.2818	0.2641	0.2868	0.2720	0.0050	0.0079
Pakistan	0.2705	0.2403	0.2876	0.2584	0.2650	0.2345	-0.0226	-0.0238
Peru	0.2171	0.2369	0.2027	0.2232	0.2223	0.2419	0.0196	0.0187
Philippines	0.2147	0.1955	0.2036	0.1868	0.2184	0.1983	0.0148	0.0116
Romania	0.2066	0.1933	0.1882	0.1790	0.2131	0.1983	0.0250	0.0193
South Africa	0.1889	0.1669	0.1955	0.1721	0.1865	0.1651	-0.0090	-0.0070
Sri Lanka	0.2249	0.2148	0.2082	0.1990	0.2306	0.2203	0.0224	0.0212
Thailand	0.2163	0.2121	0.2018	0.1957	0.2212	0.2177	0.0194	0.0221
Turkey	0.3454	0.3187	0.3541	0.3291	0.3425	0.3152	-0.0116	-0.0139
Sub Total	0.2597	0.2453	0.2496	0.2359	0.2629	0.2483	0.0134	0.0124
Total	0.2357	0.2196	0.2287	0.2126	0.2380	0.2219	0.0093	0.0093

Table 5. 8 Regression analysis of country-level synchronicity around the earnings season

This table shows the results of the regression analysis as follows:

$$SYNCH_{jt} = \alpha + \beta_1 ES_{jt} + \sum_k \beta_k Control_{jt}^k + Country + Year + \varepsilon_{jt},$$

where $SYNCH_{jt}$ is the stock return synchronicity measured as the logarithmic transformation of the equal-weighted R^2 (columns (1) and (2)) or variance-weighted R^2 (columns (3) and (4)) estimated from the extended standard market model for country *j* at season *t*, ES_{it} is a dummy variable taking value of 1 if the country *j* at season *t* is in the earnings season, and 0 otherwise, *Control* denotes a set of control variables, and *Country* and *Year* are dummies control for country and year fixed effects in the two way fixed effects model (columns (2) and (4)). Columns (1) and (3) report the regression results with Pooled OLS. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is the quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. *Ln(Country Size)* is logarithm of the land area in square kilometers from WDI. *Ln(No. of Stocks)* is the logarithm of the number of listed stocks in the sample. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *No. of obs* indicates the number of the observations in the pooled sample. T-statistics reported in the parentheses are calculated using standard errors clustered by country and year. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively.

	Equal-W Synchronicity		Variance-W Synchronicity	
	(1)	(2)	(3)	(4)
ES	-0.0397**	-0.0348***	-0.0389**	-0.0317***
	(-2.42)	(-3.15)	(-2.26)	(-2.6)
Ln(GDP Per Capita)	-0.0667***	-0.1988*	-0.0786***	-0.0096
	(-8.42)	(-1.68)	(-9.54)	(-0.08)
GDP Per Capita Growth	-0.1818	0.1044	-0.3274	-0.3881
	(-0.28)	(0.2)	(-0.47)	(-0.69)
Var(GDP Per Capita Growth)	0.2772***	0.1698***	0.277***	0.1564***
	(7.73)	(3.73)	(7.1)	(3.11)
Ln(Country Size)	0.0038	-2.0781	-0.0001	-1.7888
	(1.06)	(-1.06)	(-0.03)	(-0.84)
Ln(No. Stocks)	0.0078	-0.2388***	-0.0046	-0.2429***
	(0.83)	(-5.23)	(-0.46)	(-5.2)
Industry Herfindahl	0.3035	-0.7365	0.4957*	-0.3134
	(1.13)	(-1.24)	(1.74)	(-0.49)
Firm Herfindahl	0.7627**	0.6201	0.4084	0.2692
	(2.42)	(0.82)	(1.2)	(0.35)
_cons	-0.8750***	35.7259	-0.7697***	29.0257
	(-9.36)	(1.15)	(-7.89)	(0.86)
Estimation Technique	Pooled OLS	Two way fixed effects	Pooled OLS	Two way fixed effects
Country Dummies	No	Yes	No	Yes
Year Dummies	No	Yes	No	Yes
R-squared	0.085	0.488	0.091	0.481
No. of obs	2925	2925	2925	2925

Table 5. 9 Regression analysis of country-level systematic and idiosyncratic volatilities around the earnings season

This table shows the results of the regression analysis as follows:

$$SYS/IDIO_{it} = \alpha + \beta_1 ES_{it} + \sum_k \beta_k Control_{it}^k + Country + Year + \varepsilon_{it},$$

where $SYS/IDIO_{it}$ is the logarithm of the systematic volatility (columns (1) and (2)) or the idiosyncratic volatility (columns (3) and (4)) estimated from the extended standard market model for country *i* at season *t*, ES_{it} is a dummy variable taking value of 1 if the country *i* at season *t* is in the earnings season, and 0 otherwise, *Control* denotes a set of control variables, and *Country* and *Year* are dummies control for country and year fixed effects in the two way fixed effects model (columns (2) and (4)). Columns (1) and (3) report the regression results with Pooled OLS. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is the quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. *Ln(Country Size)* is logarithm of the land area in square kilometers from WDI. *Ln(No. of Stocks)* is the logarithm of the number of listed stocks in the sample. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *No. of obs* indicates the number of the observations in the pooled sample. T-statistics reported in the parentheses are calculated using standard errors clustered by country and year. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively.

