Aggregate analyst forecast errors, price delay, and business cycle

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AGGREGATE ANALYST FORECAST ERRORS, PRICE DELAY, AND BUSINESS CYCLE

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ABSTRACT

This dissertation consists of two essays. The first essay, “Stock market liquidity, aggregate analyst forecast errors, and the economy,” is motivated by Næs, Skjeltorp, and Ødegaard (2011), who suggest that stock market liquidity is a good leading indicator of the economy. To further understand the mechanism in the economic forecastability of stock market liquidity, we hypothesize that analyst earnings forecast errors have a systematic component, which is predictable and related to changes in the economy, and that smart investors exploit analyst forecast errors, which leads to the economic forecastability of stock market liquidity. Consistent with our hypothesis, we find that there is a strong correlation between detrended aggregate analyst forecast errors and concurrent GDP growth and that a large part of the forecast errors can be predicted using lagged macro variables. Once we control for the predictable forecast errors, the economic forecastability of stock market liquidity disappears. Thus, our study reveals that aggregate analyst forecast errors are very informative about business cycle and contain all the relevant information for stock market liquidity as a leading economic indicator.

The second essay, “Stock price delay and business cycle,” is motivated by Hou and Moskowitz (2005), who use common stock price delay in reflecting market-wide information to measure market frictions each individual firm faces. To better understand how the price formation process is affected by business cycle, we examine the relation between the aggregate stock price delay and changes in the economy. Surprisingly, while the stock market liquidity declines and market frictions increase before economic downturns, we find that the aggregate price delay decreases before recessions; and it increases before economic expansions when the stock market liquidity increases and market frictions decrease. Aggregate institutional holdings

and aggregate analyst coverage as proxies for information production cannot account for the behavior of aggregate price delay. Instead, we find that the flight-to-quality behavior of investors is most responsible for changes in aggregate price delay.

CHAPTER 1: INTRODUCTION

This dissertation consists of two essays. The first one, “stock market liquidity, aggregate analyst forecast errors, and the economy,” studies the role played by aggregate analyst forecast errors in the economic predictability of stock market liquidity, and the second essay, “stock price delay and business cycle,” examines what factors may affect aggregate stock price delay during a business cycle. The common theme of my two essays is how the economy and the stock market are interrelated, particularly on how market frictions anticipate and react to changes in economic conditions.

Næs, Skjeltorp, and Ødegaard (2011) document stock market liquidity has a predicting power on future economy. My first essay extends their finding and addresses the following research questions. Since trading in the stock market affects stock market liquidity, could trading from more informed investors provide an explanation for the predictability of stock market liquidity on future economy? In addition, because analysts' earnings forecasts of firms influence investors' expectation about future economy, could aggregate analyst forecast errors play a role to facilitate those informed investors to utilize their information advantage over other investors? We find that aggregate analyst forecast errors are predictable and that stock market liquidity loses its explanation power on future economy once we control aggregate analyst forecast errors. Our findings suggest that informed investors foresee changes of economy unexpected by analysts and aggregate analyst forecast errors help informed investors' trading on their private information.

Hou and Moskowitz (2005) document that stocks with a delay to reflect public market information possess a price delay premium cross-sectionally. In a time series fashion, my second essay studies whether stocks reflect public market information at different speeds during a business cycle. We find that aggregate stock price delay tends to decrease before a recession

starts and tends to increase after a recession ends. Even though Hameed, Kang, Viswanathan (2010) document stock market liquidity worsens when stock market declines, the trading difficulty does not seem to delay public market information impounded into stocks. In addition, although Brockman, Liebenberg, and Schutte (2010) document information production activities are pro-cyclical, lower information production activities also fail to account for the pro-cyclical behavior of aggregate stock price delay. We find that the flight-to-quality behavior of investors mentioned in McQueen, Pinegar, and Thorley (1996) and Næs, Skjeltorp, and Ødegaard (2011) are most responsible for the pro-cyclical aggregate stock price delay behavior. Our findings help our understanding of stock price formation process during a business cycle and suggest aggregate stock price delay could be a state variable.

This dissertation contributes to our understanding of the systematic component of financial analysts earnings forecast errors, stock price delay changes in a business cycle, and flight-to-quality behavior of investors. First of all, aggregate analyst forecast errors highly correlate with concurrent GDP growth and could be predicted by past macro variables such as stock market excess return, stock market volatility, term spread, and default spread. Our findings suggest aggregate analyst forecast errors also help informed trading and provide an explanation of the predictability of stock market liquidity on the economy. Second, aggregate stock price delay exhibits a pro-cyclical pattern. The information quality of the stock market seems better when the economy is bad and when the uncertainty of investors is high. Finally, aggregate analyst forecast errors facilitate flight-to-quality behavior of smart investors. In addition, flight-to-quality behavior of investors is most responsible for the pro-cyclical behavior of aggregate stock price delay. Those findings further help us understand the interaction between the stock market and the real economy.

CHAPTER 2: STOCK MARKET LIQUIDITY, AGGREGATE ANALYST FORECAST ERRORS, AND THE ECONOMY

2.1 Introduction

Stock market liquidity usually starts to fall before recessions. According to Næs, Skjeltorp, and Ødegaard (2011), this phenomenon is closely related to the "flight-to-quality" behavior of investors.[1] Their finding suggests that a group of smart investors could foresee the future economy conditions which could not be predicted by other investors who buy shares sold by those smart investors. When anticipating economic downturns, in order to protect their wealth, smart investors adjust their portfolio compositions from riskier and less liquid stocks to stocks with higher liquidity and lower risk, Treasury securities, or even just cash. Their sells tend to lead stock market liquidity to decrease. As a result, we often observe declines in overall stock market liquidity level before recessions start. Thus, Næs et al. (2011) suggest that stock market liquidity is a good leading indicator of the economy. In this paper, we extend their study to provide a better understanding of the channel through which stock market liquidity is a good economic predictor. Our main finding is that smart investors' economic forecastability is largely built on foreseeing systematic analyst forecast errors, which are predictable and vary with business cycle.

Financial analysts spend their efforts on gathering, studying, and analyzing available information on individual companies and then forecast their earnings. Fried and Givoly (1982) document that financial analyst forecasts provide a better surrogate for market expectations than those generated by time-series models because analysts tend to use a broader information set and

[1] According to Næs, Skjeltorp, and Ødegaard (2011), the term "flight-to-quality" refers to a situation where market participants suddenly shift their portfolios toward securities with less risk.

more timely information.[2] Recently, Howe, Unlu, and Yan (2009) further show that, in addition to firm-specific information, analyst recommendations are also partly based on market-level and industry-level information. They find that aggregation of analysts' stock recommendations cancels out the idiosyncratic components and that the aggregate analyst recommendations corrrespond to systematic factors. They also find that changes in the aggregate analyst recommendations can predict future stock market returns. Their finding suggests that aggregate analyst recommendations are informative and useful to stock market investors.

However, facing economic uncertainty and firm-specific risk factors, analysts are bound to produce forecast errors on individual firms' earnings. Furthermore, financial analysts may also provide biased reports. For example, Dreman and Berry (1995) find that analysts tend to overestimate earnings, on average, by a significant amount. Similarly, Easterwood and Nutt (1999) find that analysts underreact to negative information, but overreact to positive information, which implies that analysts exhibit systematic optimism in response to information. To explain the optimism behavior, Hong and Kubik (2003) show that controlling for accuracy, analysts who are optimistic relative to the consensus are more likely to experience favorable job separations. Thus, in addition to economic uncertainty, analysts' behavioral bias could add to their forecast errors.

Following the logic of Howe, Unlu, and Yan (2009), we aggregate individual firms' analyst earnings forecast errors to cancel out their idiosyncratic components in the forecast errors, and to isolate their systematic component, which would largely reflect changes in the economy unforeseen by analysts and their systematic behavioral biases. In particular, if analysts do not

[2] See also Givoly and Lakonishok (1979), who document that information on revisions in analysts' forecasts of earnings is valuable to investors. More recently, Chen and Zhao (2010) show that using direct cash flow (analyst earnings) forecasts, there is a significant component of cash flow news in stock returns.

fully anticipate when economic downturns and expansions would occur, their earnings forecasts are likely to be too optimistic before recessions and too pessimistic before expansions. This suggests that aggregate analyst earnings forecast errors and changes in the economy are likely to be correlated.

Would smart investors foresee and exploit systematic analyst forecast errors? If they do, then systematic analyst forecast errors could be a major culprit in facilitating the “flight-to-quality” behavior in which smart investors sell risky securities and other (less informed) investors are willing to buy them before economic downturns. Thus, we believe the question is important and could lead us to better understand the mechanism in the economic forecastability of stock market liquidity.

Specifically, we hypothesize that analyst earnings forecast errors have a systematic component, which is predictable and related to changes in the economy, and that smart investors exploit analyst forecast errors, which leads to the economic forecastability of stock market liquidity. Our hypothesis is built on the following assumptions. First, smart investors can foresee analyst earnings forecast errors and sell risky securities when analysts are collectively too optimistic, and buy risky securities when they are collectively too pessimistic. Second, analysts tend to be too optimistic (pessimistic) before economic downturns (expansions) occur. Third, smart investors’ sells (buys) can trigger other market participants to sell (buy) as they learn more about market conditions and lead to decreases (increases) in stock market liquidity.

Thus, our hypothesis suggests that decreases in stock market liquidity would precede negative aggregate analyst earnings forecast errors (i.e., actual earnings are collectively lower than analyst forecasts), which tend to take place in economic downturns. Conversely, increases in stock market liquidity would precede positive aggregate analyst earnings forecast errors (i.e.,

actual earnings are collectively higher than analyst forecasts), which tend to arise during economic expansions. In other words, our hypothesis suggests that the economic forecastability of stock market liquidity is through systematic analyst forecast errors.

We test our hypothesis using quarterly real GDP growth to represent the change in economy in each quarter and our sample period is from 1987Q1 to 2010Q4. Consistent with our hypothesis, we find a strong correlation between detrended aggregate analyst forecast errors and concurrent real GDP growth. Furthermore, detrended aggregate analyst forecast errors are negatively correlated to lagged stock market volatility, and positively correlated to lagged term spread and lagged market excess returns. Using the lagged macro variables, about one third of the variation in detrended aggregate analyst forecast errors can be predicted.

The predicted forecast errors have a strong relation with stock market liquidity, while the part of the forecast errors not predicted by the macro variables has a very weak relation with stock market liquidity. Interestingly, the economic forecastability of stock market liquidity, as documented by Næs, Skjeltorp, and Ødegaard (2011), disappear once we control for the predicted forecast errors. To further illustrate, we decompose real GDP growth into two parts, one related and the other unrelated to aggregate analyst earnings forecast errors, and find that while the part of real GDP growth related to aggregate analyst forecast errors can be significantly explained by the previous quarter's stock market liquidity change, the part unrelated to the aggregate analyst forecast errors has virtually no relation with the previous quarter's stock market liquidity change.

In sum, the evidence implies that stock market liquidity as an economic leading indicator is built on systematic analyst forecast errors. While analysts provide useful information to market participants, smart investors foresee systematic analyst forecast errors. Stock market liquidity, by

capturing smart investors' collective behavior on systematic analyst forecast errors, becomes informative on changes in the economy.

The rest of the paper is organized as follows. In the next section, we review the literature on analyst earnings forecasts and on business cycle, and then discuss our hypothesis. Section 1.3 describes the data and the variables used in our study. Section 1.4 reports empirical results, and sectional 1.5 contains our concluding remarks.

2.2 Literature Review and Hypothesis

This study links two strands of the finance and accounting literature. The first one is analysts' information production, and the second strand is the flight-to-quality behavior of investors. We first review each strand of the literature relevant to our study, after which we form our hypothesis.

2.2.1 Analysts and Information Production

Are financial analysts' earnings forecasts informative? Givoly and Lakonishok (1979) study the information content of revisions in analyst earnings forecasts by analyzing the relation between the direction of revisions and stock price behavior. They find that stocks have significant abnormal returns during the two months following the revision month, suggesting that analyst earnings forecasts provide useful information to investors and that the information diffuses over time. Fried and Givoly (1982) further compare analyst earnings forecasts to predictions generated by time-series models commonly used in research, and show that analyst forecasts provide a better surrogate for market expectations than forecasts generated by time-series models. They argue that the advantage of financial analysts' forecasts comes from two factors: one is the broadness of the information set (firm-specific, industry, and market) available

to them and the other is their timing advantage, in that financial analysts employ information that becomes available after the last accounting reports.

However, numerous studies document biases in analyst forecasts. For example, Dreman and Berry (1995) examine the quality of analyst earnings forecasts from 1974 through the first quarter of 1991. They find that analysts' forecast errors are larger than one might expect; that these errors are increasing over time; and that analysts are optimistic on the average. Easterwood and Nutt (1999) show that analysts underreact to negative information but overreact to positive information and conclude that analysts exhibit systematic optimism in response to information. Francis and Philbrick (1993) argue that optimistic forecasts allow analysts to maintain close relationships with company managers, while Clayman and Schwartz (1994) attribute the optimism to the tendency of analysts to "fall in love" with the stocks they cover. Lim (2001) suggest that because financial analysts trade off bias to improve management access and forecast accuracy, statistically optimal forecasts, in the sense of minimum expected squared error, may be positively and predictably biased. Hong and Kubik (2003) further explain that biased earnings forecasts may come from analysts' career concerns. They show that although analysts who produce relatively accurate forecasters are more likely to experience favorable career outcomes, such as moving up to a high-status brokerage house, after controlling for accuracy, analysts who are optimistic relative to the consensus are more likely to experience favorable job separations. Thus, analysts have incentives to provide optimistic reports.

Furthermore, Ljungqvist et al. (2009) demonstrate that analyst optimism increases chances of analysts' banks to win co-management appointments, which increases the likelihood of winning underwriting businesses in the future. Malmendier and Shanthikumar (2007) show that while institutional investors tend to discount analyst recommendations, individual investors

tend to follow analysts' buy, hold and sell recommendations literally. Also, Kolasinski and Kothari (2008) find that target and acquirer analysts use earnings forecasts and recommendations to increase the odds of approving the deal by shareholders.

Nevertheless, Kadan et al. (2009) document that following the Global Analyst Research Settlement,[3] optimistic recommendations have become less frequent and more informative, whereas neutral and pessimistic recommendations have become more frequent and less informative. Thus, existing studies on analyst behavior suggest that possible systematic forecast errors may exist and vary over time.

Sadka and Sadka (2009) find that when they include more firms into a portfolio, the portfolio returns are better able to predict the portfolio earnings changes. Their findings are consistent with the hypothesis that predictability increases in the process of aggregation. Howe, Unlu, and Yan (2009) also argue that aggregation of analyst recommendations cancels out the idiosyncratic components and isolate their common response to systematic factors. Moreover, Hameed, Morck, Shen, and Yeung (2008) use the number of analysts following a stock to distinguish "high profile" stocks from neglected stocks and document that the prices of neglected stocks tend to co-move with those of intensively covered stocks in the same industry. Their results suggest that analyst forecasts include common information, which could also be relevant to neglected stocks.

2.2.2 The Flight-to-quality Behavior of Investors

The "flight-to-quality" or "flight-to-liquidity" phenomenon describes the notion that anticipating bad markets ahead, market participants shift their portfolios toward liquid securities

[3] The Global Analyst Research Settlement was an enforcement agreement reached on Apr 28, 2003 between the SEC, NASD, NYSE and ten of the United States's largest investment firms to address issues of conflict of interest within their businesses.

with less risk. In particular, in times of economic turmoil, Treasury bonds are considered by many market participants as a safe haven. Longstaff (2004) compare zero-coupon Treasury bond prices with prices of zero-coupon bonds issued by Refcorp, a U.S. government agency, which are guaranteed by the Treasury, and find a large flight-to-liquidity premium in Treasury bonds even though the two bonds have identical future cash flows and the same credit risk. Longstaff (2004) shows that the yield difference between Refcorp and Treasury bonds tend to be larger when Treasury bonds become more popular, for example, when the consumer confidence index reported by the Conference Board shows a sudden decline, which "may signal that there is a greater wariness among market participants holding riskier assets, perhaps encouraging some to migrate to the safe haven of Treasuries."