	ln(Systematic Volatility)		ln(Idiosyncratic Volatility)	
	(1)	(2)	(3)	(4)
ES	-0.0498*	-0.0523***	-0.0108	-0.0206*
	(-1.82)	(-2.86)	(-0.45)	(-1.84)
Ln(GDP Per Capita)	-0.1320***	-0.5700**	-0.0534***	-0.5604***
	(-10.43)	(-2.4)	(-4.84)	(-2.63)
GDP Per Capita Growth	-6.7978***	-4.3994***	-6.4704***	-4.0113***
	(-6.28)	(-4.9)	(-6.97)	(-5.54)
Var(GDP Per Capita Growth)	0.5933***	0.2824***	0.3163***	0.1260**
	(9.8)	(3.49)	(5.92)	(1.99)
Ln(Country Size)	0.0116*	4.9735*	0.0118*	6.7623***
	(1.74)	(1.83)	(1.95)	(2.98)
Ln(No. Stocks)	0.1223***	-0.0342	0.1268***	0.2086***
	(8.89)	(-0.52)	(10.84)	(3.94)
Industry Herfindahl	-0.2215	0.1765	-0.7172*	0.4899
	(-0.53)	(0.17)	(-1.95)	(0.67)
Firm Herfindahl	0.147	1.6733	-0.2614	1.4041
	(0.28)	(1.32)	(-0.64)	(1.45)
_cons	-4.176***	-78.6789*	-3.4063***	-107.7046***
	(-24.81)	(-1.82)	(-22.65)	(-2.98)
Estimation Technique	Pooled OLS	Two way fixed effects	Pooled OLS	Two way fixed effects
Country Dummies	No	Yes	No	Yes
Year Dummies	No	Yes	No	Yes
R-squared	0.133	0.532	0.115	0.697
No. of obs	2925	2925	2925	2925

Table 5. 10 High income countries and Middle income countries (country-level)

This table shows the results of the regression analysis of the stock return synchronicity or the systematic volatility on the earnings season dummy and other control variables for the high income and middle income countries respectively. The countries are classified into high income countries (*High Income*) and upper and lower middle income countries (*Middle Income*) according to the World Bank. The dependent variables are the stock return synchronicity estimated as the logarithmic transformation of the equal-weighted R^2 (*Equal-W Synchronicity* for columns (1) and (2)), the stock return synchronicity estimated as the logarithmic transformation of the variance-weighted R^2 (*Variance-W Synchronicity* for columns (3) and (4)), and the logarithmic of the systematic volatility (*ln(Systematic Volatility)* for columns (5) and (6)). *ES* is a dummy variable taking value of 1 if it is in the earnings season. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is the quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. *Ln(Country Size)* is logarithm of the land area in square kilometers from WDI. *Ln(No. of Stocks)* is the logarithm of the number of listed stocks in the sample. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *No. of obs* indicates the number of the observations in the pooled sample. T-statistics reported in the parentheses are calculated using standard errors clustered by country and year. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively.

Table 5.10 (Cont.)

	Equal-W Synchronicity		Variance-W Synchronicity		ln(Systematic Volatility)	
	High Income Countries	Middle Income Countries	High Income Countries	Middle Income Countries	High Income Countries	Middle Income Countries
	(1)	(2)	(3)	(4)	(5)	(6)
ES	-0.0307**	-0.0565**	-0.0299**	-0.0551**	-0.0439**	-0.0616**
	(-2.46)	(-2.53)	(-2.15)	(-2.26)	(-2.03)	(-1.81)
Ln(GDP Per Capita)	-0.1227***	0.0501*	-0.1193***	0.008	-0.0442	-0.1008**
	(-4.04)	(1.74)	(-3.73)	(0.26)	(-0.83)	(-2.25)
GDP Per Capita Growth	-2.8918***	1.2466	-3.0968***	1.1656	-9.3915***	-4.2332**
	(-3.76)	(1.21)	(-3.63)	(0.99)	(-5.66)	(-2.13)
Var(GDP Per Capita Growth)	0.2786***	0.3199***	0.1737*	0.3697***	1.0702***	0.3734***
	(3.06)	(4.58)	(1.9)	(4.6)	(6.3)	(3.25)
Ln(Country Size)	-0.012*	0.1285***	-0.0165**	0.1208***	0.0081	0.0124
	(-1.89)	(6.73)	(-2.56)	(5.9)	(0.59)	(0.47)
Ln(No. Stocks)	0.002	0.0356	-0.0211	0.0319	0.1548***	0.0587
	(0.12)	(1.36)	(-1.22)	(1.12)	(5.6)	(1.5)
Industry Herfindahl	0.3742	2.7256**	0.6956	2.9831**	-2.3985***	0.0006
	(0.81)	(2.4)	(1.43)	(2.44)	(-2.65)	(0)
Firm Herfindahl	0.8574	-3.0608	0.1698	-3.4314	1.5971*	0.998
	(1.64)	(-1.58)	(0.31)	(-1.64)	(1.7)	(0.65)
_cons	-0.1571	-3.6415***	-0.1083	-3.3419***	-4.9951***	-4.1134***
	(-0.54)	(-9.32)	(-0.35)	(-7.99)	(-9.75)	(-7.05)
R-squared	0.072	0.165	0.070	0.144	0.134	0.068
No. of obs	1976	949	1976	949	1976	949

Table 5. 11 Univariate analysis of firm-level R^2 and systematic and idiosyncratic volatilities

This table shows the descriptive statistics in the earnings season and non-earnings seasons for the firm level R^2, systematic volatility and idiosyncratic volatility respectively. R^2 is the R-Square value estimated from the extended standard market model using daily returns for each season. *Systematic volatility* and *idiosyncratic volatility* are the systematic and idiosyncratic volatilities estimated from the extended market model respectively. The countries are classified into high income countries (*High Income*) and upper and lower middle income countries (*Middle Income*) according to the World Bank. Both mean and median values are reported for all the countries and high/middle income groups respectively and the means are both equal-weighted and market-value weighted. I calculate the differences of the average R^2s as well as the systematic and idiosyncratic volatilities between the non-earnings seasons and the earnings season, and the significance of the differences is based on 2-tailed tests (t-test for mean and rank sum test for median). ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