Næs et al. (2011) note that the "flight-to-quality" phenomenon leads to declines in stock market liquidity,[4] and show that changes in stock market liquidity can predict future business cycle in both the United States and Norway. Furthermore, they show that participation in small firms decreases when the economy (and market liquidity) worsens and that the economic forecastability of stock market liquidity is largely derived from changes in liquidity of small firms, rather than from large firms. Their findings are consistent with the notion that since it would be difficult to sell risky assets in turbulent markets, smart investors anticipate economic downturns and dispose stocks of small firms before market turmoil occurs. Consequently, Næs et al. (2011) suggest that stock market liquidity change in one quarter is a good predictor of the

[4] Numerous studies have linked stock liquidity to informed trading. For example, Nyholm (2002) examines the relation between stock liquidity and the probability of informed trading (PIN) developed by Easley, Kiefer, O'Hara, and Paperman (1996). They document that a firm's quoted spread is positively correlated with its estimated PIN. Similarly, Heflin and Shaw (2000) use block ownership as a proxy for informed investors and document that firms with greater block ownership have larger quoted spreads, effective spreads, adverse selection spread components, and smaller depths. Also, Cheng, Firth, Leung, and Rui (2006) examine the impacts of directors' dealings on firm liquidity and find that bid-ask spread widens and depth falls on insider trading days as compared to non-insider trading days. However, in the setting of information diffusion, smart investors' buys (sells) could signal good (bad) markets ahead and attract more (less) liquidity traders and lead to increases (decreases) in stock liquidity.

next quarter's GDP change. The predictability holds even after controlling for well known explanatory variables, including the term spread, the default spread, stock market volatility, and stock market excess returns.

2.2.3 Hypothesis

Næs et al.'s (2011) study raises an intriguing question: When smart investors dispose stocks of risky firms before market turmoil occurs, why would other investors be willing to buy those shares? Could it be that analysts are still optimistic at that time and that while general investors believe analyst earnings forecasts, smart investors foresee errors in analyst earnings forecasts?

It is conceivable that if changes in economy are somewhat surprises to analysts, their forecasts would be too optimistic before economic downturns and too pessimistic before economic expansions, and that smart investors would first act on and then other investors would catch up on systematic analyst forecast errors. Based on this presumption, we hypothesize that systematic analyst forecast errors is a channel through which smart investors' trading leads to changes in stock market liquidity before changes in economy are realized.

To obtain systematic analyst forecast errors, we can aggregate individual firms' analyst forecast errors. Our hypothesis suggests that aggregate analyst earnings forecast errors are predictable and related to business cycle, and play a key role in the economic forecastability of stock market liquidity. We next discuss the data we use for testing our hypothesis.

2.3 Data

2.3.1 Stock Market Liquidity

Following Næs et al. (2011), we use Amihud's (2002) price impact measure

$$ILLIQ_{i,t} = 1 / D_T \sum_{s=1}^{D_T} \frac{|R_{i,s}|}{VOL_{i,s}} \tag{2.1}$$

to measure stock liquidity in a quarter, where D_T is the number of trading days in the quarter *t*; and $|R_{i,s}|$ and $VOL_{i,s}$ are stock *i*'s absolute return and dollar trading volume (in millions), respectively, on day *s*. Specifically, we first collect a sample of common stocks, which meet two conditions: (1) listed on the NYSE for the whole calendar year and (2) having share price above $1 in the whole year.[5] On the quarterly average, there are about 1611 firms in the sample. Next, we calculate each stock's *ILLIQ* and then average across the sample stocks to obtain the stock market liquidity measure in the quarter *t*. Since it is an illiquidity measure, a higher number of the measure means that the stock market is less liquid. The major advantage of this measure is its responsiveness to the changes in the market liquidity environment.[6] Finally, we take the difference in the logarithm to measure the liquidity change in the stock market, i.e.,

$$dILLIQ_t = \ln(ILLIQ_t / ILLIQ_{t-1}) \tag{2.2}$$

2.3.2 Analyst Forecast Errors

We use I/B/E/S database from Thomson Reuters to collect individual firms' quarterly analyst earnings forecasts and actual earnings, and obtain two measures for a firm's analyst earnings forecast in a given quarter: one is the mean of all available earnings forecasts for the

[5] Dr. Randi Næs kindly tells us their data selection criteria as follows: We use only common shares of firms listed at the NYSE. We also apply some filters where we require a stock to be in the sample (i.e. listed) for the whole year to be included in the calculations, and require the stocks to have a price above 1 USD during the entire year. This is mainly to reduce some noise. It does not affect the market-wide series in any way since the cross-section is so large.

[6] During the financial crisis from 2007 to 2009, the aggregate illiquidity (Amihud 2002) measure reached the highest point in the first quarter of 2009, when the stock market hit the bottom.

firm in the quarter,[7] and the other is the last forecast in the quarter for the firm. Since our analysis yields virtually the same results, we focus on the mean in this paper. Since firms usually announce their earnings in a month or two after the end of a fiscal quarter, which vary across firms, we use the following scheme to synchronize calendar quarters and fiscal quarters. For firms' fiscal quarter ends in January, February, or last December, their analysts' quarterly earnings forecasts are classified into the first quarter in the current year. For firms' fiscal quarter ends in March, April, or May, their analysts' quarterly earnings forecasts are classified into the second quarter in the current year. For firms' fiscal quarter ends in June, July, or August, their analysts' quarterly earnings forecasts are classified into the third quarter in the current year. Similarly, for firms' fiscal quarter ends in September, October, and November, their analysts' quarterly earnings forecasts will be classified into the fourth quarter in the current year. The synchronization allows us later on to match analyst forecast errors and changes in GDP in calendar time.

Following Chan, Jegadeesh, and Lakonishok (1996),[8] we define the standardized analyst forecast error (*SAFE*) of a quarter as the current quarterly difference between a firm's actual quarterly earnings and the firm's quarterly analyst earnings forecast and then standardize the difference with the standard deviation of the quarterly earning difference from past eight quarters, i.e.,[9]

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[7] With a fixed forecast period end date (FPEDATS), there will be several I/B/E/S statistical periods (STATPERS). We use all available mean estimate (MEANEST) to get the average analyst earnings forecast of a firm in a quarter.

[8] Chan, Jegadeesh, and Lakonishok (1996) define their standardized unexpected earnings as

$$SUE = \frac{\text{Quarterly earnings - Expected quarterly earnings}}{\text{Standard deviation of earnings change in the prior eight quarters}}$$

[9] Therefore, stocks without sufficient previous analyst earnings forecasts will not be included in the sample.

$$SAFE = \frac{\text{Quarterly actual EPS- Expected quarterly EPS from analysts}}{\text{Standard deviation of EPS difference in the prior eight quarters}} \tag{2.3}$$

Furthermore, following the data selection criteria of Næs et al. (2011), we include only common stocks (with share code 10 or 11 from the Center for Research in Security Prices (CRSP)) listed on the NYSE for the whole calendar year and with stock price above $1 per share in our construction of aggregate analyst earnings forecast errors. From 1987 to 2010, there are around 1,728 common stocks listed on NYSE; among them, 1,611 were traded above $1 per share and listed for the whole year. From the above sample, there are about 778 firms with analyst coverage each quarter on the average from 1987 to 2010. We construct the aggregate analyst forecast errors (*AAFE*) by taking the equally-weighted average of the standardized analyst forecast error (*SAFE*) of each firm with analyst coverage in a quarter.

After the Global Settlement in 2003,[10] analysts tend to become more conservative than before. Figure 2.1 shows that there is an upward trend for the aggregate analyst forecast errors during the sample period. We remove the time trend of the aggregate analyst forecast errors and test whether the detrended aggregate analyst forecast errors are stationary. The augmented Dickey-Fuller (ADF) test rejects the null hypothesis that the aggregate analyst forecast errors have a unit root, suggesting the aggregate analyst forecast errors series are stationary. Hence, we use the level of detrended aggregate analyst forecast errors to perform our analysis.

2.3.3 Economy Data

We use seasonally adjusted quarterly real gross domestic product (GDP) from Bureau of Economic Analysis to measure the economy state. The quarterly data are in the unit of billions of

[10] See Kadan, Madureira, Wang, and Zach (2009).

chained 2005 dollars. Following Næs, et al. (2011), we take the difference in the logarithm of real GDP to measure the quarterly change in the economy, i.e.,

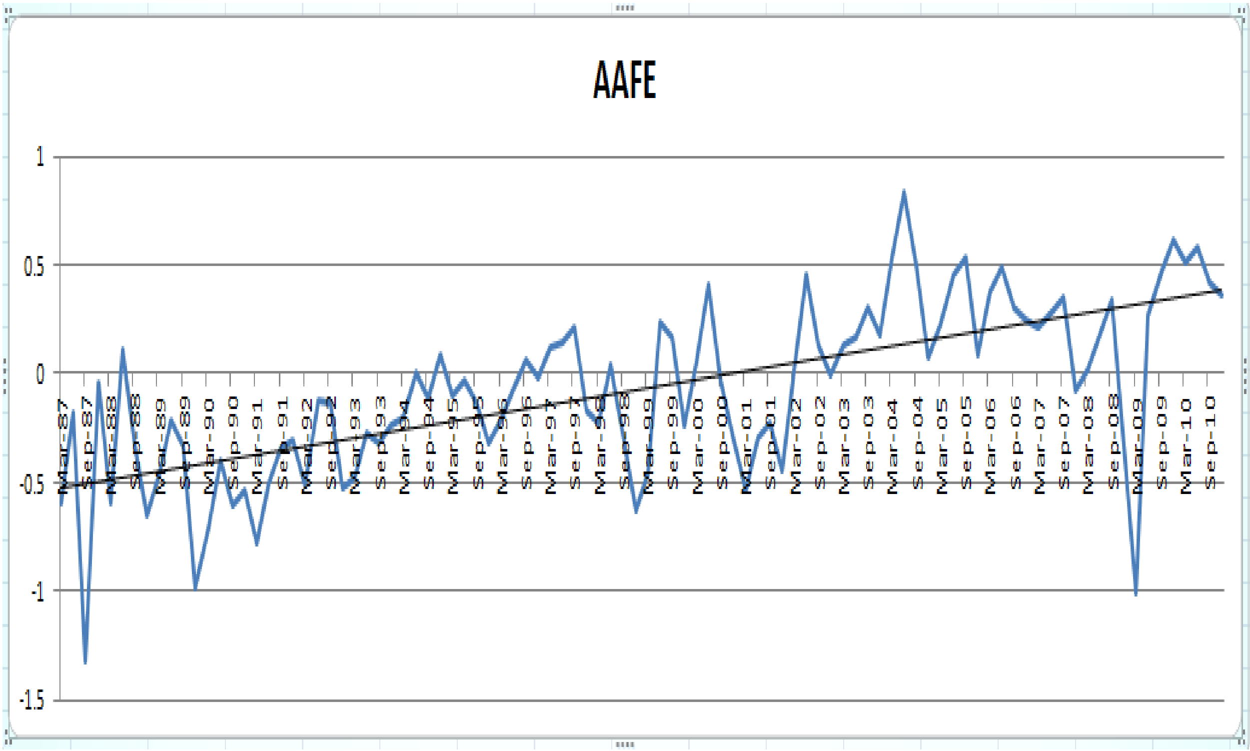

Figure 2.1 Aggregate Standardized Analyst Forecast Errors (*AAFE*) and Their Time Trend

The figure shows time-series plots of the original aggregate standardized analyst forecast errors from the sample firms in this study. The sample firms include common stocks listed on the NYSE with stock price above $1 per share, listing for the whole calendar year, and with analyst coverage. The sample period is from 1987Q1 to 2010Q4. The solid line describes the time-trend of the aggregate standardized analyst earnings forecast errors during the sample period.

$$dGDPR_t = \ln(GDPR_t / GDPR_{t-1}) \tag{2.4}$$

While our focus is to examine the role of aggregate analyst earnings forecast errors in economic forecastability of stock market liquidity, we include several control variables, which could also be linked to the economy state. First, Fama and French (1989) document that the default spread (yield difference between low grade bonds and high grade bonds) is high during periods like the Great Depression when business is persistently poor and low during periods when the economy is persistently strong. Fama and French (1989) also show that the term spread

(yield difference between 10-year Treasury note and 3-month Treasury bill) tends to be low near business cycle peaks and high near troughs. Thus, they suggest that the default spread is a long-term business condition variable, and the term spread as a short-term business cycle variable. In our analysis, we include the term spread and the default spread as control variables.[11]

Also included as control variables are the market excess return and market return volatility since stock market prices have been considered as an important leading indicator of the economy. Following Næs, et al. (2011), we use the 3-month cumulative monthly S&P 500 index return in excess of monthly risk-free rate as the quarterly market excess return (*Mkt_Ret*). As for market return volatility, we calculate each common stock's quarterly return volatility from daily returns for common stocks in our sample (listed on NYSE with stock price above $1 for the whole calendar year), and then take the equally-weighted average as quarterly market volatility (*Mkt_Vol*). The augmented Dickey-Fuller (ADF) tests show that all of these control variables are stationary.

2.3.4 Summary Statistics of the Variables

Table 2.1 reports the summary statistics of the variables discussed above. During the 96 quarters from 1987Q1 to 2010Q4, the mean (and last forecast) of the aggregate standardized analyst forecast errors (*AAFE*) change from negative in the first time period (1987Q1 to 1990Q4) to positive in the last decade (2001Q1 to 2010Q4). Figure 1 plots the time series of *AAFE*, which shows an obvious time trend, indicating that analysts collectively tend to exhibit more optimism in the early period than in the later period. In the analyses that follow, we use the *detrended_AAFE* to capture systematic analyst forecast errors.

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[11] Our analysis uses the default spread defined as the difference between Moody's Baa rate and Moody's Aaa rate.

In terms of market liquidity, the aggregate illiquidity level decreases from 0.73 in the late 80s to 0.35 from 1991 to 2000, and further decreases to 0.07 in the past decade (2001 to 2010). The average real GDP growth rate is around 0.65% per quarter during the sample period but has a lower growth rate of 0.41% during the past decade, compared to 0.69% during the earlier period from 1987 to 1990 and 0.87% from 1991 to 2000. The average stock market volatility during the sample period is around 2.46% and the overall market tends to have higher volatility during the most recent decade. This suggests that investors tend to face more uncertainty during the recent period than before, consistent with Campbell, et al. (2001).

The average term spread is around 1.81% during the sample period and has a higher mean of 1.98% during the most recent decade, compared to 1.53% in the earlier period from 1987 to 1990 and 1.74% from 1991 to 2000. The average default spread is around 0.97% during the sample period and it also has a higher mean value of 1.16% during the most recent decade, relative to 0.75% from 1991 to 2000. The mean market excess return is around 1.02% per quarter during the sample period, and ranges from -0.71% per quarter during the most recent decade to 2.92% per quarter from 1991 to 2000.

Table 2.2 shows the Pearson correlation coefficients between the variables. The GDP growth rate in a quarter shows significant negative correlations with stock market liquidity change, default spread, and market volatility in the previous quarter, but has a positive correlation with the previous quarter's market excess return.

These correlations suggest that stock market illiquidity, default spread, and market volatility tend to increase (decrease) and the stock market tends to fall (rise) before economic downturns (upturns). In short, stock market liquidity, volatility, and excess returns, and default spread appear to be good leading economic indicators, and can be used to help forecast the

direction of the economy. Interestingly, the GDP growth rate has a significant positive correlation of 0.45 with the concurrent *detrended_AAFE(mean)* and 0.43 with *detrended_AAFE(last forecast)*.

Figure 2.2 shows that there is clear comovement between these two series (GDP growth and *detrended_AAFE(mean))*. Furthermore, like GDP growth, *detrended_AAFE* also has significant positive correlations with term spread and market excess return in the previous quarter and significant negative correlations with previous quarter's default spread and market volatility. These correlations are consistent with the notion that analyst earnings forecast errors on individual firms contain a systematic component and that analysts collectively tend to be too optimistic right before economic downturns, which results in negative forecast errors, and too pessimistic right before economic upturns, which results in positive forecast errors.

It is worth pointing out that while the GDP growth has a significant negative correlation of -0.33 with the previous quarter change in stock market liquidity, *detrended_AAFE (mean)* seems to have a stronger negative correlation of -0.47 with the previous quarter change in stock market liquidity. If the economic forecastability of stock market liquidity reflects smart investors' information advantages, the stronger negative correlation between $detrended\_AAFE_t$ (mean) and $ILLIQ_{t-1}$, along with a large positive correlation between $detrended\_AAFE_t$ and $dGDPR_t$, provide a first hint that smart investors' information advantages could lie on their foreseeing and exploiting systematic analyst forecast errors. In the next section, we formally address this issue using regression analysis.

2.4 Regression Results

This section first uses multivariate regression analyses to address two issues. First, to what extent aggregate analyst forecast errors can be predicted using macro variables?

Table 2.1 Summary Statistics of the Relevant Variables

Variables	1987Q1to2010Q4	1987Q1to1990Q4	1991Q1to2000Q4	2001Q1to2010Q4
Sample firms				
ILLIQ	0.30	0.73	0.35	0.07
dILLIQ	-0.0223	0.0624	-0.0499	-0.0287
Mkt_Vol	2.46%	2.36%	2.42%	2.55%
Avg_number_of_firms	1610.54	1670.75	1815.80	1381.20
Sample firms with analyst coverage (mean)				
AAFE	-0.0685	-0.4900	-0.1621	0.1937
detrended_AAFE	-0.0004	-0.0379	0.0212	-0.0070
avg_number_of_firms	778.31	645.31	828.25	781.58
Sample firms with analyst coverage (last forecast)				
AAFE	0.2176	-0.3164	0.1370	0.5118
detrended_AAFE	0.0086	-0.0814	0.0612	-0.0079
avg_number_of_firms	619.47	412.63	662.73	658.95
Sample firms with earnings information				
SUE	-0.0274	-0.0430	-0.0309	-0.0177
avg_number_of_firms	1271.36	1229.63	1362.50	1196.93
Economy variables				
GDPR	10434.19	7711.76	9436.77	12520.58
dGDPR	0.0065	0.0069	0.0087	0.0041
Term_Spread	1.81%	1.53%	1.74%	1.98%
Default_Spread	0.97%	1.08%	0.75%	1.16%
Mkt_Ret	1.02%	0.57%	2.92%	-0.71%

This table reports the average values of the variables used in this study during the whole sample period and each sub-period. The sample firms include NYSE common stocks with stock price above $1 and listed for the whole calendar year. The sample firms with analyst coverage include the aforementioned sample firms that have I/B/E/S analyst earnings forecast data (summary history and detail history) available. The standardized aggregate analyst forecast error of a firm in a given quarter is the difference between actual earnings and estimated earnings from analysts standardized by the previous eight quarters' standard deviation of the difference. The aggregate standardized analyst forecast error, *AAFE*, is the equally-weighted average across the sample firms with analyst coverage. The detrended aggregate standardized analyst forecast error, *detrended_AAFE*, removes the time trend of the original series during the sample period. Mean is from summary history and last forecast is from detail history. *SUE* uses the actual earnings reported 4 quarters before as the benchmark. *ILLIQ* is the average illiquidity measure of Amihud (2002) across the sample firms, and *dILLIQ* is the logarithm difference between the current quarter's and the previous quarter's *ILLIQ*. *Mkt_Vol* is market volatility obtained from equally weighted average of the sample firms' stock daily return standard deviation during the quarter. *GDPR*

(Table 2.1 continued)
is the real GDP is in billions of chained 2005 dollars, and *dGDPR* is real GDP growth, measured by the logarithm difference between the current quarter's and the previous quarter's *GDPR*. *Term_Spread* is the yield difference between 10-year Treasury note rate and 3-month Treasury bill rate; and *Default_Spread* is the difference between Moody's Baa bond yield and Moody's Aaa bond yield. *Mkt_Ret* is the market excess return proxied by the 3-month cumulative monthly excess return between S&P 500 index return and the risk-free rate.

Table 2.2 Correlation Matrix

	$detrended\_AAFE_t$ (mean)	$detrended\_AAFE_t$ (last forecast)	$ASUE_t$	$dILLIQ_{t-1}$	$Term\_Spread_{t-1}$	$Default\_Spread_{t-1}$	Mkt_Ret_{t-1}	Mkt_Vol_{t-1}
$dGDPR_t$	0.4475 (<.0001)	0.4323 (<.0001)	0.3880 (<.0001)	-0.3341 (0.0009)	0.0114 (0.9122)	-0.4685 (<.0001)	0.3547 (0.0004)	-0.4113 (<.0001)
$detrended\_AAFE_t$ (mean)		0.7591 (<.0001)	0.6152 (<.0001)	-0.4714 (<.0001)	0.2172 (0.0335)	-0.3583 (0.0003)	0.3813 (0.0001)	-0.4883 (<.0001)
$detrended\_AAFE_t$ (last forecast)			0.4355 (<.0001)	-0.4206 (<.0001)	0.0536 (0.6038)	-0.4133 (<0.0001)	0.3435 (0.0006)	-0.3915 (<.0001)
$ASUE_t$				-0.3791 (<.0001)	-0.0383 (0.7113)	-0.6275 (<.0001)	0.3024 (0.0028)	-0.6715 (<.0001)
$dILLIQ_{t-1}$					-0.0644 (0.5329)	0.3511 (0.0005)	-0.4159 (<.0001)	0.5272 (<.0001)
$Term\_Spread_{t-1}$						0.2689 (0.0081)	-0.0354 (0.7323)	0.1401 (0.1733)
$Default\_Spread_{t-1}$							-0.2928 (0.0038)	0.7262 (<.0001)
Mkt_Ret_{t-1}								-0.4441 (<.0001)

This table shows the Pearson correlation coefficients between variables used in the analysis. The associated p-values are reported in parentheses below each correlation coefficient. $dGDPR_t$ is the logarithm difference between current real GDP and previous real GDP. $detrended\_AAFE_t$ is the aggregate standardized analyst forecast error series taken out time trend. $ASUE_t$ is the aggregate standardized earnings surprises. The following variables are from previous quarter. For the following lagged variables, $dILLIQ_{t-1}$ is the logarithm difference between current aggregate liquidity level and previous aggregate liquidity level. $Term\_Spread_{t-1}$ is the yield difference between 10-year Treasury note and 3-month Treasury bill. $Default\_Spread_{t-1}$ is the yield difference between Moody's Baa and Moody's Aaa. Mkt_Ret_{t-1} is the 3-month cumulative S&P500 monthly return and risk-free rate difference. Mkt_Vol_{t-1} is the equal-weighted 3-month stock return standard deviation among NYSE common stocks with share price above $1 and listing for the whole calendar year.

Second, could changes in stock market liquidity be linked to predicted aggregate analyst forecast errors? Addressing the issues help us connect the notions that changes in stock market liquidity reflect smart investors' trading behavior and that smart investors take advantage of predicted analyst forecast errors. The analyses provide a basis for us to further test our hypothesis that the economic forecastability of stock market liquidity is through systematic analyst forecast errors. We focus on the results from summary history of I/B/E/S (mean) and also report results from detail history (last forecast) and standardized earnings surprises.

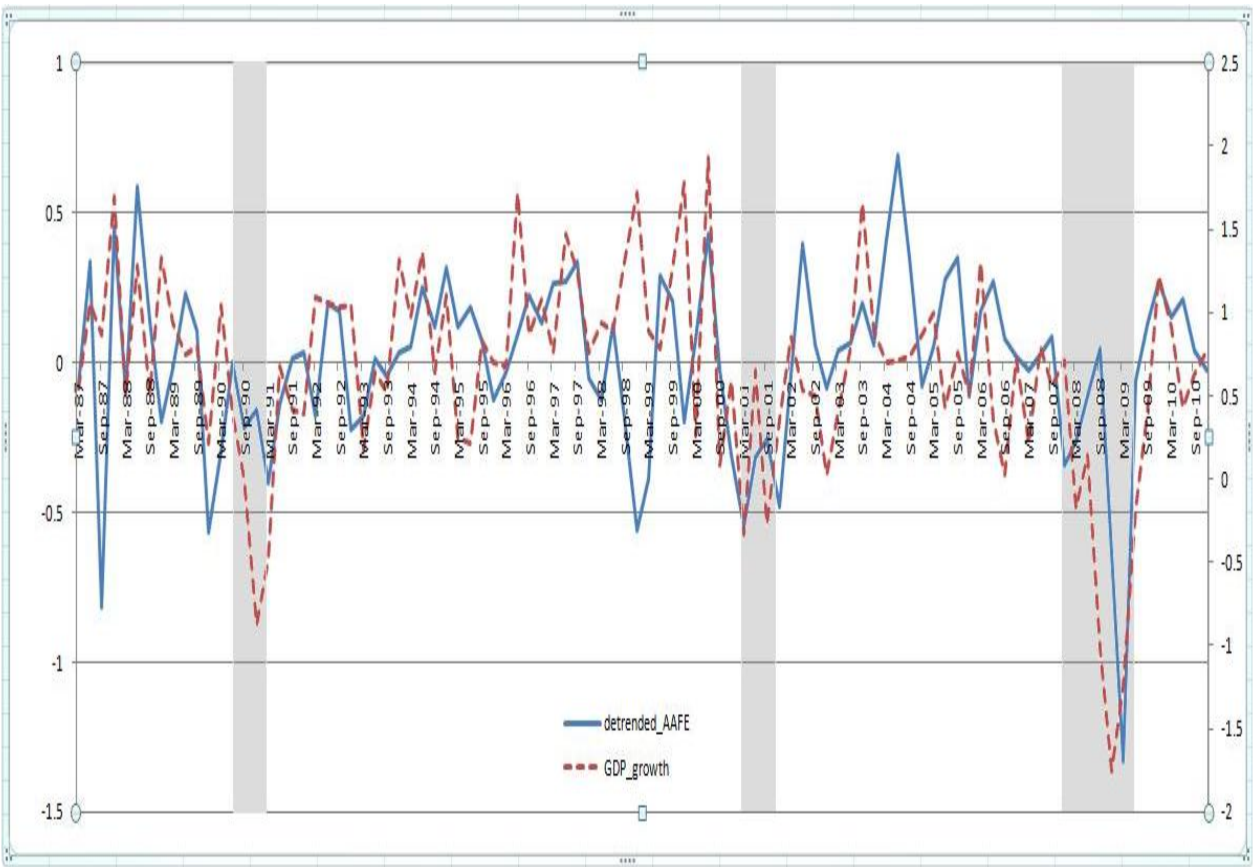

Figure 2.2 Detrended Aggregate Analyst Forecast Errors (*detrended_AAFE*) and GDP Growth

The figure shows the trends of two time series from 1987Q1 to 2010Q4: detrended standardized aggregate analyst forecast errors and GDP growth. We take out the linear time trend from the original standardized aggregate analyst forecast errors to get the detrended series, and take the logarithm difference between the current real GDP and previous quarter's real GDP number to get the GDP growth series. The left axis is for the detrended aggregate standardized analyst forecast errors and the right axis is for the GDP growth. The shaded areas mark the following three NBER recessions: July 1990-March1991, March 2001-November 2001, and December 2007-June 2009.

2.4.1 Predicting Aggregate Analyst Forecast Errors

To examine the predictability of aggregate analyst forecast errors, we use the following regression model:

$$\begin{aligned} detrended\_AAFE_t = b_0 + b_1 * Mkt\_Vol_{t-1} + b_2 * Term\_Spread_{t-1} \\ + b_3 * Default\_Spread_{t-1} + b_4 * Mkt\_Ret_{t-1} + \varepsilon_t \end{aligned} \tag{2.5}$$

Table 2.3 reports the regression results, which show that $detrended\_AAFE_t$ is significantly and negatively related to lagged stock market volatility, and significantly and positively related to lagged term spread and lagged market excess returns. The results suggest that analysts collectively tend to be too optimistic when stock market returns are lower and more volatile and when term spread is smaller, and that, conversely, they tend to be too pessimistic when stock market returns are higher and less volatile and when term spread is larger. The adjusted-R^2 of the regression in (2.5) is 0.33, suggesting that about one third of the variation in aggregate analyst forecast errors is predictable.

Based on the results in Table 2.3, we obtain the predicted aggregate analyst forecast error in time *t* as

$$\begin{aligned} E_{t-1}(detrended\_AAFE_t) = 0.28 - 13.68 * Mkt\_Vol_{t-1} + 7.84 * Term\_Spread_{t-1} \\ - 9.31 * Default\_Spread_{t-1} + 0.71 * Mkt\_Ret_{t-1} \end{aligned} \tag{2.6}$$

and the residual part as

$$residual\_detrended\_AAFE_t = detrended\_AAFE_t - E_{t-1}(detrended\_AAFE_t) \tag{2.7}$$

If smart investors exploit systematic analyst forecast errors, the predictable part of aggregate analyst forecast errors is likely to be more useful than the unpredictable part to smart investors. Indeed, Table 2.4 shows that stock market liquidity, $dILLIQ_{t-1}$, is strongly associated with $E_{t-1}(detrended\_AAFE_t)$ but is only marginally associated with $residual\_detrended\_AAFE_t$.

The strong association between changes in stock market liquidity and predicted *detrended_AAFE* and the strong correlation between real GDP growth and aggregate analyst forecast errors reported earlier lead us to consider that the source of the economic forecastability of stock market liquidity may lie in analyst forecast errors. We next turn to explore this issue.

2.4.2 The Source of the Economic Forecastability of Stock Market Liquidity

We use the following regression model to compare the link strength to real GDP growth, $dGDPR_t$, of changes in stock market liquidity to that of predicted aggregate analyst forecast errors:

$$dGDPR_t = b_0 + b_1 * dILLIQ_{t-1} + b_2 * dGDPR_{t-1} + b_3 * E_{t-1}(detrended\_AAFE_t) + e_t \tag{2.8}$$

Similar to Naes, Skjeltorp, and Odegaard (2011), Table 2.5 shows that, without $E_{t-1}(detrended\_AAFE_t)$ in the regression model, $dGDPR_t$ is negatively related to $dILLIQ_{t-1}$, with a Newey-West corrected *t*-value of -2.65. This confirms the stock market liquidity's economic forecastability in our sample period from 1987 to 2010. However, in the presence of $E_{t-1}(detrended\_AAFE_t)$, $dGDPR_t$ is no longer significantly related to $dILLIQ_{t-1}$ since its Newey-West corrected *t*-value becomes -1.22. Instead, $dGDPR_t$ is significantly related to $E_{t-1}(detrended\_AAFE_t)$, with a Newey-West corrected *t*-value of 2.85. The results suggest that while stock market liquidity contains useful information for forecasting future economic activity, this information content of stock market liquidity is largely encompassed by predicted aggregate analyst forecast errors. Thus, the evidence is consistent with our hypothesis that stock market liquidity as an economic leading indicator is built on systematic analyst forecast errors.