Variable	All	Earnings Season	Non-Earnings seasons	Difference (NES-ES)
Panel A: R^2				
Equal Weighted Mean	0.2426	0.2321	0.2461	0.0140***
Value Weighted Mean	0.3802	0.3741	0.3823	0.0082***
Median	0.2044	0.1966	0.2072	0.0106***
<u>High Income</u>				
- Equal Weighted Mean	0.2279	0.2200	0.2307	0.0106***
- Value Weighted Mean	0.3761	0.3715	0.3777	0.0062***
- Median	0.1908	0.1854	0.1927	0.0073***
<u>Middle Income</u>				
- Equal Weighted Mean	0.2871	0.2699	0.2928	0.0228***
- Value Weighted Mean	0.4055	0.3906	0.4105	0.0199***
- Median	0.2519	0.2361	0.2574	0.0213***
Panel B: Systematic Volatility				
Equal Weighted Mean	0.0145	0.0132	0.0149	0.0017***
Value Weighted Mean	0.0117	0.0098	0.0123	0.0025***
Median	0.0078	0.0075	0.0080	0.0005***
<u>High Income</u>				
- Equal Weighted Mean	0.0134	0.0126	0.0137	0.0011***
- Value Weighted Mean	0.0104	0.0091	0.0108	0.0017***
- Median	0.0071	0.0068	0.0071	0.0003***
<u>Middle Income</u>				
- Equal Weighted Mean	0.0176	0.0150	0.0185	0.0036***
- Value Weighted Mean	0.0196	0.0143	0.0214	0.0071***
- Median	0.0104	0.0095	0.0108	0.0013***
Panel C: Idiosyncratic Volatility				
Equal Weighted Mean	0.0503	0.0503	0.0502	0.0000
Value Weighted Mean	0.0180	0.0169	0.0184	0.0015***
Median	0.0283	0.0282	0.0284	0.0001
<u>High Income</u>				
- Equal Weighted Mean	0.0524	0.0528	0.0523	-0.0006***
- Value Weighted Mean	0.0170	0.0162	0.0172	0.0011***
- Median	0.0278	0.0278	0.0278	-0.0001
<u>Middle Income</u>				
- Equal Weighted Mean	0.0437	0.0423	0.0442	0.0018***
- Value Weighted Mean	0.0246	0.0215	0.0256	0.0041***
- Median	0.0297	0.0292	0.0299	0.0007***

Table 5. 12 Regression analysis of firm-level synchronicity around the earnings season

This table shows the results of the regression analysis as follows:

$$SYNCH_{it} = \alpha + \beta_1 ES_{it} + \sum_k \beta_k Control_{it}^k + Country/Industry + Year + \varepsilon_{it},$$

where $SYNCH_{it}$ is the stock return synchronicity measured as a logarithmic transformation of the R^2 estimated from the extended standard market model for firm *i* at season *t*, ES_{it} is a dummy variable taking value of 1 if the firm i at season *t* is in the earnings season, and 0 otherwise, *Control* denotes a set of control variables, and *Country/Industry* and *Year* are dummies control for country (Industry) and year fixed effects in the two way fixed effects model (columns (2) and (3)). While column (1) reports the regression results with Pooled OLS. *SIZE* is the logarithm of the quarterly market capitalization in thousand US dollars. *MTBV* is quarterly market capitalization to common equity ratio. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is the quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. *Ln(Country Size)* is logarithm of the land area in square kilometers from WDI. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *No. of obs* indicates the number of the observations in the pooled sample. T-statistics reported in the parentheses are calculated using standard errors clustered by country and year. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)
ES	-0.0636**	-0.0772***	-0.0718***
	(-2.22)	(-2.63)	(-4.79)
SIZE	0.2081***	0.1971***	0.2081***
	(37.45)	(35.93)	(78.88)
MTBV	-0.0241***	-0.0244***	-0.0222***
	(-5.72)	(-8.32)	(-13.42)
Ln(GDP Per Capita)	-0.1481***	-0.7227***	-0.1318***
	(-5.83)	(-4.58)	(-22.03)
GDP Per Capita Growth	0.2605	-1.0755	1.4422***
	(0.17)	(-1.05)	(3.58)
Var(GDP Per Capita Growth)	0.2958**	0.094	0.2016***
	(2.42)	(1.04)	(8.84)
Ln(Country Size)	0.0014	-13.5131***	0.0088***
	(0.13)	(-2.74)	(3.8)
Industry Herfindahl	1.0892*	1.9585*	0.6163***
	(1.66)	(1.79)	(3.69)
Firm Herfindahl	-1.648**	-3.9693***	-1.0486***
	(-2.41)	(-2.82)	(-6.96)
_cons	-2.6244***	219.5089***	-2.862***
	(-9.12)	(2.79)	(-19.1)
Estimation Technique	Pooled OLS	Two way fixed effects	
Country Dummies	No	Yes	No
Industry Dummies	No	No	Yes
Year Dummies	No	Yes	Yes
R-squared	0.200	0.304	0.247
No. of obs	636727	636727	636727

Table 5. 13 Regression analysis of firm-level systematic and idiosyncratic volatilities around the earnings season