To further illustrate our point, we decompose real GDP growth into two components: one is related and the other is unrelated to aggregate analyst forecast errors.

Table 2.3 Predicting Aggregate Analyst Forecast Errors

Panel A: Analyst Earnings Forecast Errors from Summary History of I/B/E/S

Dependent Variable	Constant	Mkt_Vol_{t-1}	$Term\_Spread_{t-1}$	$Default\_Spread_{t-1}$	Mkt_Ret_{t-1}	$Adjustedj\_R^2$
$detrended\_AAFE_t$ *(mean)*	0.47*** (4.25)	-19.14*** (-4.06)				0.2303
$detrended\_AAFE_t$ *(mean)*	0.37*** (3.86)	-17.48*** (-2.71)	7.93*** (3.52)	-8.50 (-0.74)		0.3057
$detrended\_AAFE_t$ *(mean)*	0.28*** (2.76)	-13.68** (-2.07)	7.84*** (3.45)	-9.31 (-0.85)	0.71*** (2.82)	0.3311

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel B: Analyst Earnings Forecast Errors from Detail History of I/B/E/S

Dependent Variable	Constant	Mkt_Vol_{t-1}	$Term\_Spread_{t-1}$	$Default\_Spread_{t-1}$	Mkt_Ret_{t-1}	$Adjustedj\_R^2$
$detrended\_AAFE_t$ *(last forecast)*	0.32*** (3.34)	-12.49*** (-3.28)				0.1443
$detrended\_AAFE_t$ *(last forecast)*	0.27*** (3.50)	-5.54 (-0.92)	3.47 (1.29)	-19.44* (-1.78)		0.1887
$detrended\_AAFE_t$ *(last forecast)*	0.19*** (2.46)	-2.14 (-0.37)	3.39 (1.28)	-20.16** (-2.01)	0.64*** (2.84)	0.2197

***, **, * significant at the 1%, 5%, and 10% level, respectively.

(Table 2.3 continued)

Panel C: Standardized Earnings Surprises

Dependent Variable	Constant	Mkt_Vol_{t-1}	$Term\_Spread_{t-1}$	$Default\_Spread_{t-1}$	Mkt_Ret_{t-1}	$Adjustedj\_R^2$
$ASUE_t$	0.78***	-32.68***				0.4450
	(3.78)	(-3.70)				
$ASUE_t$	0.73***	-21.57***	3.62	-30.42**		0.4881
	(4.95)	(-2.79)	(1.07)	(-2.40)		
$ASUE_t$	0.72***	-21.24***	3.61	-30.11**	0.06	0.4827
	(5.08)	(-2.77)	(1.06)	(-2.41)	(0.21)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

The table reports the results of regressing detrended aggregate analyst forecast errors on lagged macro variables. The model estimated is

$$detrended\_AAFE_t = b_0 + b_1 * Mkt\_Vol_{t-1} + b_2 * Term\_Spread_{t-1} + b_3 * Default\_Spread_{t-1} + b_4 * Mkt\_Ret_{t-1} + e_t.$$

The explanatory variables include market volatility, term spread, default spread, and market excess return. The Newey-West corrected *t*-statistics (Bartlett kernel with a lag length of 2) are reported in parentheses below the coefficient estimates.

Table 2.4 Aggregate Analyst Forecast Errors and Stock Market Liquidity Changes

Panel A: Analyst Earnings Forecast Errors from Summary History of I/B/E/S

Dependent variable	Constant	$dILLIQ_{t-1}$	$Adjustedj\_R^2$
$E_{t-1}(detrended\_AAFE_t)$	-0.0065	-0.3607***	0.2994
(mean)	(-0.30)	(-3.31)	
$residual\_dtrended\_AAFE_t$	-0.0026	-0.1516*	0.0201
(mean)	(-0.10)	(-1.81)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

(Table 2.4 continued)

Panel B: Analyst Earnings Forecast Errors from Detail History of I/B/E/S

Dependent variable	Constant	$dILLIQ_{t-1}$	$Adjustedj\_R^2$
$E_{t-1}(detrended\_AAFE_t)$ *(last forecast)*	0.0048 (0.31)	-0.2279** (-2.54)	0.2553
$residual\_dtrended\_AAFE_t$ *(last forecast)*	-0.0024 (-0.09)	-0.1439** (-2.21)	0.0295

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel C: Standardized Earnings Surprises

Dependent variable	Constant	$dILLIQ_{t-1}$	$Adjustedj\_R^2$
$E_{t-1}(ASUE_t)$	-0.0356 (-0.98)	-0.4879** (-2.30)	0.2513
$residual\_ASUE_t$	-0.0004 (-0.01)	-0.02365 (-0.15)	-0.0100

***, **, * significant at the 1%, 5%, and 10% level, respectively.

The table reports the results of regressing the two components (predicted and residual) of detrended aggregate analyst forecast errors on stock market liquidity changes from 1987 Q1 to 2010 Q4. The regression model used to get the predicted component of detrended aggregate analyst forecast errors, $E_{t-1}(detrended\_AAFE_t)$, is reported in table 2.3:

$$detrended\_AAFE_t = b_0 + b_1 * Mkt\_Vol_{t-1} + b_2 * Term\_Spread_{t-1} + b_3 * Default\_Spread_{t-1} + b_4 * Mkt\_Ret_{t-1} + e_t$$

And the residual component is

$$residual\_detrended\_AAFE_t = detrended\_AAFE_t - E_{t-1}(detrended\_AAFE_t).$$

The Newey-West corrected *t*-statistics (Bartlett kernel with a lag length of 2) are reported in parentheses below the coefficient estimates.

That is, based on the regression model,

$$dGDPR_t = b_0 + b_1 * detrended\_AAFE_t + e_t \tag{2.9}$$

the related component is $AAFE\_related\_dGDPR_t = \hat{b}_0 + \hat{b}_1 * detrended\_AAFE_t$ and the unrelated component is $residual\_dGDPR_t = dGDPR_t - AAFE\_related\_dGDPR_t$.

If systematic analyst forecast errors contain all the relevant information for the economic forecastability of stock market liquidity, then we expect that stock market liquidity has predictive power on $AAFE\_related\_dGDPR_t$, but not on $residual\_dGDPR_t$.

Indeed, Table 2.6 shows that $AAFE\_related\_dGDPR_t$ is significantly and negatively related to $dILLIQ_{t-1}$ and that the predictive power of $dILLIQ_{t-1}$ remains after controlling for market volatility, term spread, default spread, and market excess returns. However, Table 2.6 also shows that $residual\_dGDPR_t$ has virtually no relation with $dILLIQ_{t-1}$, suggesting that $dILLIQ_{t-1}$ has no predictive power on $residual\_dGDPR_t$. The results validate that systematic analyst forecast errors possess all the pertinent information for stock market liquidity as an economic leading indicator.

2.5 Conclusion

This paper extends Næs, Skjeltorp, and Ødegaard's (2011) study to better understand the mechanism for stock market liquidity to have the economic forecastability. According to Næs, et al. (2011), our empirical results show that the reason that stock market liquidity contains useful information for inferring the future state of the economy is because changes in stock market liquidity can capture smart investors' flight-to-quality behavior in which smart investors sell risky and hard-to-dispose securities before economic downturns, and buy them before economic expansions.

Our inquiry starts with a simply question: Why are other investors willing to buy (sell) risky and hard-to-dispose securities when smart investors sell (buy) them before economic downturns (upturns)? The question leads us to consider that while analyst earnings forecasts provide useful information to market participants and help them form market expectations, smart investors may foresee and exploit systematic analyst forecast errors. If systematic analyst forecast errors are correlated with economic conditions, stock market liquidity, by capturing smart investors' collective behavior on analyst forecast errors, could become informative on changes in the economy.

Thus, we hypothesis that analyst earnings forecast errors have a systematic component, which is predictable and related to changes in the economy, and that smart investors exploit analyst forecast errors, which leads to the economic forecastability of stock market liquidity. Consistent with our hypothesis, we find that there is a strong correlation between detrended aggregate analyst forecast errors and concurrent GDP growth and that a large part of the forecast errors can be predicted using lagged macro variables. Furthermore, once we control for the predictable forecast errors, the economic forecastability of stock market liquidity disappears. In sum, our analysis reveals that aggregate analyst forecast errors are very informative on business cycle. They contain all the relevant information for stock market liquidity as an economic leading indicator. Smart investors foresee changes in economy unexpected by analysts and trade upon this private information, causing changes in stock market liquidity. Hence, we observe a relationship between stock market liquidity and business cycle. Specifically, smart investors sell stocks before the general investment public knows the economy is worsening and before a recession starts, and they buy stocks before the general investment public knows the economy is improving and before the economy is going to be better.

Table 2.5 GDP Growth Rate, Stock Market Liquidity Change, and Predicted Aggregate Analyst Forecast Error

Dependent variable	Constant	$dILLIQ_{t-1}$	$dGDPR_{t-1}$	$E_{t-1}(AAFE_t)(mean)$	$Adjustedj\_R^2$
$dGDPR_t$	0.0014***		0.4564***		0.2000
	(2.58)		(2.97)		
$dGDPR_t$	0.0040***	-0.0048***	0.3908***		0.2334
	(3.30)	(-2.65)	(2.99)		
$dGDPR_t$	0.0046***		0.3007**	0.0110***	0.2686
	(4.00)		(2.31)	(3.69)	
$dGDPR_t$	0.0046***	-0.0022	0.2963**	0.0092***	0.2671
	(4.08)	(-1.22)	(2.29)	(2.85)	
Dependent variable	Constant	$dILLIQ_{t-1}$	$dGDPR_{t-1}$	$E_{t-1}(AAFE_t)(last)$	$Adjustedj\_R^2$
$dGDPR_t$	0.0050***		0.2147	0.0207***	0.3004
	(4.47)		(1.65)	(4.51)	
$dGDPR_t$	0.0049***	-0.0018	0.2143	0.0186***	0.2976
	(4.55)	(-1.06)	(1.66)	(3.83)	
Dependent variable	Constant	$dILLIQ_{t-1}$	$dGDPR_{t-1}$	$E_{t-1}(ASUE_t)$	$Adjustedj\_R^2$
$dGDPR_t$	0.0050***		0.2616*	0.0078***	0.2631
	(4.20)		(1.97)	(4.07)	
$dGDPR_t$	0.0050***	-0.0026	0.2604*	0.0064***	0.2654
	(4.21)	(-1.32)	(1.98)	(2.99)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

This table reports the result of regressing GDP growth rate, $dGDPR_t$, on lagged stock market liquidity change, $dILLIQ_{t-1}$, and the predicted component of the aggregate analyst forecast error, $E_{t-1}(detrended\_AAFE_t)$, obtained from the regression results reported in Table 2.3. The model is

$$dGDPR_t = b_0 + b_1 * dILLIQ_{t-1} + b_2 * dGDPR_{t-1} + b_3 * E_{t-1}(detrended\_AAFE_t) + \varepsilon_t$$

The Newey-West corrected t-statistics (Bartlett kernel with a lag length of 2) are reported in parentheses below the coefficient estimates.

Table 2.6 Stock Market Liquidity and the Components of GDP Growth

Panel A: Analyst Earnings Forecast Errors from Summary History of I/B/E/S

Dependent variable	Constant	$dILLIQ_{t-1}$	Mkt_Vol_{t-1}	$Term\_Spread_{t-1}$	$Default\_Spread_{t-1}$	Mkt_Ret_{t-1}	$Adjustedj\_R^2$
$AAFE\_related\_dGDPR_t$ *(mean)*	0.0064*** (21.44)	-0.0048*** (-3.29)					0.2140
$AAFE\_related\_dGDPR_t$ *(mean)*	0.0084*** (9.40)	-0.0021** (-2.24)	-0.0929 (-1.54)	0.0665*** (3.05)	-0.0877 (-0.91)	0.0051** (2.37)	0.3547
$residual\_dGDPR_t$	-0.0001 (-0.07)	-0.0028 (-1.23)					0.0083
$residual\_dGDPR_t$	0.0025 (1.37)	-0.0003 (-0.14)	0.1122 (1.06)	-0.0017 (-0.04)	-0.5454*** (-2.81)	0.0100 (1.52)	0.0922

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel B: Analyst Earnings Forecast Errors From Detail History of I/B/E/S

Dependent variable	Constant	$dILLIQ_{t-1}$	Mkt_Vol_{t-1}	$Term\_Spread_{t-1}$	$Default\_Spread_{t-1}$	Mkt_Ret_{t-1}	$Adjustedj\_R^2$
$AAFE\_related\_dGDPR_t$ *(last forecast)*	0.0065*** (19.85)	-0.0041*** (-3.33)					0.1681
$AAFE\_related\_dGDPR_t$ *(last forecast)*	0.0077*** (7.80)	-0.0024** (-2.40)	0.0154 (0.23)	0.0300 (1.02)	-0.2242** (-2.11)	0.0053** (2.21)	0.2532

(Table 2.6 continued)

Dependent variable	Constant	$dILLIQ_{t-1}$	Mkt_Vol_{t-1}	$Term\_Spread_{t-1}$	$Default\_Spread_{t-1}$	Mkt_Ret_{t-1}	$Adjustedj\_R^2$
$residual\_dGDPR_t$	-0.0001 (-0.08)	-0.0034 (-1.42)					0.0180
$residual\_dGDPR_t$	0.0031 (1.69)	0.0000 (0.00)	0.0039 (0.04)	0.0348 (0.87)	-0.4089*** (-2.20)	0.0098 (1.50)	0.0796

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel C: Standardized Earnings Surprises

Dependent variable	Constant	$dILLIQ_{t-1}$	Mkt_Vol_{t-1}	$Term\_Spread_{t-1}$	$Default\_Spread_{t-1}$	Mkt_Ret_{t-1}	$Adjustedj\_R^2$
$ASUE\_related\_dGDPR_t$	0.0065*** (19.63)	-0.0033 (-1.49)					0.1346
$ASUE\_related\_dGDPR_t$	0.0113*** (13.06)	-0.0002 (-0.27)	-0.1346*** (-2.75)	0.0228 (1.07)	-0.1962** (-2.43)	0.0002 (0.13)	0.4774
$residual\_dGDPR_t$	-0.0001 (-0.10)	-0.0042** (-2.20)					0.0310
$residual\_dGDPR_t$	-0.0005 (-0.28)	-0.0022 (-1.16)	0.1542 (1.46)	0.0419 (0.90)	-0.4368** (-2.11)	0.0149** (2.37)	0.0741

***, **, * significant at the 1%, 5%, and 10% level, respectively.

We decompose GDP growth into two components, one related and the other unrelated to aggregate analyst forecast errors, using the regression model $dGDPR_t = b_0 + b_1 * detrended\_AAFE_t + e_t$. The first two rows report the results of regressing the component of GDP growth related to aggregate analyst forecast errors, $AAFE\_related\_dGDPR_t$, on stock market liquidity change, $dILLIQ_t$, from 1987Q1 to 2010Q4. The last two rows report the results of regressing the component of GDP growth unrelated to aggregate analyst forecast errors, $residual\_dGDPR_t$, on stock market liquidity change, $dILLIQ_t$, from 1987Q1 to 2010Q4. The controlling variables include stock market volatility, term spread, default spread, and market excess return. The Newey-West corrected *t*-statistics (Bartlett kernel with a lag length of 2) are reported in parentheses below the coefficient estimates.

Since aggregate analyst forecast errors are very informative on changes in the economy, aggregate analyst forecast errors could become an important state variable for future accounting and finance research. Also, since aggregate analyst forecast errors are predictable, the predictable part could be a useful investment tool. Moreover, since a large part of aggregate analyst forecast errors can be predicted using lagged macro variables, analysts could improve their earnings forecasts by taking into account the macro variables' predictability. We leave these issues for future research.

CHAPTER 3: STOCK PRICE DELAY AND BUSINESS CYCLE

3.1 Introduction

Fama's (1970) efficient market hypothesis posits that stock price quickly reflects available information. However, some stocks reflect market-wide information with a delay. Hou and Moskowitz (2005) use stock price delay in reflecting market-wide information to measure the extent of market frictions each individual firm encounters. Market frictions include transaction costs, stock illiquidity, and information asymmetry. They find that market frictions associated with lack of investor recognition appears the most responsible for causing price delay.[12] As firms become more popular, according to Hou and Moskowitz (2005), price delay measures of those stocks should decrease.

While Hong, Lim, and Stein (2000) show that bad firm specific news of small firms and firms with low analyst coverage travels slowly, McQueen, Pinegar, and Thorley (1996) find that small stocks tend to quickly adjust to bad common information as conveyed through large stocks, but adjust slowly to good common information.[13] It is conceivable that small stocks are less liquid and face higher market frictions, which may cause price delay in reflecting information.

[12] Hou and Moskowitz (2005)'s investor recognition variables are log of institutional ownership, log of number of analysts, shareholders, and employees, log of advertising expense, a regional exchange dummy, the average distance between each stock's headquarters and all U.S. airports as well as the nearest airport, and the average airfare between the nearest airport and all U.S. airports.

[13] McQueen, Pinegar, and Thorley (1996) document a directional asymmetry in the small stock concurrent and lagged response to large stock movements. When returns on large stocks are negative, the concurrent beta for small stocks is high, but the lagged beta is insignificant. This regression result shows bad common information travels fast to large and small stocks. However, when returns on large stocks are positive, small stocks have small concurrent betas and very significant lagged betas. This finding suggests good common information travels slowly to small stocks.

What makes the findings of these studies interesting is that price delay is asymmetric and depends on information types.

To further understand the price formation process at the market level, we extend Hou and Moskowitz (2005) to study aggregate price delay. In particular, we are interested in learning what factors may affect aggregate price delay and how aggregate price delay behaves in business cycles. By examining these issues, we hope to shed some light on investor trading behavior around business cycles and on the source of asymmetric price delay in reflecting good versus bad common information. We find that aggregate stock price delay is pro-cyclical, i.e., more price delay during economic expansions and less so during economic recessions. Intriguingly, we also find that, instead of market frictions or information production, it is the flight-to-quality behavior of investors that is most responsible for changes in the aggregate stock price delay around business cycles.[14]

To assist our analysis, we lay out three hypotheses for explaining how aggregate price delay may change as investors anticipate and/or respond to business cycles. The first one is related to market frictions. It is well known that market frictions could cause price delay.[15] As Fama (1991) notes that "A weaker and economically more sensible version of the efficiency hypothesis says that prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs (Jensen (1978))." Chordia, Roll, and Subrahmanyam (2000) show that transaction costs on individual stocks are

[14] According to Næs, Skjeltorp, and Ødegaard (2011), the term "flight to quality" refers to a situation where market participants suddenly shift their portfolios toward securities with less risk.

[15] Stocks may have no trading due to large bid-ask spreads. Lesmond, Ogden, and Trzcinka (1999) derive a transaction cost measure from zero return days. French and Roll (1986) uses stock return variances to study the arrival of information and reaction of traders.

time-varying and tend to comove together. Hameed, Kang, and Viswanathan (2010) document that large stock market declines increase the demand for liquidity as agents liquidate their positions across many assets and reduce the supply of liquidity as liquidity providers hit their wealth or funding constraints. Similarly, Næs, Skjeltorp, and Ødegaard (2011) show that stock liquidity tends to decline before a recession comes and start to improve before an expansion begins. Thus, the market frictions hypothesis predicts that aggregate price delay would increase as the economy heads towards a recession and decrease as the economy starts to expand.

The second hypothesis is related to information production. Information production activities, such as economists making macroeconomic forecasts, financial analysts generating research reports on individual firms, and companies announcing earnings, help institutional investors and individual investors to make investment decisions and allocate their wealth to the most efficient use. Veldkamp (2005) shows that information production activities increase during periods of economic expansions and decrease during periods of recessions.[16] Brockman, Liebenberg, and Schutte (2010) further explore connections among comovement of stocks, information production, and business cycle.[17] They find that when information production is high (low), comovement is low (high) and that comovement patterns are countercyclical. Their findings imply that when information production on individual firms is lower, market-wide information becomes more important, causing individual stocks to comove more. Thus, to the

[16] Veldkamp (2006) hypothesizes when information is costly, rational investors only buy information about a subset of assets. Because information production has high fixed costs, competitive producers charge more for low-demand information than for high-demand information. The low price of high-demand information makes investors want to purchase the same information that others are purchasing.

[17] Barberis, Shleifer, and Wurgler (2005) use additions to the S&P 500 to distinguish two views of return comovement: the traditional view, which attributes it to comovement in news about fundamental value, and an alternative view, in which frictions or sentiment delink it from fundamentals.

extent that more comovement speeds up the incorporating of market-wide information into stock prices, the information production hypothesis predicts that less information production would lead to less aggregate stock price delay during recessions.

The third hypothesis is related to the flight-to-quality behavior of investors, which refers to the tendency that when they anticipate the economy is going to enter a recession, investors sell risky stocks quickly and shift their funds toward safe securities (see, e.g., Longstaff (2004) and Næs, Skjeltorp, and Ødegaard (2011)). In line with this hypothesis, McQueen, Pinegar, and Thorley (1996) conjecture that investors attempt to sell all stocks quickly when news about the economy is bad; conversely, when the news is good, investors quickly buy large, easy to price stocks but take their time and shop around before buying smaller stocks. Thus, the flight-to-quality hypothesis argues that the rush to sell risky stocks, large and small, could speed up stock prices to reflect the market-wide information about the coming of a recession, and that aggregate price delay would increase due to small, illiquid stocks being left behind when the economy starts to expand.

We empirically test the aforementioned three hypotheses. First of all, to test the market frictions hypothesis, we use Amihud's (2002) illiquidity measure and aggregate it across stocks in each quarter to obtain an aggregate quarterly measure of market frictions. Our empirical results show that, consistent with Næs, Skjeltorp, and Ødegaard (2011), the aggregate market illiquidity starts to increase before a recession is declared and begins to decrease before an expansion starts. Interestingly, the aggregate stock price delay is inversely related to the aggregate stock market illiquidity. The aggregate stock price delay declines before a recession

comes, and rises before a recession ends. Thus, the evidence is inconsistent with the hypothesis that the change in aggregate stock price delay is caused by market frictions.

Secondly, to proxy for information production, we use institutional holding change, analyst coverage change, and dispersion of analyst earnings estimates, and use them to test the information production hypothesis.[18] When stocks have lower institutional holdings, lower analyst coverage, and lower dispersion of analyst earnings estimates, information production activities on individual firms are usually low. Our empirical results show that the aggregate stock price delay is not significantly related to aggregate institutional holding changes, analyst coverage changes, or dispersion of analyst earnings estimates. Thus, the information production hypothesis also fails to account for the behavior of the aggregate stock price delay.

Finally, to measure uncertainty about the economy investors face, we use market returns, aggregate volatility from individual stocks, implied market volatility (VIX),[19] consumer confidence index, and U.S. dollar index, and analyze these variables to test the flight-to-quality hypothesis. We find that both concurrent market returns and aggregate market volatility have significant explanation power on the aggregate stock price delay. In particular, the aggregate stock price delay decreases when aggregate market volatility increases and stock market returns are negative, and vice versa. The evidence is consistent with the hypothesis that the flight-to-quality behavior of investors speeds up the incorporation of negative market-wide information

[18] Brockman, Liebenberg, and Schutte (2010) expect a positive correlation between variability of analyst coverage and the degree of association between comovement and real GDP growth.

[19] Whaley (2008) mentions that financial news services have begun routinely reporting the level of the CBOE's Market Volatility Index or "VIX", for short. Practitioners normally use this index as a fear gauge.

into stock prices. Conversely, while better informed investors may start to speculate that the market conditions would improve soon, investors in general are uncertain about whether weak firms would survive from economic downturns and thus hesitate to buy their shares, causing aggregate stock price delay to rise before the onset of economic expansions.

Our findings contribute to the market frictions literature in the following ways. First, we show that the aggregate stock price delay varies with business cycles. This is contrary to the concept that stock price delay is just a firm-specific characteristic. Second, our findings show that market information travels faster when investors feel more uncertainty about the future economy. It is possible that since it takes two consecutive negative GDP growth quarters to start a recession, investors tend to be more alert when they have experienced a negative GDP growth quarter and started to pay more attention to changes in economic conditions and contemplate to move their wealth to less risky assets if conditions deteriorate, thus speeding up the incorporation of market information. Third, we document that the price delay of individual stocks tends to decrease and illiquidity of stocks tends to increase before and during a market downturn. This finding is different from the cross-section finding of Hou and Moskowitz (2005), who show that illiquid stocks tend to have larger price delay. Finally, while trading costs may increase before economic downturns arrive, the marginal benefits of acting on the information of possible economic downturns may outweigh the increased trading costs. Thus, applying the flight-to-quality hypothesis to explain the aggregate price delay surrounding business cycles is not inconsistent with Fama's (1991) efficient market hypothesis.

The rest of the paper is organized as follows. In the next section, we review the literature on market frictions hypothesis, information production hypothesis, and flight-to-quality

hypothesis. Section 3.3 describes our data and variables used in this paper. Section 3.4 reports empirical results. Section 3.5 concludes this essay.

3.2 Literature Review

3.2.1 Market Frictions Hypothesis

Fama (1970) argues that the theory of efficient markets is concerned with whether prices at any point in time "fully reflect" available information. While presenting several supporting evidence of semi-strong form market efficiency in which stock prices fully reflect all public available information, Fama (1991) proposes a weaker and economically more sensible version of the efficiency hypothesis in which prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs. Accordingly, an increase in trading costs would reduce investors' trading propensity, and slow down the speed with which information is impounded into stock prices.

While Hou and Moskowitz (2005) argue that price delay in reflecting public information is mainly due to low investor recognition, Lin et al. (2012) show that the price delay phenomenon can be better explained by the incidence of nontrading, as measured by Liu's (2006) turnover adjusted non-trading days. Since investors may endogenously decide not to trade if transaction costs outweigh the trading benefits (Lesmond, Ogden, and Trzcinka (1999)), more incidence of nontrading implies higher (latent) transaction costs. Thus, the evidence presented by Lin et al. (2012) is consistent with the market frictions hypothesis that transaction costs hinder the transmission of market-wide information, and are the main source of price delay.

In addition, previous studies also provide evidence that price delay results from high transaction costs. For example, Lin and Rozeff (1995) examine price adjustment between in-the-money convertible preferred stock prices and their underlying common stock prices, and find that the price deviation from theoretical prediction between these two securities could be largely attributed to the transaction costs of arbitrage. Chordia, Roll, and Subrahmanyam (2008) study the relationship between the size of bid-ask spread and market efficiency. They find that short-horizon return predictability from order flows is diminished when bid-ask spreads are narrower, and has declined over time with the minimum tick size. Their findings indicate that liquidity stimulates arbitrage activity, which, in turn, enhances market efficiency. Therefore, stock market liquidity affects arbitrage activities and further enhance market efficiency.

Chordia, Roll, and Subrahmanyam (2000) show that transaction costs, such as quoted spreads, quoted depth, and effective spreads, of individual stocks are time-varying and tend to comove with the aggregate transaction cost of the stock market. Hameed, Kang, and Viswanathan (2010) use proportional bid-ask spread as their key measure of liquidity and find changes in spreads are negatively related to market returns. Acharya and Pedersen (2005) identify those two correlations as commonality and flight-to-quality liquidity risk measures. Næs, Skjeltorp, and Ødegaard (2011) also find stock market liquidity declines before recessions and starts to improve before expansions. Since an increase in transaction costs may lead to more stock price delay, the market frictions hypothesis posits that aggregate stock price delay will increase as the economy approaches to a recession and the stock market becomes less liquid, and that aggregate stock price delay will decrease as the economy starts to expand and the market becomes more liquid.

3.2.2 Information Production Hypothesis

Morck, Yeung, and Yu (2000) document that stock prices move together more in poor economies than in rich economies. They attribute their finding to investor property rights - higher firm-specific returns variation is associated with stronger public investor property rights. In addition, Jin and Myers (2006) show that opaqueness (lack of transparency) is positively correlated with R-square of economies observed in the world. Their studies imply that stocks comove less in a more open information sharing environment and in an environment which encourages information production.

Veldkamp (2005) derives a model to show that agents undertake more economic activities in good times than in bad and that economic activity generates public information about the state of the economy. Following the logic of Morck et al. (2000) and Jin and Myers (2006), we can assume stocks may comove less in good times since good economy state encourages information production. Brockman, Liebenberg, and Schutte (2010) empirically substantiate the relation between information production and stock price comovement. They find when information production is high (low), stock price comovement is low (high). In addition, they find that comovement patterns are countercyclical.

Veldkamp (2006) provides a possible explanation for countercyclical behavior of stock price comovement. She derives a model to examine the relationship between information production costs and comovement of asset prices. When information is costly, rational investors only buy information about a subset of assets. Moreover, when investors price assets using a common subset of information, news about one asset affects other assets' prices and asset prices

comove. Hameed, Morck, Shen, and Bernard (2008) provide evidences to support this argument. They document that neglected stocks are priced using easily available information about other stocks that share similar fundamentals. They use number of analysts following a stock to distinguish "high profile" stocks from neglected stocks and find that prices of neglected stocks tend to comove with those stocks covered by analysts.

Since information production activity is low in bad times, we may assume information is more costly in bad times. Hence, stocks comove more with easily available market-wide information. To the extent that more comovement speeds up the incorporation of market-wide information into stock prices, our information production hypothesis assumes that less information production activity will cause less aggregate price delay during bad times.

3.2.3 Flight-to-quality Hypothesis

Investors tend to be more alerted and to seek safety when market news is bad. Barberis, Shleifer, and Wurgler (2005) use additions to the S&P 500 to examine the comovement of stocks and suggest stocks respond to general public news more quickly (less price delay) if investors recognize those stocks. They attribute the comovement of stocks to friction or sentiment-based explanation. Brunnermeier and Pedersen (2009) show that when the stock market declines, traders are forced to liquidate their assets to meet margin requirement or redemption from clients and could not provide enough liquidity in the market. Market liquidity and funding liquidity are mutually reinforcing and leading to liquidity spirals. At the same time, traders in the market move their wealth into assets with lower margin requirement and less volatility : a flight-to-quality phenomenon when risky securities become especially illiquid.

Longstaff (2004) documents that changes in consumer confidence, the amount of Treasury debt available to investors, and flows into equity and money market mutual funds affect the flight-to-quality liquidity premium in Treasury bond prices by comparing them with prices of bonds issued by Refcorp, a U.S. government agency, whose repayment of both coupon payments and principal amounts is implicitly guaranteed by the U.S. Treasury. Næs, Skjeltorp, and Ødegaard (2011) continue examining the flight-to-quality phenomenon. They use Lesmond et al. (1999) implicit trading cost measure, Roll (1984) estimate of the implicit spread, and Amihud (2002) price impact measure as liquidity measures in their study and find changes of these liquidity measures can predict future real GDP growth, changes in unemployment rate, real consumption growth, and growth in private investment after controlling current real GDP growth, term spread, credit spread, market volatility, and market excess return. They suggest their findings emerge from the flight-to-quality behavior of investors changing their portfolio compositions from small, illiquid stocks to liquid, low risk securities.