This table shows the results of the regression analysis as follows:

$$SYS/IDIO_{it} = \alpha + \beta_1 ES_{it} + \sum_k \beta_k Control_{it}^k + Country/Industry + Year + \varepsilon_{it},$$

where $SYS/IDIO_{it}$ is the logarithmic of the systematic volatility (columns (1), (2) and (3)) or the idiosyncratic volatility (columns (4), (5) and (6)) estimated from the extended standard market model for firm *i* at season *t*, ES_{it} is a dummy variable taking value of 1 if the firm *i* at season *t* is in the earnings season, and 0 otherwise, *Control* denotes a set of control variables, and *Country/Industry* and *Year* are dummies control for country (Industry) and year fixed effects in the two way fixed effects model (columns (2), (4) and (3), (5)). While columns (1) and (4) report the regression results with Pooled OLS. *SIZE* is the logarithm of the quarterly market capitalization in thousand US dollars. *MTBV* is quarterly market capitalization to common equity ratio. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is the quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. *Ln(Country Size)* is logarithm of the land area in square kilometers from WDI. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *No. of obs* indicates the number of the observations in the pooled sample. T-statistics reported in the parentheses are calculated using standard errors clustered by country and year. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively.

	ln(Systematic Volatility)			ln(Idiosyncratic Volatility)		
	(1)	(2)	(3)	(4)	(5)	(6)
ES	-0.0654	-0.0716*	-0.07***	-0.0018	0.0056	0.0019
	(-1.58)	(-1.68)	(-2.96)	(-0.18)	(0.28)	(0.17)
SIZE	-0.0648***	-0.0662***	-0.0523***	-0.2728***	-0.2633***	-0.2604***
	(-5.55)	(-7.94)	(-11.14)	(-53.7)	(-41.38)	(-84.72)
MTBV	0.0457***	0.0248***	0.038***	0.0697***	0.0492***	0.0603***
	(6.51)	(5.23)	(16.88)	(27.61)	(14.76)	(28.08)
Ln(GDP Per Capita)	-0.0937***	-0.0119	-0.1222***	0.0544***	0.7108***	0.0096
	(-2.8)	(-0.04)	(-12.42)	(4.37)	(2.66)	(1.21)
GDP Per Capita Growth	-2.8212	-4.0934**	1.5869*	-3.0817***	-3.0178***	0.1447
	(-1.09)	(-2.28)	(1.8)	(-4.02)	(-2.7)	(0.25)
Var(GDP Per Capita Growth)	0.1582	0.1998	0.0565*	-0.1376***	0.1058	-0.1451***
	(1.05)	(1.56)	(1.73)	(-3.67)	(1.46)	(-6.5)
Ln(Country Size)	0.0574***	-15.72**	0.033***	0.0559***	-2.2069	0.0243***
	(3.31)	(-2.36)	(9.89)	(8.5)	(-0.6)	(8.31)
Industry Herfindahl	-0.0806	0.2906	-1.3646***	-1.1697***	-1.668	-1.981***
	(-0.07)	(0.16)	(-5.44)	(-4.82)	(-1.24)	(-12.24)
Firm Herfindahl	-0.7351	-0.6191	0.2472	0.9129***	3.3502**	1.2958***
	(-0.63)	(-0.32)	(1.05)	(3.71)	(2.27)	(7.19)
_cons	-4.1148***	248.0563**	-3.0061***	-1.4904***	28.5475	-0.1441
	(-9.73)	(2.35)	(-13.85)	(-10.82)	(0.49)	(-0.58)
Estimation Technique	Pooled OLS	Two way fixed effects		Pooled OLS	Two way fixed effects	
Country Dummies	No	Yes	No	No	Yes	No
Industry Dummies	No	No	Yes	No	No	Yes
Year Dummies	No	Yes	Yes	No	Yes	Yes
R-squared	0.042	0.181	0.167	0.267	0.395	0.362
No. of obs	636727	636727	636727	636727	636727	636727

Table 5. 14 High income countries and Middle income countries (firm-level)

This table shows the results of the regression analysis of the firm level stock return synchronicity on the earnings season dummy and other control variables for the high income and middle income countries respectively. The countries are classified into high income countries (*High Income*) and upper and lower middle income countries (*Middle Income*) according to the World Bank. I conduct the regression for the sub-sample firms in the high income countries (columns (1)-(3)) and in the middle income countries (columns (4)-(6)) respectively. Columns (1) and (4) report the regression results with Pooled OLS. The regression results with two fixed effects of country (industry) and year dummies are reported in columns (2) and (5) (columns (4) and (6)). *ES* is a dummy variable taking value of 1 if it is in the earnings season. *SIZE* is the logarithm of the quarterly market capitalization in thousand US dollars. *MTBV* is quarterly market capitalization to common equity ratio. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is the quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. *Ln(Country Size)* is logarithm of the land area in square kilometers from WDI. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *No. of obs* indicates the number of the observations in the pooled sample. T-statistics reported in the parentheses are calculated using standard errors clustered by country and year. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively.