McQueen, Pinegar, and Thorley (1996) provide another evidence to support the flight-to-quality phenomenon. They find public bad news reflects in small stocks without much delay and a delayed reaction to good news for small stocks. They conjecture investors attempt to sell all stocks quickly when the market news is bad and take time to shop around small stocks when the market news is good. Intrigued by their findings and the flight-to-quality behavior of investors, we develop our flight-to-quality hypothesis. Our flight-to-quality hypothesis claims that the rush of investors to sell all risky stocks will speed up stock prices to reflect the market-wide information about the coming of a recession and that aggregate stock price delay will decrease due to small, illiquid stocks being left behind when the economy starts to expand. Aggregate stock price delay should be pro-cyclical according to the flight-to-quality hypothesis.

3.3 Data

We use Center for Research in Security Prices (CRSP) to collect stock return information. Our sample includes common stocks (with share code 10 or 11) listed on the NYSE from Jan 1945 to Dec 2010. In addition, we require each stock in our sample to be listed for the whole calendar year and its daily share price should be greater than $1 per share during the whole calendar year. We use the quarterly real GDP number from 1947Q1 to 2010Q4 of the Bureau of Economic Analysis (BEA) to construct the real GDP growth in each quarter. The institutional holding (13f) data is from Thomson Reuters for the period from 1980Q1 to 2008Q4. We use Institutional Brokers Estimate System (I/B/E/S) to collect quarterly analyst coverage (number of analysts following) of each firm in our sample. The analyst coverage data starts from 1984Q4 (1032 firms with analyst coverage) to 2010Q4 since there are only 110 firms with analyst coverage for our sample in 1984Q3. We use the Bloomberg terminal to collect consumer confidence index and U.S. dollar index data. The consumer confidence index data starts from February 1967 and the U.S. dollar index starts from January 1967.

3.3.1 Price Delay Measure

We follow Hou and Moskowitz (2005) to construct our price delay measure. The regression equations are as follows:

$$r_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_{j,t} \tag{3.1}$$

$$r_{j,t} = \alpha_j + \beta_j R_{m,t} + \sum_{n=1}^{4} \delta_{j,(-n)} R_{m,t-n} + \varepsilon_{j,t} \tag{3.2}$$

where $r_{j,t}$ is the weekly return of stock j and $R_{m,t}$ is the CRSP value-weighted market return in week t. For stocks in our sample, we run time series regressions (52 past weekly observations) for both equation (1) and (2) every week from 1947 to 2010 to get the R^2 from both the restricted regression (1) and unrestricted regression (2). The price delay measure in our study is defined as follows:

$$D1 = 1 - \frac{R^2_{restricted}}{R^2_{unrestrcted}} \tag{3.3}$$

The intuition of this measure could be described as follows: the $R^2_{restricted}$ measures a stock's return variation explained by the concurrent market return and the $R^2_{unrestricted}$ measures a stock's return variation explained by the concurrent plus four past weekly market returns. If the ratio between this two number is high (approaching to 1), there is not much additional explanatory power by adding past weekly market returns in the regression and the delay of market information transmission for the stock is low. Hence, the larger $D1$, the more stock return variation is captured by lagged weekly market returns and then the more price delay for the stock. After we get weekly price delay measures for each stock from 1947 to 2010, we keep the price delay observation in the end of March, June, September, and December to be each stock's price delay measure in the end of each quarter. We further take the equally weighted average of each stock's individual price delay measure to get aggregate stock price delay measure $AggreD1$ and its change for each quarter from 1947Q2 to 2010Q4. The augmented Dicky-Fuller test shows that aggregate stock price delay is stationary.

$$dAggreD1_t = \ln(AggreD1_t / AggreD1_{t-1}) \tag{3.4}$$

3.3.2 GDP Growth

We use seasonally adjusted quarterly real gross domestic product (GDP) from Bureau of Economic Analysis to measure the economy state. The quarterly data are in the unit of billions of chained 2005 dollars. Following Næs, Skjeltorp, and Ødegaard (2011), we take logarithm difference of the real GDP series to measure changes in economy from 1947Q2 to 2010Q4.

$$dGDPR_t = \ln(GDPR_t / GDPR_{t-1}) \tag{3.5}$$

3.3.3 Market Frictions Variable

We use daily Amihud (2002) price impact measure

$$ILLIQ_{i,T} = 1/D_T \sum_{t=1}^{D_T} \frac{|R_{i,t}|}{VOL_{i,t}} \tag{3.6}$$

to measure stock market illiquidity (market friction) in a quarter in this study, where D_T is the number of trading days within a time window T, $|R_{i,t}|$ is the absolute return on day t for security i, and $VOL_{i,t}$ is the dollar trading volume (in millions) of security i on day t. We calculate each stock's daily price impact, defined as its absolute return divided by its daily dollar trading volume (in millions) first and then take each stock's quarterly price impact average to be each stock's quarterly price impact. We further use equally-weighted quarterly price impact of each stock in the sample to represent the stock market friction measure. Since it is an illiquidity measure, a higher number of the measure means a less liquid stock market and the market friction is high. We also take a logarithm difference of the aggregate price impact to measure the market friction change in the stock market from 1947Q2 to 2010Q4.

$$dILLIQ_t = \ln(ILLIQ_t / ILLIQ_{t-1}) \tag{3.7}$$

3.3.4 Information Production Variables

We use institutional ownership, analyst coverage, and dispersion of analyst earnings estimates for information production proxies in our study. For institutional ownership, we divide the sum of shares owned of institutions by shares outstanding of the firm to calculate each sample firm's institutional holding. For each quarter, we take the equally-weighted average of each sample firm's institutional holding to be the aggregate institutional holding and take logarithm difference of the aggregate institutional holding to measure changes in aggregate institutional ownership from 1985Q1 to 2010Q4.

$$dINSHD_t = \ln(INSHD_t / INSHD_{t-1}) \tag{3.8}$$

For analyst coverage, for firms' fiscal quarter end in January, February, and last December, their observations on I/B/E/S are classified into the first quarter of the current year. Similarly, for firms' fiscal quarter end in September, October, and November, their observations on I/B/E/S are classified into the fourth quarter of the current year. For each firm, we take the latest number of analysts for earnings estimates for each estimated period to be a firm's analyst coverage. We further take the equally-weighted average of each firm's analyst coverage to be the aggregate analyst coverage and take logarithm difference of the aggregate analyst coverage to measure changes in aggregate analyst coverage from 1985Q1 to 2010Q4.

$$dANALYST_t = \ln(ANALYST_t / ANALYST_{t-1}) \tag{3.9}$$

For the dispersion of analyst earnings estimates, we follow the same quarter definition as analyst coverage. We take the standard deviation of each analyst's earnings forecast of a firm in a quarter to be the firm's dispersion of analyst earnings estimates. We winsorize firms with extreme value at 99%. We further take the equally-weighted average of each firm's dispersion of analyst earnings estimates to be aggregate dispersion of analyst earnings estimates and take logarithm difference of aggregate analyst earnings estimates to measure changes in aggregate dispersion of analyst earnings estimates from 1985Q1 to 2010Q4.

$$dDispersion_t = \ln(Dispersion_t / Dispersion_{t-1}) \tag{3.10}$$

3.3.5 Flight-to-quality Variables

When the market news is bad, investors tend to sell all stocks quickly. Under this circumstance, the stock market return is usually very negative and the market volatility is relatively high. Therefore, we use stock market return and stock market volatility to be flight-to-quality variables in our study. For the stock market return, we use the cumulative 3-month monthly S&P 500 index return to calculate the quarterly stock market return. For the stock market volatility, we calculate each sample stock’s quarterly return volatility and then take the equally-weighted average of these sample stocks’ return volatility to be the quarterly market volatility. We also include equally-weighted average of daily VIX to represent the quarterly market volatility from 1990Q1 to 2010Q4. In addition, Longstaff (2004) finds investors tend to move their wealth into less risky securities when consumer confidence is lower. Furthermore, investors also have higher demand for U.S. dollars when their uncertainty about the economy is high. Therefore, we also use quarterly change of consumer confidence index and quarterly

change of U.S. dollar index from Bloomberg to be another two proxies for flight-to-quality variables from 1967Q3 to 2010Q4.

3.4 Results

3.4.1 Summary Statistics of Variables

Our study investigates the relation between stock price delay and business cycle. As shown in Fig 3.1, the aggregate stock price delay comoves with the real GDP growth rate. The aggregate stock price delay tends to go higher when the GDP growth rate is higher. In addition, Fig 3.2 shows the change of aggregate stock price delay has a positive relation with the real GDP growth rate in the next quarter. Furthermore, from the past 11 recessions (defined by National Bureau of Economic Research), Fig 3.3 shows that the aggregate stock price delay declines in the starting quarter of each past 11 recession and the aggregate stock price delay remains low for the following quarters after recessions start. Fig 3.4 shows that the aggregate stock price delay starts to increase after each recession ends. From 1947 to 2010, our data show that aggregate stock price delay tends to comove with a business cycle. Therefore, market information transmission becomes faster when the economy is going to be bad and market information transmission becomes slower when the economy is going to recover. Table 3.1 summarizes our sample characteristics. During the overall sample period from 1947 to 2010, the quarterly change of the aggregate price delay is – 0.03%, showing that the market information transmission is becoming faster through these years. In addition, the aggregate price impact (our market friction) measure also declines over these years. The aggregate price delay may become lower due to a more liquid stock market. From 1985Q1 to 2008Q4 when we have our institutional ownership, analyst coverage, and dispersion of analyst earnings estimates data, the quarterly average

changes for those three variables are positive during this period. However, during past recession starting quarters after 1985, the number of analyst coverage tends to decline although the institutional holding does not change much. The aggregate dispersion of analyst earnings estimates seems increasing from the start of past three recessions. This fact shows that analysts may have more diverse opinions about a firm's earnings per share when the overall market uncertainty is high even though the information production activity may decrease. Our sample period for flight-to-quality variables such as market return, market volatility, change in consumer confidence index and change in U.S. dollar index is from 1967Q3 to 2010Q4. Over the whole period, average quarterly market return and volatility are positive and average quarterly changes

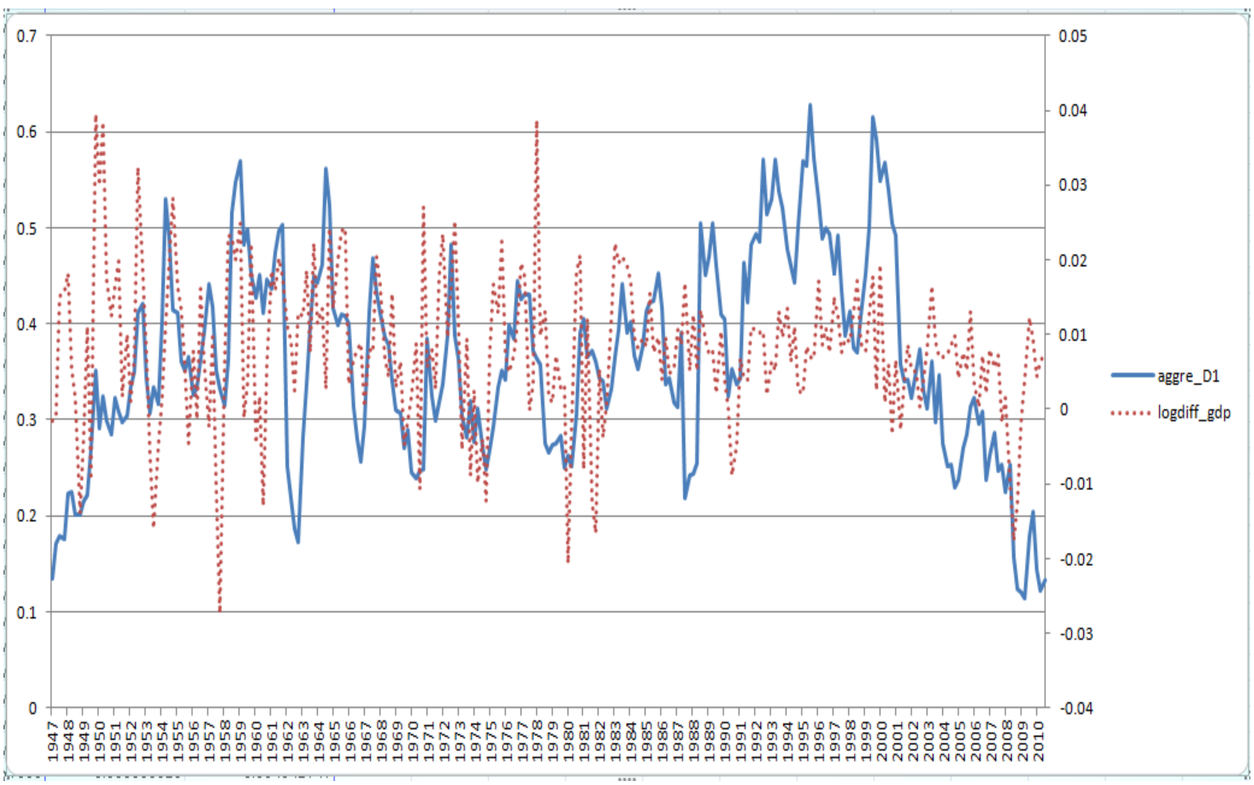

Figure 3.1 Aggregate Stock Price Delay and Real GDP Growth

The figure shows time-series plots of the aggregate stock price delay of sample firms and real GDP growth from 1947 to 2010. The sample firms include common stocks listed on the NYSE with stock price above $1 per share, listing for the whole calendar year. The left axis is for the solid line and aggregate price delay measure. The right axis is for the dotted line and real GDP growth rate.

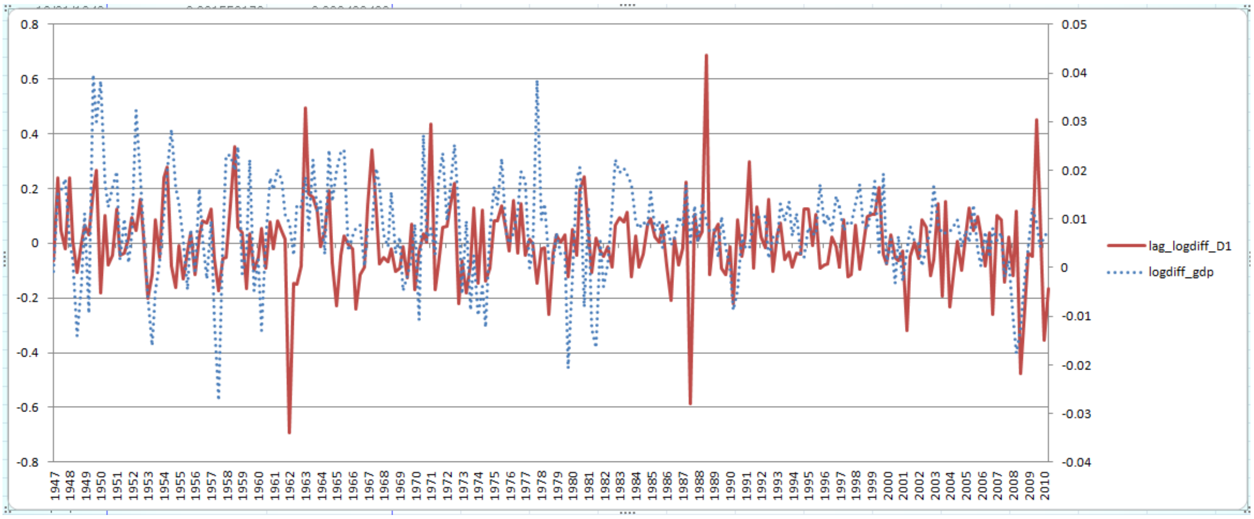

Figure 3.2 Lagged Aggregate Stock Price Delay Change and Real GDP Growth

The figure shows time-series plots of the lagged aggregate stock price delay change of sample firms and real GDP growth from 1947 to 2010. The sample firms include common stocks listed on the NYSE with stock price above $1 per share, listing for the whole calendar year. The left axis is for the solid line and the lagged aggregate stock price delay change measure. The right axis is for the dotted line and real GDP growth rate.