	High Income Countries			Middle Income Countries		
	(1)	(2)	(3)	(4)	(5)	(6)
ES	-0.0478	-0.0638**	-0.0572***	-0.1136	-0.1155	-0.1077***
	(-1.53)	(-2.00)	(-3.95)	(-1.62)	(-1.63)	(-5.47)
SIZE	0.203***	0.2101***	0.2065***	0.1487***	0.1465***	0.1431***
	(32.8)	(36.61)	(71.38)	(28.34)	(26.87)	(45.07)
MTBV	-0.0289***	-0.016***	-0.0257***	-0.0195***	-0.0387***	-0.0239***
	(-7.45)	(-6.27)	(-14.22)	(-2.84)	(-6.82)	(-11.48)
Ln(GDP Per Capita)	0.0027	-1.46***	-0.0002	0.1486***	-0.0507	0.1761***
	(0.05)	(-6.03)	(-0.01)	(2.7)	(-0.22)	(14.53)
GDP Per Capita Growth	-5.6546***	-1.3955	-3.9335***	4.4552**	-0.0105	3.6697***
	(-3.73)	(-1.00)	(-10.29)	(2.53)	(-0.01)	(11.3)
Var(GDP Per Capita Growth)	0.6558***	0.0263	0.4634***	0.152	0.0682	0.217***
	(3.47)	(0.16)	(8.58)	(1.5)	(0.67)	(7.59)
Ln(Country Size)	-0.025*	-7.5303*	-0.0181***	0.1664***	48.5557	0.1823***
	(-1.89)	(-1.78)	(-6)	(5.63)	(0.39)	(29.45)
Industry Herfindahl	0.6176	2.3211*	0.1966	6.421***	2.039	6.707***
	(0.84)	(1.81)	(1.07)	(4.52)	(1.49)	(20.62)
Firm Herfindahl	-2.0013**	-4.2418***	-1.5299***	-7.5576***	-1.4428	-8.6027***
	(-2.45)	(-2.74)	(-8.37)	(-3.51)	(-0.88)	(-16.88)
_cons	-3.5714***	130.3323*	-3.8164***	-6.6596***	-660.3621	-6.4245***
	(-7.3)	(1.95)	(-22.22)	(-9.48)	(-0.39)	(-39)
Estimation Technique	Pooled OLS	Two way fixed effects		Pooled OLS	Two way fixed effects	
Country Dummies	No	Yes	No	No	Yes	No
Industry Dummies	No	No	Yes	No	No	Yes
Year Dummies	No	Yes	Yes	No	Yes	Yes
R-squared	0.194	0.270	0.238	0.256	0.364	0.318
No. of obs	479082	479082	479082	157645	157645	157645

Table 5. 15 Large firms and Small firms (firm-level)

This table shows the results of the regression analysis of the firm level stock return synchronicity on the earnings season dummy and other control variables for the large firms and small firms respectively. I classify the sample firms into two groups according to the market capitalization (in US dollars) for each country each year. I conduct the regression for the sub-sample firms with high market value (columns (1)-(3)) and low market value (columns (4)-(6)) respectively. Columns (1) and (4) report the regression results with Pooled OLS. The regression results with two fixed effects of country (industry) and year dummies are reported in columns (2) and (5) (columns (4) and (6)). *ES* is a dummy variable taking value of 1 if it is in the earnings season. *SIZE* is the logarithm of the quarterly market capitalization in thousand US dollars. *MTBV* is quarterly market capitalization to common equity ratio. *Ln(GDP per capita)* is the logarithm of the quarterly gross domestic product per capita in constant 2010 US dollars with seasonal adjustment. *GDP Per capita Growth* is the quarterly percentage growth rate of GDP per capita. *Var(GDP Per capita Growth)* is the variance of the quarterly percentage growth rate of GDP per capita in the last three years. *Ln(Country Size)* is logarithm of the land area in square kilometers from WDI. *Industry Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *Firm Herfindahl* is the sum of the squared ratio of the industry sales to the total sales within the country. *No. of obs* indicates the number of the observations in the pooled sample. T-statistics reported in the parentheses are calculated using standard errors clustered by country and year. Coefficients marked ***, ** and * are significant at the 1%, 5% and 10% levels respectively.

	Large Firms			Small Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
ES	-0.0643***	-0.0784***	-0.0725***	-0.0614***	-0.0768***	-0.0707***
	(-18.67)	(-2.57)	(-4.49)	(-18.33)	(-2.63)	(-4.81)
SIZE	0.2266***	0.2012***	0.229***	0.1961***	0.1749***	0.1913***
	(229.67)	(33.78)	(76.22)	(170.03)	(11.13)	(37.58)
MTBV	-0.0394***	-0.0333***	-0.0356***	-0.0052***	-0.0136***	-0.006***
	(-56.73)	(-9.88)	(-17.45)	(-7.17)	(-5.08)	(-3.92)
Ln(GDP Per Capita)	-0.1127***	-0.8109***	-0.0984***	-0.19***	-0.6173***	-0.1731***
	(-70.65)	(-5.17)	(-14.54)	(-124.39)	(-3.72)	(-27.69)
GDP Per Capita Growth	0.0623	-0.9944	1.2872***	0.3741***	-1.1285	1.5443***
	(0.46)	(-0.92)	(2.97)	(2.89)	(-1.09)	(3.45)
Var(GDP Per Capita Growth)	0.3423***	0.1338	0.2407***	0.2539***	0.0588	0.1656***
	(38.69)	(1.42)	(8.66)	(30.13)	(0.65)	(7.03)
Ln(Country Size)	0.0112***	-15.1059**	0.0199***	-0.0104***	-11.8514***	-0.0054**
	(14.86)	(-2.53)	(8.89)	(-13.96)	(-2.86)	(-2.03)
Industry Herfindahl	1.2553***	1.5737	0.6004***	0.9452***	2.4417**	0.6313***
	(28.85)	(1.32)	(3.14)	(22.76)	(2.28)	(4.09)
Firm Herfindahl	-2.1889***	-3.7509**	-1.2423***	-1.1795***	-4.3417***	-0.8787***
	(-36.53)	(-2.45)	(-7.05)	(-21.54)	(-3.06)	(-6.02)
_cons	-3.2823***	246.0578***	-3.2646***	-1.9999***	191.9023***	-2.2517***
	(-147.44)	(2.58)	(-37.88)	(-92.33)	(2.91)	(-13.63)
Estimation Technique	Pooled OLS	Two way fixed effects		Pooled OLS	Two way fixed effects	
Country Dummies	No	Yes	No	No	Yes	No
Industry Dummies	No	No	Yes	No	No	Yes
Year Dummies	No	Yes	Yes	No	Yes	Yes
R-squared	0.145	0.277	0.216	0.136	0.246	0.174
No. of obs	318549	318549	318549	318178	318178	318178