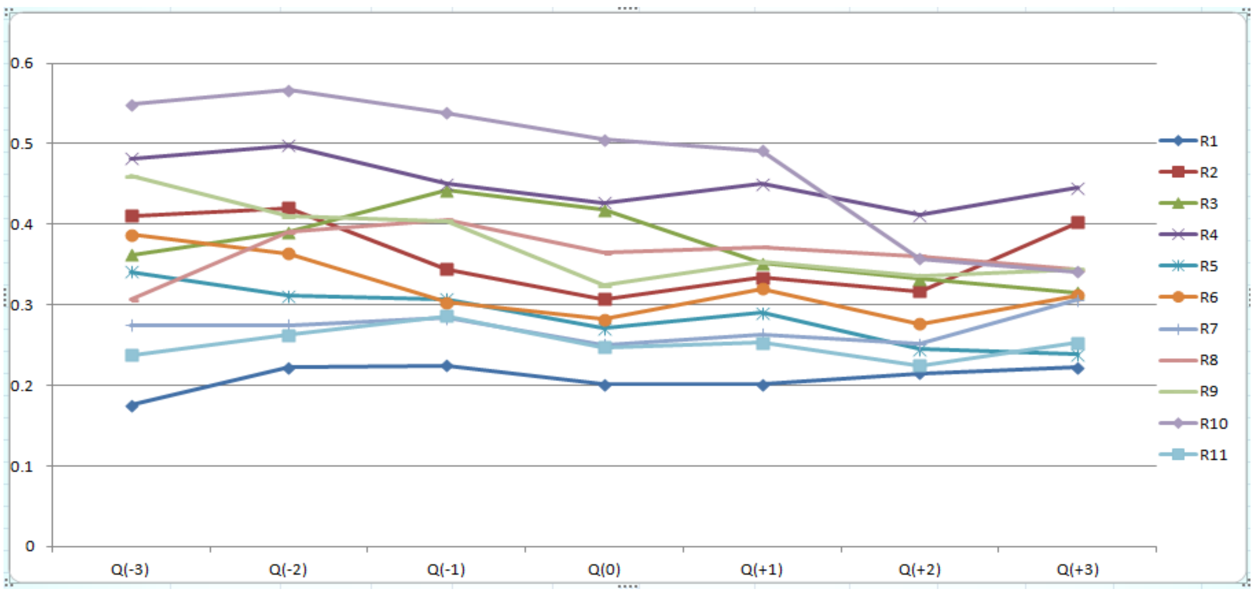

Figure 3.3 Aggregate Stock Price Delay in the Quarters around the Past 11 Recession Starting Quarter

The figure shows the aggregate stock price delay of sample firms in this study from 3 quarters before each recession starts to 3 quarters after each recession starts. The sample firms include common stocks listed on the NYSE with stock price above $1 per share, listing for the whole calendar year. According to the National Bureau of Economic Research (NBER), R1 is from Nov 1948 to Oct 1949, R2 is from July 1953 to May 1954, R3 is from Aug 1957 to Apr 1958, R4 is from Apr 1960 to Feb 1961, R5 is from Dec 1969 to Nov 1970, R6 is from Nov 1973 to March 1975, R7 is from Jan 1980 to July 1980, R8 is from July 1981 to Nov 1982, R9 is from July 1990 to March 1991, R10 is from March 2001 to Nov 2001, and R11 is from Dec 2007 to June 2009. Q(-3) indicates the quarter in which three quarters before the recession starts, Q(0) indicates the recession starting quarter, and Q(+3) indicates the quarter in which three quarters after the recession starts.

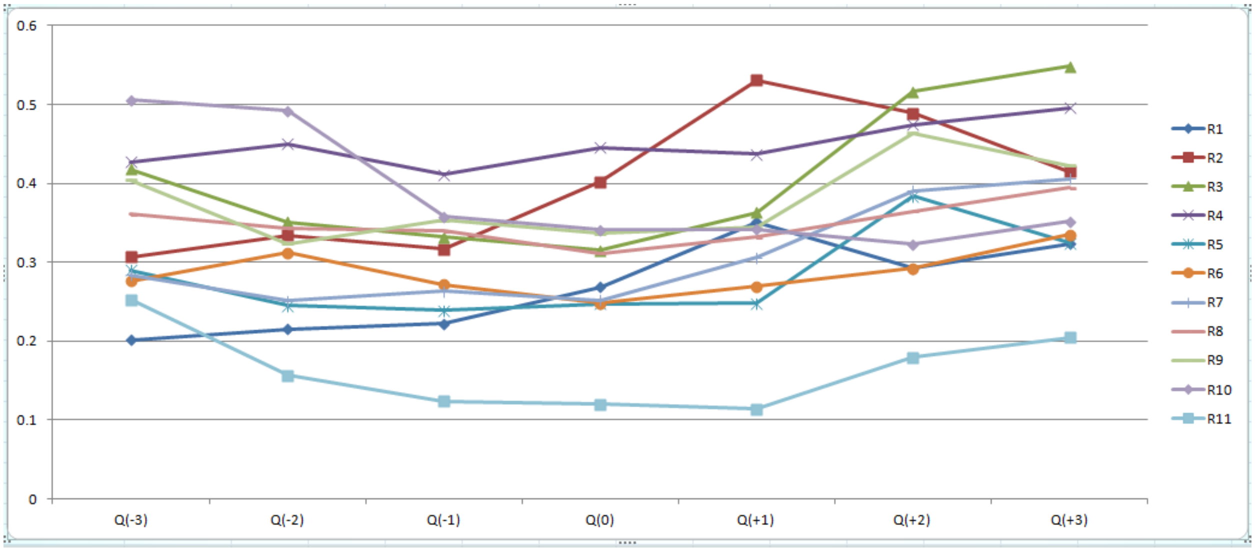

Figure 3.4 Aggregate Stock Price Delay in the Quarters around the Past 11 Recession Ending Quarter
The figure shows the aggregate price delay of sample firms in this study from 3 quarters before each recession ends to 3 quarters after each recession ends. The sample firms include common stocks listed on the NYSE with stock price above $1 per share, listing for the whole calendar year. According to the National Bureau of Economic Research (NBER), R1 is from Nov 1948 to Oct 1949, R2 is from July 1953 to May 1954, R3 is from Aug 1957 to Apr 1958, R4 is from Apr 1960 to Feb 1961, R5 is from Dec 1969 to Nov 1970, R6 is from Nov 1973 to March 1975, R7 is from Jan 1980 to July 1980, R8 is from July 1981 to Nov 1982, R9 is from July 1990 to March 1991, R10 is from March 2001 to Nov 2001, and R11 is from Dec 2007 to June 2009. Q(-3) indicates the quarter in which three quarters before the recession ends, Q(0) indicates the recession ending quarter, and Q(+3) indicates the quarter in which three quarters after the recession ends.

in consumer confidence index and U.S. dollar index are negative. The VIX measure starts from 1990Q1 and the average VIX is 20.40 from 1990Q1 to 2010Q4.

For the past eleven recessions, aggregate stock price delay tends to decline, analyst coverage tends to decrease, price impact increases, market return is negative, consumer confidence drops, and term spread also shortens. On average in the recession starting quarter, aggregate stock price delay declines 10.8%, analyst coverage decreases 2.22%, stock market price impact increases 7.59%, quarterly market return is negative 6.94%, consumer confidence index drops 9.18%, and term spread becomes narrower to 0.36%. When recessions end, aggregate stock price delay increases 1.24% , analyst coverage increases 3.57%, stock market price impact decreases 35.91%, quarterly market return is positive 12.46%, consumer confidence index increases 7.38%, and term spread becomes wider to 2.20%. Table 3.2 reports the

Table 3.1 Sample Characteristics

	1947Q1 to 2010Q4	1953Q3 to 2010Q4	1967Q3 to 2010Q4	1985Q1 to 2008Q4	1990Q1 to 2010Q4	Past 11 recession Starting quarters	Past 11 recession Ending quarters
main variables							
$dAggreD1_t$	-0.03%	-0.41%	-0.45%	-0.85%	-1.47%	-10.80%	1.24%
$dGDPR_t$	0.79%	0.75%	0.71%	0.69%	0.62%	0.22%	-0.21%
information production							
$dINSHD_t$				0.87%	0.82%	0.50%	1.21%
$dANALYST_t$				1.07%	1.06%	-2.22%	3.57%
$dDispersion_t$				0.68%	0.20%	8.65%	-0.44%
market friction							
$dILLIQ_t$	-1.79%	-1.62%	-1.23%	-1.20%	-2.80%	7.59%	-35.91%
Flight-to-quality							
$Mkret_t$		2.05%	1.88%	2.11%	1.86%	-6.94%	12.46%
$Volatility_t$		2.21%	2.37%	2.39%	2.48%	2.35%	2.45%
VIX_t					20.40	24.32	27.81
$dCCI_t$			-0.51%	-0.94%	-0.84%	-9.18%	7.38%
$dUSDindex_t$			-0.24%	-0.58%	-0.25%	-0.52%	-1.21%
control variables							
$Term\_spread_t$		1.41%	1.58%	1.75%	1.85%	0.36%	2.20%
$Default\_\ spread_t$		0.98%	1.10%	0.96%	0.95%	0.97%	1.34%
number of firms	1408	1467	1605	1610	1561	1316	1345
number of quarters	264	230	174	96	84	11	11

This table reports the average value of variables used in this study during the whole sample period and each sub-periods. The sample firms include NYSE common stocks with stock price above $1 and listing for the whole calendar year during the sample period from 1947Q1 to 2010Q4. The aggregate price delay change $dAggreD1_t$ is the logarithm difference between each equally-weighted individual stock price delay of each quarter *t* and previous quarter *t-1*. The real GDP growth $dGDPR_t$ is the logarithm difference of real GDP between current quarter *t* and previous quarter *t-1*. The aggregate institutional holding change $dINSHD_t$ is the logarithm difference between the equally-weighted average of percentages of sample stocks held by institution investors of quarter *t* and previous quarter *t-1*. The aggregate analyst coverage change $dANALYST_t$ is the logarithm difference between the equally-weighted number of analysts of individual stocks of quarter *t* and previous quarter *t-1*. The aggregate dispersion of analyst earnings estimates is the logarithm difference between the equally-weighted standard deviation of analyst earnings estimates of each company of quarter *t* and previous quarter *t-1*. The aggregate price impact change $dILLIQ_t$ is the logarithm difference between the equally-weighted quarterly individual stock price impact from Amuhuid (2002) of quarter *t* and previous quarter *t-1*. The market return $Mkret_t$ is the 3-month cumulative monthly S&P 500 index return of the quarter. The market volatility $Volatility_t$ is from equally weighted average of the sample firms' stock return standard deviation during the quarter. The VIX index VIX_t is the implied volatility of S&P500 index from CBOE. The consumer confidence index change $dCCI_t$ is the logarithm difference between the quarter *t* and previous quarter *t-1*. The U.S. dollar index change $dUSDindex_t$ is the logarithm

(Table 3.1 continued)
difference between the quarter *t* and previous quarter *t-1*. The term spread $Term\_spread_t$ is the yield difference between 10-year Treasury note rate and 3-month Treasury bill rate. The default spread $Default\_ spread_t$ is the difference between Moody's Baa bond yield and Moody's Aaa bond yield. Throughout the study, the term spread information starts from 1953Q3, the consumer confidence index and U.S. dollar index start from 1967Q3, the institutional ownership change and the aggregate analyst coverage change information starts from 1985Q1, the aggregate institutional holding change information ends in 2008Q4, and the S&P implied volatility index starts from 1990Q1.

Table 3.2 Correlation Matrix

	$dAggreD1_{t-1}$	$dINSHD_{t-1}$	$dANALYST_{t-1}$	$dDispersion_{t-1}$	$dILLIQ_{t-1}$	$Mkret_{t-1}$	$Volatility_{t-1}$	VIX_{t-1}	$dCCI_{t-1}$	$dUSDindex_{t-1}$	$Term\_spread_{t-1}$	$Default\_ spread_{t-1}$
$dGDPR_t$	**0.23**	**0.13**	**0.20**	0.03	**-0.35**	**0.29**	**-0.28**	**-0.34**	**0.38**	-0.05	**0.15**	**-0.22**
	(0.0002)	**(<.0001)**	**(0.0411)**	(0.7525)	**(<.0001)**	**(<.0001)**	**(<.0001)**	**(0.0017)**	**(<.0001)**	(0.5402)	**(0.0276)**	**(0.0005)**
$dAggreD1_{t-1}$		0.13	0.04	0.13	**-0.29**	**0.33**	**-0.32**	**-0.35**	0.12	0.08	0.03	-0.09
		(0.2119)	(0.6875)	(0.1733)	**(<.0001)**	**(<.0001)**	**(<.0001)**	**(0.0011)**	(0.1116)	(0.2641)	(0.6439)	(0.1393)
$dINSHD_{t-1}$			-0.06	0.17	**-0.47**	**0.24**	**-0.23**	-0.12	0.09	0.05	0.08	-0.03
			(0.5353)	(0.1070)	**(<.0001)**	**(0.0187)**	**(0.0248)**	(0.2880)	(0.3966)	(0.6104)	(0.4140)	(0.7614)
$dANALYST_{t-1}$				**0.33**	0.07	-0.04	0.01	0.04	-0.17	-0.07	-0.05	-0.04
				(0.0007)	(0.4795)	(0.7169)	(0.9525)	(0.6869)	(0.0833)	(0.5121)	(0.5947)	(0.7143)
$dDispersion_{t-1}$					0.05	0.07	0.03	0.14	**-0.19**	0.04	-0.12	0.11
					(0.6243)	(0.4673)	(0.7598)	(0.1999)	**(0.0482)**	(0.6964)	(0.2208)	(0.2502)
$dILLIQ_{t-1}$						**-0.46**	**0.27**	**0.43**	**-0.41**	0.02	-0.10	0.07
						(<.0001)	**(<.0001)**	**(<.0001)**	**(<.0001)**	(0.7810)	(0.1349)	(0.2337)
$Mkret_{t-1}$							**-0.30**	**-0.35**	**0.21**	-0.14	0.11	-0.02
							(<.0001)	**(0.0011)**	**(0.0055)**	(0.0713)	(0.1014)	(0.8147)
$Volatility_{t-1}$								**0.89**	**-0.29**	0.10	**0.13**	**0.54**
								(<.0001)	**(0.0001)**	(0.2028)	**(0.0498)**	**(<.0001)**
VIX_{t-1}									**-0.37**	0.11	0.09	**0.76**
									(0.0005)	(0.3207)	(0.4409)	**(<.0001)**
$dCCI_{t-1}$										0.06	0.13	**-0.16**
										(0.4365)	(0.0843)	**(0.0401)**
$dUSDindex_{t-1}$											-0.07	**0.15**
											(0.3407)	**(0.0401)**
$Term\_spread_{t-1}$												**0.29**
												(<0.0001)

This table shows the Pearson correlation coefficients between variables used in the analysis. The associated p-values are reported in parentheses below each correlation coefficient.

correlation among variables used in this study. The real GDP growth has statistically significant correlation with variables in the previous quarter: positive correlation 23% with the aggregate price delay change, positive correlation 13% with institutional holding change, positive correlation 20% with analyst coverage change, negative correlation 35% with stock market price impact, positive correlation 29% with stock market return, negative correlation 28% with stock market volatility, negative correlation 34% with VIX, positive correlation 38% with consumer confidence change, positive correlation 15% with term spread, and negative correlation 22% with default spread.