Table A1 The dynamic pattern of R^2 in US

This table shows the clustered earnings announcement dates and the dynamic pattern of R^2 around the earnings season in US. The sample contains stocks listed on the NYSE, AMEX, and NASDAQ from 1975 to 2015 with a CRSP share code of 10 or 11, and excludes firms in finance and banking (SIC 6000-6999) and regulated utilities (SIC 4900-4999). Panel A shows the distribution of the number of annual earnings announcements. '% in the earnings season' shows the percentage of the annual earnings announcements released during the earnings season from January 15th to April 15th, to the total number of announcements in that period. The bottom row '%' shows the percentage of earnings announcements in that period to the total number of annual reports. Panel B shows the descriptive statistics of R^2 in the earnings season (January 15th to April 15th) and the non-earnings seasons. It presents both the statistics with all observations and the statistics excluding the observations in financial crisis in 1987, the crash of internet bubble from 2000 to 2001 and the subprime crisis from 2008 to 2009. R-squares and the systematic and idiosyncratic volatilities are estimated based on the standard market model. Both mean and median values are reported and the means are both equal-weighted and market-value weighted. I calculate the differences of average R^2s and the systematic and idiosyncratic volatilities between the non-earnings seasons and the earnings season, and the significance of the differences is based on 2-tailed tests (t-test for mean and rank sum test for median). ***, ** and * indicate significance at 1%, 5% and 10% levels respectively.

Panel A: Earnings announcement dates					
Time Period	Jan.15th ~ Feb.15th	Feb.15th ~ Mar.15th	Mar.15th ~ Apr.15th	Others	% in the earnings season
1975~1980	2620	1992	741	3043	63.76%
1981~1990	5633	4093	1896	8639	57.36%
1991~2000	11145	7958	3955	13994	62.23%
2001~2010	10848	9633	3778	9792	71.24%
2011~2015	3878	5655	1681	3485	76.29%
Total	34124	29331	12051	38953	66.18%
%	29.81%	25.63%	10.53%	34.03%	

(Cont.)

Table A1 (Cont.)

Panel B: Dynamic pattern of R^2	All Seasons			Earnings Season			Non-Earnings Seasons			Difference (NES-ES)		
	Mean		Median	Mean		Median	Mean		Median	Mean		Median
	Equal-W	MV-W		Equal-W	MV-W		Equal-W	MV-W		Equal-W	MV-W	
All observations												
R-Square	0.1259	0.3064	0.0661	0.1181	0.2844	0.0644	0.1286	0.3143	0.0667	0.0106***	0.0299***	0.0024***
Systematic Volatility	0.0091	0.0117	0.0031	0.0081	0.0091	0.0029	0.0095	0.0126	0.0031	0.0014***	0.0035***	0.0002***
Idiosyncratic Volatility	0.0797	0.0240	0.0456	0.0777	0.0243	0.0447	0.0803	0.0240	0.0459	0.0026***	-0.0003**	0.0012***
Normal Years												
R-Square	0.1191	0.3006	0.0621	0.1105	0.2777	0.0600	0.1221	0.3086	0.0629	0.0116***	0.0309***	0.0029***
Systematic Volatility	0.0065	0.0071	0.0027	0.0051	0.0052	0.0025	0.0069	0.0078	0.0028	0.0018***	0.0026***	0.0002***
Idiosyncratic Volatility	0.0719	0.0181	0.0414	0.0678	0.0167	0.0398	0.0734	0.0186	0.0419	0.0055***	0.0019***	0.0022***

Table A2 Selection process for non-common equities

This table lists the detailed screen process for non-common equities in DataStream. Panel A lists the DataStream industry codes for non-common equities and Panel B lists the general filter rules for all securities covered by DataStream and WorldScope. The country-specific identifiers for the non-common equities are listed in Panel C. In Panel A, the left column is the DataStream Industry Code and right column is the corresponding industry. All securities with the industry codes listed in the left column are excluded from the sample. In Panel B, *Equity Type* is the non-common equity type whose names contain the words listed in the right column. Similarly, the right column in Panel C lists the country-specific words contained in non-common equities' names. The non-common securities identified in Panel B and Panel C are excluded from the sample.

Panel A: Non-Common Equity Industry Code (DataStream)

CODE	INDUSTRY GROUP
112	Real Estate Hold, Dev
160	Ind. & Office REITs
161	Retail REITs
162	Residential REITs
163	Diversified REITs
164	Specialty REITs
165	Mortgage REITs
166	Hotel & Lodging REITs
167	Real Estate Services

Panel B. General Filter Rules for non-common equities

Equity Type	Words Contained in Security Names
Preferred Stocks	PF PF. PREF PREFERRED PREFERENCE
Unit/Trusts	UNIT UNITS UNT UT UTS. FD.UNT. LP.UNITS PTNS.UNITS
	TRUST TST. INC.TST. INC.UTS INVESTMENT INV.TST.
	TRUST INV. INV. TST.UTS. TST.UNIT TST. UNITS
	TST.UNT. UNT.TST. FD. UTS. PTNS. UTS. IT.
Fund/Income Fund	FD. FUND FUNDS FUNDING INFD. INC.FD. IN.FUND
	INC.FUND INFR.FD. INCOME FD. INCOME FUND
Depository Receipts/Interest/Unit	ADR CDR ADS CDI DPREC. DEPY.RECPT. RECPT.
	DEPOSIT DEPOSITS DUT. DI INT INT
Venture/Credit Capital	VCT. VET.CAP. VENTURE CAP. VENTURE CAPITAL
	CR.CAPITAL CAPITAL CAP.
Others	BOND CERT.AUTH. CFAR. ETF EXPIRED LP. PC.
	PARTICIPACOES PARTICIPATION PARTS
	PARTICIPATIONS PPC. PTNS. REIT RIGHTS
	RSTS. SPLIT WT YIELD YLD.

(Cont.)

Table A2 (Cont.)

Panel C. Country Specific Identifiers for non-common equity

Country	Words Contained in Security Names
Belgium	VVPR
Brazil	PNE PNG
Canada	VTG SHS SBVTG SUBD SR RECPT. EXH
France	ADP CI CCI CIP
Indonesia	FB
Israel	1 5
Italy	RNC PV RP RSP
Mexico	CV CPO 'C' 'L' 'O' ACP
Netherlands	CERTS.
Peru	Inversion Trab
Philippines	PDR
Portugal	R 'R'
South Africa	N 'N'
South Korea	SPU.ACQ
Sri Lanka	NON VOTING
Sweden	CONVERTED USE
Switzerland	P 'P' USE CONVERTED
United Kingdom	NV

Table A3 Number of sample firms by country and year

This table shows the number of sample firms for each of the 40 countries from 1995 to 2015. *Total* denotes the summary of the number of the firms for each year.

Country	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Australia	111	125	132	153	181	306	439	406	511	583	609	640	637	607	722	803	835	772	769	759	625
Belgium	-	35	38	39	32	34	40	50	56	60	58	57	61	61	60	63	67	65	57	58	59
Brazil	-	-	-	-	-	27	-	33	49	53	58	59	81	74	74	83	101	100	104	111	107
Canada	165	166	184	176	235	298	301	349	412	463	477	707	732	735	741	851	890	857	764	792	708
Chile	-	-	-	-	-	-	34	35	45	47	49	43	46	39	47	56	54	44	44	43	46
China	-	-	44	67	77	379	550	644	725	843	906	953	989	1078	1090	1142	1252	1324	1427	1764	2005
Denmark	43	49	53	54	55	60	46	48	57	62	65	63	60	59	56	65	67	68	67	67	65
Egypt	-	-	-	-	-	-	-	-	-	-	-	30	35	38	41	40	40	44	42	45	48
Finland	-	31	32	46	49	57	53	61	85	93	95	96	95	93	97	100	101	96	94	94	92
France	185	203	215	233	225	244	251	285	318	365	368	348	334	290	290	339	347	322	321	321	327
Germany	140	149	167	164	146	163	178	207	290	374	380	370	364	345	341	370	407	400	384	364	336
Greece	57	57	65	113	131	151	158	168	189	225	227	221	226	220	206	180	156	141	136	113	87
Hong Kong	44	69	77	84	94	117	140	161	186	209	235	262	322	328	390	427	472	474	523	593	651
India	163	181	191	189	212	231	250	259	284	349	371	617	631	645	691	1544	1635	1657	1522	1711	1626
Indonesia	38	61	81	79	102	100	122	125	123	130	128	128	151	142	144	165	179	205	210	229	222
Israel	-	-	-	-	-	-	-	42	47	51	59	186	214	199	217	235	221	194	193	203	190
Italy	68	70	77	81	89	91	98	104	110	128	134	132	135	136	135	145	155	158	151	149	146
Japan	1304	1326	1388	1559	1729	1747	1812	1839	1910	2007	2074	2068	2021	1945	1954	2046	2047	2030	2049	2019	2002
Malaysia	75	94	105	115	126	154	238	255	275	299	288	326	357	342	364	394	377	378	365	388	362
Mexico	-	-	41	41	42	43	42	38	40	47	46	44	44	40	44	50	45	44	50	47	48

(Cont.)

Table A3 (Cont.)

Country	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Netherlands	86	92	95	100	100	95	87	91	94	97	92	94	89	82	74	75	76	73	69	65	64
Norway	46	51	52	55	63	67	74	64	74	83	89	86	83	87	95	110	120	120	115	121	117
Pakistan	-	-	-	-	-	-	-	33	34	34	57	59	69	67	70	67	70	73	71	78	70
Peru	-	-	-	-	-	-	-	-	-	26	31	43	46	43	42	46	51	46	47	41	34
Philippines	-	-	-	-	44	47	49	29	41	58	54	65	64	57	62	65	78	90	84	87	92
Poland	-	-	-	-	-	30	39	51	64	96	106	125	127	143	160	177	218	245	253	262	274
Portugal	-	36	43	47	40	40	32	28	31	38	34	35	34	31	28	30	27	29	28	30	28
Romania	-	-	-	-	-	-	-	-	-	-	-	71	89	72	57	63	54	44	41	39	31
Singapore	57	60	68	79	84	85	100	104	132	155	156	173	213	226	241	266	239	259	265	259	262
South Africa	42	49	45	60	64	58	56	57	64	66	61	61	55	51	55	58	66	63	63	58	50
South Korea	177	194	206	244	321	493	511	505	558	604	655	1011	1089	1140	1235	1276	1308	1321	1347	1411	1469
Spain	49	57	63	66	66	65	70	72	73	78	82	77	74	68	70	71	78	75	74	74	69
Sri Lanka	-	-	-	-	-	-	-	-	-	-	63	62	70	75	94	105	110	103	95	107	99
Sweden	86	89	93	104	109	112	137	145	175	201	207	211	198	201	211	244	248	245	244	244	238
Switzerland	75	78	85	86	87	86	93	100	108	112	121	120	114	107	112	113	116	113	113	114	113
Taiwan	93	159	184	200	222	269	314	452	541	632	717	826	905	982	1033	1086	1189	1212	1261	1366	1457
Thailand	95	120	131	141	152	144	195	202	211	186	187	203	217	241	274	302	295	320	333	340	341
Turkey	32	33	46	58	77	100	118	136	163	178	180	204	196	207	207	215	217	217	215	220	225
United Kingdom	246	266	285	322	326	307	346	346	355	383	372	366	368	375	414	425	417	431	434	432	410
United States	899	995	1109	1124	1173	1242	1320	1318	1400	1423	1383	1410	1370	1350	1316	1319	1352	1371	1357	1365	1334
Total	4376	4895	5395	5879	6453	7442	8293	8842	9830	10838	11274	12652	13005	13021	13554	15211	15777	15823	15781	16583	16529

Table A4 Exchange lists and GDP series description

This table lists the major exchange names for each country and the descriptions of the real gross domestic product per capita (GDP Per Capita) from DataStream. The series of GDP per capita is in constant 2010 US dollars. If the seasonal adjustment has not been performed in the original quarterly dataset, I applied the X12-ARIMA model (the US Census Bureau) to the unadjusted series. *Seasonal Adjustment* denotes whether the original series is seasonal adjusted or not. The data sources for the GDP Per capita series are listed in the last column.

Country	Exchange Name	GDP Per Capita			
		DataStream Symbol	Frequency	Seasonal Adjustment	Source
Australia	Australian	AUXGDHD.C	Quarterly	No	Oxford Economics
Belgium	Euronext.liffe Brussels	BGXGDHD.C	Quarterly	No	Oxford Economics
Brazil	Sao Paulo	BRXGDHD.C	Quarterly	No	Oxford Economics
Canada	Toronto/TSX Ventures	CNXGDHD.D	Quarterly	Yes	Oxford Economics
Chile	Santiago	CLXGDHD.D	Quarterly	Yes	Oxford Economics
China	Shanghai/Shenzen	CHXGDHD.C	Quarterly	No	Oxford Economics
Denmark	Copenhagen Stock Exchange	DKXGDHD.D	Quarterly	Yes	Oxford Economics
Egypt	Egypt	EYCGDP..D/SP. POP.TOTL	Quarterly	Yes	Ministry of Planning, Egypt/Thomson Reuters
Finland	Helsinki	FNXGDHD.D	Quarterly	Yes	Oxford Economics
France	Euronext.liffe Paris	FRXGDHD.D	Quarterly	Yes	Oxford Economics
Germany	Frankfurt	BDXGDHD.D	Quarterly	Yes	Oxford Economics
Greece	Athens	GRXGDHD.D	Quarterly	Yes	Oxford Economics
Hong Kong	Hong Kong	HKXGDHD.C	Quarterly	No	Oxford Economics
India	National India/BSE Ltd	INXGDHD.C	Quarterly	No	Oxford Economics
Indonesia	Indonesia	IDXGDHD.C	Quarterly	No	Oxford Economics
Israel	Tel Aviv	ISCGDP..D/SP.P OP.TOTL	Quarterly	Yes	Central Bureau of Statistics, Israel/Thomson Reuters
Italy	Milan	ITXGDHD.D	Quarterly	Yes	Oxford Economics
Japan	Tokyo Stock Exchange/Japan OTC	JPXGDHD.D	Quarterly	Yes	Oxford Economics
Malaysia	Kuala Lumpur/MESDAQ/2n d. Board	MYXGDHD.C	Quarterly	No	Oxford Economics
Mexico	Mexico	MXXGDHD.D	Quarterly	Yes	Oxford Economics
Netherlands	Euronext.liffe Amsterdam	NLXGDHD.C	Quarterly	No	Oxford Economics
Norway	Oslo Stock Exchange	NWXGDHD.D	Quarterly	Yes	Oxford Economics
Pakistan	Karachi	PKCGDP..D/SP. POP.TOTL	Quarterly	Yes	State Bank of Pakistan/Thomson Reuters
Peru	Lima	PECGDP..D/SP. POP.TOTL	Quarterly	Yes	Central Reserve Bank of Peru/Thomson Reuters

Cont.

Table A4 (cont.)

Country	Exchange Name	GDP Per Capita			
		DataStream Symbol	Frequency	Seasonal Adjustment	Source
Philippines	Philippine Stock Exchange	PHXGDHD.C	Quarterly	No	Oxford Economics
Poland	Warsaw/Warsaw Continuous	POXGDHD.D	Quarterly	Yes	Oxford Economics
Portugal	Euronext.liffe Lisbon	PTXGDHD.D	Quarterly	Yes	Oxford Economics
Romania	Spot Regulated Market – BVB /RASDAQ	RMXGDHD.D	Quarterly	Yes	Oxford Economics
Singapore	Singapore/Singapore Catalist	SPXGDHD.C	Quarterly	No	Oxford Economics
South Africa	Johannesburg	SAXGDHD.D	Quarterly	Yes	Oxford Economics
South Korea	Korea Stock Exchange/KOSDAQ	KOXGDHD.D	Quarterly	Yes	Oxford Economics
Spain	Madrid/Madrid SIBE	ESXGDHD.D	Quarterly	Yes	Oxford Economics
Sri Lanka	Colombo	LKCGDP..D/SP. POP.TOTL	Quarterly	Yes	Department of Census and Statistics, Sri Lanka/Thomson Reuters
Sweden	Stockholm	SDXGDHD.D	Quarterly	Yes	Oxford Economics
Switzerland	SIX Swiss	SWXGDHD.D	Quarterly	Yes	Oxford Economics
Taiwan	Taiwan/Taiwan OTC	TWXGDHD.C	Quarterly	No	Oxford Economics
Thailand	Bangkok	THXGDHD.C	Quarterly	No	Oxford Economics
Turkey	Borsa Istanbul	TKXGDHD.C	Quarterly	No	Oxford Economics
United Kingdom	London	UKXGDHD.D	Quarterly	Yes	Oxford Economics
United States	New York Stock Exchange/NASDAQ	USXGDHD.D	Quarterly	Yes	Oxford Economics