One interesting observation here is the aggregate analyst coverage change has a positive correlation with future GDP growth. For the main variable aggregate price delay change, we find it has a negative correlation 29% with the aggregate stock market price impact change, a positive correlation 33% with market return, a negative correlation 32% with stock market volatility, and a negative correlation 35% with VIX. We continue investigating aggregate stock price delay change property in the following tables. For the institutional ownership change, we find it has a negative correlation 47% with stock market price impact change, a positive correlation 24% with stock market return, and a negative correlation 23% with stock market volatility. Analyst coverage change has a positive correlation 33% with dispersion of analyst earnings estimates and suggests that more information productivity may lead to more different opinions from analysts. Changes in dispersion of analyst earnings estimates have negative correlation 19% with changes in consumer confidence index and this fact suggests that analysts tend to have more diverse opinions when the market uncertainty is high. Stock market price impact change has a negative correlation 46% with stock market return, a positive correlation 27% with stock market volatility a positive correlation 43% with VIX, and a negative correlation 41% with changes in consumer

confidence index. Stock market return has a negative correlation 30% with stock market volatility, a negative correlation 35% with VIX, and a positive correlation 21% with changes in consumer confidence index. Stock market volatility has a positive correlation 89% with VIX, a negative correlation 29% with changes in consumer confidence index, a positive correlation 13% with term spread, and a positive correlation 54% with default spread. VIX has a negative correlation 37% with changes in consumer confidence index and a positive correlation 76% with default spread. Changes in consumer confidence index have a negative correlation 16% with default spread. Changes in U.S. dollar index have a positive correlation 15% with default spread. Finally, term spread has a positive correlation 29% with default spread.

3.4.2 Regression Results

We examine the prediction power of the aggregate stock price delay change on future GDP growth in Table 3.3. The model estimated is as follows:

$$\begin{aligned} dGDPR_t &= \alpha + \beta_1 * dAggreD1_{t-1} + \beta_2 * dGDPR_{t-1} + \beta_3 * dILLIQ_{t-1} \\ &+ \beta_4 * term\_spread_{t-1} + \beta_5 * default\_spread_{t-1} + \beta_6 * Volatility_{t-1} + \beta_7 * MKret_{t-1} + \varepsilon_t \end{aligned} \tag{3.11}$$

The aggregate price delay change significantly predict future GDP growth rate after we add current GDP growth rate, aggregate stock price impact change, term spread, and default spread. However, the predictable power of the aggregate stock price delay change disappears after we add market excess return and stock market volatility into our regression. This result may be due to the high correlation 33% between stock market return and the aggregate stock price delay change. The aggregate stock price impact change still maintains its explanatory power on future GDP growth rate. Hence, stock market liquidity change is more powerful than stock price delay change in predicting future economy change.

We test the market frictions hypothesis in Table 3.4. The model estimated is as follows:

$$dAggreD1_t = \alpha + \beta_1 * dILLIQ_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.12}$$

The results show that the change in the aggregate stock price impact significantly explains the change in the aggregate price delay. However, the sign is negative, which is in contrast to our prediction that higher market frictions lead to higher stock price delay. Our results show that the aggregate stock price delay tends to decline when market frictions are higher. Hence, our empirical evidence contradicts our market frictions hypothesis.

We test our information production hypothesis in Table 3.5. The models estimated are as follows:

$$dAggreD1_t = \alpha + \beta_1 * dINSHD_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.13}$$

$$dAggreD1_t = \alpha + \beta_1 * dANALYST_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.14}$$

$$dAggreD1_t = \alpha + \beta_1 * dANALYST_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.15}$$

The results show that changes in institutional ownership, changes in analyst coverage, and changes in dispersion of analyst earnings estimates fail to significantly explain the change in the aggregate stock price delay although their coefficients are positive. Hence, we reject our information production hypothesis. Finally, we test our flight-to-quality hypothesis in Table 3.6. The models estimated are as follows:

$$dAggreD1_t = \alpha + \beta_1 * Mkret_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.16}$$

Table 3.3 Aggregate Price Delay Change and Real GDP Growth

Dependent variable	*intercept*	*dAggreD1$_{t-1}$*	*dGDPR$_{t-1}$*	*dILLIQ$_{t-1}$*	*Term_spread$_{t-1}$*	*Default_ spread$_{t-1}$*	*Volatility$_{t-1}$*	*Mkret$_{t-1}$*	*Adj_RSQ*
dGDPR$_t$	0.0053***	0.0121***	0.3420***						0.1610
	(6.83)	(3.80)	(5.64)						
dGDPR$_t$	0.0055***	0.0076**	0.2986***	-0.0086***					0.2172
	(7.63)	(2.50)	(4.94)	(-4.19)					
dGDPR$_t$	0.0069***	0.0060**	0.2444***	-0.0080***	0.1211**	-0.3088**			0.2404
	(3.97)	(2.13)	(3.19)	(-3.99)	(2.44)	(-2.33)			
dGDPR$_t$	0.0079***	0.0038	0.2459***	-0.0062***	0.1118**	-0.2558*	-0.0647	0.0150**	0.2482
	(2.86)	(1.26)	(3.11)	(-2.83)	(2.31)	(-1.79)	(-0.61)	(2.05)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

This table reports the results by regressing the real GDP growth in the current quarter on the aggregate price delay change in the previous quarter after controlling several variables in the previous quarter. The model estimated is

$$dGDPR_t = \alpha + \beta_1 * dAggreD1_{t-1} + \beta_2 * dGDPR_{t-1} + \beta_3 * dILLIQ_{t-1} + \beta_4 * term\_spread_{t-1} + \beta_5 * default\_spread_{t-1} + \beta_6 * Volatility_{t-1} + \beta_7 * Mkret_{t-1} + \varepsilon_t$$

For regression without the term spread, the time period is from 1947Q3 to 2010Q4 and for regression including the term spread, the time period is from 1953Q3 to 2010Q4. The Newey-West corrected t-statistics (with Bartlett kernel with a lag length of 4) are reported in parentheses below the coefficients estimates.

Table 3.4 Aggregate Price Delay and Market Frictions

Dependent variable	*intercept*	$dILLIQ_t$	$Term\_spread_t$	$Default\_spread_t$	Adj_RSQ
$dAggreD1_t$	-0.0028	-0.1427***			0.0777
	(-0.34)	(-3.85)			
$dAggreD1_t$	0.0087	-0.1380***	0.2624	-1.9884	0.0710
	(0.34)	(-3.76)	(0.36)	(-0.74)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.
This table reports the results by regressing the aggregate price delay change in the current quarter on the aggregate price impact change in the concurrent quarter after controlling current term spread and default spread. The model estimated is

$$dAggreD1_t = \alpha + \beta_1 * dILLIQ_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

For regression without term spread, the time period is from 1947Q3 to 2010Q4 and for regression including term spread, the time period is from 1953Q3 to 2010Q4. The Newey-West corrected t-statistics (with Bartlett kernel with a lag length of 4) are reported in parentheses below the coefficients estimates.

Table 3.5 Aggregate Price Delay and Information Production

Panel A

Dependent variable	*Intercept*	$dINSHD_t$	$Term\_spread_t$	$Default\_spread_t$	Adj_RSQ
$dAggreD1_t$	-0.0239	1.7672			0.0061
	(-1.28)	(1.55)			
$dAggreD1_t$	0.0605	1.7147	-0.3647	-8.0611	0.0277
	(1.24)	(1.53)	(-0.31)	(-1.64)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

(Table 3.5 continued)

Panel B

Dependent variable	*Intercept*	$dANALYST_t$	$Term\_spread_t$	$Default\_spread_t$	Adj_RSQ
$dAggreD1_t$	-0.0100	0.0549			0.0016
	(-0.77)	(0.59)			
$dAggreD1_t$	0.0773**	0.0450	0.4932	-9.6338**	0.0325
	(2.19)	(0.49)	(0.39)	(-2.46)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel C

Dependent variable	*Intercept*	$dDispersion_t$	$Term\_spread_t$	$Default\_spread_t$	Adj_RSQ
$dAggreD1_t$	-0.0109	0.1221			0.0082
	(-0.85)	(1.12)			
$dAggreD1_t$	0.0790**	0.1590	0.9302	-10.6434**	0.0625
	(2.18)	(1.71)	(0.76)	(-2.64)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

This table reports the results by regressing the aggregate price delay change in the current quarter on the aggregate institutional holding change , the aggregate analyst coverage change, and the dispersion of analyst earnings estimates change in the concurrent quarter after controlling current term spread and default spread. The models estimated are

$$dAggreD1_t = \alpha + \beta_1 * dINSHD_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

$$dAggreD1_t = \alpha + \beta_1 * dANALYST_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

$$dAggreD1_t = \alpha + \beta_1 * dDispersion_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

For regression with the aggregate institutional holding, the time period is from 1984Q4 to 2008Q4 and for regression with the aggregate analyst coverage and dispersion of analyst earnings estimates change, the time period is from 1984Q4 to 2010Q4. The Newey-West corrected t-statistics (with Bartlett kernel with a lag length of 4) are reported in parentheses below the coefficients estimates.

$$dAggreD1_t = \alpha + \beta_1 * Volatility_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.17}$$

$$dAggreD1_t = \alpha + \beta_1 * VIX_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.18}$$

$$dAggreD1_t = \alpha + \beta_1 * dCCI_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.19}$$

$$dAggreD1_t = \alpha + \beta_1 * dUSDindex_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t \tag{3.20}$$

$$\begin{aligned} dAggreD1_t &= \alpha + \beta_1 * Mkret_t + \beta_2 * Volatility_t + \beta_3 * dILLIQ_t \\ &+ \beta_4 * term\_spread_t + \beta_5 * default\_spread_t + \varepsilon_t \end{aligned} \tag{3.21}$$

Our empirical results show that both current market return and market volatility significantly explain the changes in the aggregate stock price delay. The aggregate stock price delay tends to increase when the stock market return is negative and when the stock market volatility is higher. Changes in consumer confidence index and changes in U.S. dollar index fail to significantly explain changes in aggregate stock price delay. After we add the change in stock market price impact into the regression, the explanation power of the flight-to-quality variables still exists. Therefore, we attribute the aggregate price delay change to flight-to-quality behavior of investors.

3.5 Conclusion

This essay studies the relationship between stock price delay and business cycle. We empirically test whether information production, market frictions, and flight-to-quality could provide explanations for stock price delay change in a business cycle. Our findings show that institutional holding, analyst coverage, and dispersion of analyst earnings estimates could not significantly account for changes in stock price delay through time. In addition, while stock market liquidity dries up and transaction costs increase during a recession, stock price delay

Table 3.6 Aggregate Price Delay and Flight-to-quality

Panel A

Dependent variable	*Intercept*	$Mkret_t$	$Term\_spread_t$	$Default\_ spread_t$	*Adj_RSQ*
$dAggreD1_t$	-0.0131	0.6266***			0.1034
	(-1.45)	(3.91)			
$dAggreD1_t$	0.0034	0.6272***	0.2110	-2.4503	0.1048
	(0.14)	(3.83)	(0.26)	(-0.93)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel B

Dependent variable	*intercept*	$Volatility_t$	$Term\_spread_t$	$Default\_ spread_t$	*Adj_RSQ*
$dAggreD1_t$	0.1678***	-7.7540***			0.0986
	(4.94)	(-5.08)			
$dAggreD1_t$	0.1543***	-9.2208***	0.5666	3.7337	0.0996
	(4.11)	(-3.86)	(0.75)	(1.28)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel C

Dependent variable	*intercept*	VIX_t	$Term\_spread_t$	$Default\_ spread_t$	*Adj_RSQ*
$dAggreD1_t$	0.1133**	-0.0063***			0.1118
	(2.53)	(-2.91)			
$dAggreD1_t$	0.1046***	-0.0036	0.8596	-6.4414	0.1071
	(3.07)	(-1.33)	(0.68)	(-1.41)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

(Table 3.6 continued)

Panel D

Dependent variable	*intercept*	$dCCI_t$	$Term\_spread_t$	$Default\_ spread_t$	*Adj_RSQ*
$dAggreD1_t$	-0.0030	0.1382			0.0089
	(-0.33)	(1.49)			
$dAggreD1_t$	0.0215	0.1197	0.2601	-2.6217	0.0039
	(0.62)	(1.45)	(0.31)	(-0.74)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel E

Dependent variable	*intercept*	$dUSDindex_t$	$Term\_spread_t$	$Default\_ spread_t$	*Adj_RSQ*
$dAggreD1_t$	-0.0029	0.3305			0.0015
	(-0.30)	(0.87)			
$dAggreD1_t$	0.0302	0.4199	0.5845	-3.8420	0.0048
	(0.82)	(1.25)	(0.71)	(-1.00)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

Panel F

Dependent variable	*intercept*	$Volatility_t$	$Mkret_t$	$dILLIQ_t$	$Term\_spread_t$	$Default\_ spread_t$	*Adj_RSQ*
$dAggreD1_t$	0.1008***	-6.2821***	0.3830***	-0.0595**	0.1166	2.3315	0.1585
	(2.95)	(-3.20)	(2.64)	(-2.05)	(0.17)	(0.92)	

***, **, * significant at the 1%, 5%, and 10% level, respectively.

This table reports the results by regressing the aggregate price delay change in the current quarter on the market return or the market volatility of the concurrent quarter after controlling current term spread and default spread. The models estimated are

(Table 3.6 continued)

$$dAggreD1_t = \alpha + \beta_1 * Mkret_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

and

$$dAggreD1_t = \alpha + \beta_1 * Volatility_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

and

$$dAggreD1_t = \alpha + \beta_1 * VIX_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

and

$$dAggreD1_t = \alpha + \beta_1 * dCCI_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

and

$$dAggreD1_t = \alpha + \beta_1 * dUSDindex_t + \beta_2 * term\_spread_t + \beta_3 * default\_spread_t + \varepsilon_t$$

For regression without the term spread, the time period is from 1947Q2 to 2010Q4 and for regression including the term spread, the time period is from 1953Q2 to 2010Q4. For regression with consumer confidence index and U.S. dollar index, the time period is from 1967Q3 to 2010Q4. The Newey-West corrected t-statistics (with Bartlett kernel with a lag length of 4) are reported in parentheses below the coefficients estimates. In the Panel F of this table, we report the regression result for the model estimated:

$$dAggreD1_t = \alpha + \beta_1 * Mkret_t + \beta_2 * Volatility_t + \beta_3 * dILLIQ_t + \beta_4 * term\_spread_t + \beta_5 * default\_spread_t + \varepsilon_t$$

declines and market information transmission become faster in the meantime. Finally, stock market return, stock market volatility, changes in consumer confidence index, and changes in U.S. dollar index subsume a great portion of stock price delay variation during business cycles. Our results imply when investors feel high level of uncertainty when market news is bad, they sell risky securities such as stocks. Because high transaction costs of stocks will not hinder investors' selling activities that much when investors' expectation about economy is bad, we conclude flight-to-quality behavior of investors most accounts for stock price delay change in a business cycle.

Previous studies show that stocks tend to comove when the market news is bad. We add new evidence that stocks reflect market information faster when current market news is bad and future GDP growth is going to slow down. We find stock price delay acts pro-cyclically and only the flight-to-quality behavior of investors explains this phenomenon well. This finding helps our understanding of stock price formation process during the transitions of business cycles and provides another indicator for the future economy state.

CHAPTER 4: CONCLUSION

This dissertation examines changes of aggregate analyst forecast errors and aggregate stock price delay in a business cycle. In the first essay we find aggregate analyst forecast errors fluctuate with concurrent GDP growth rate. After controlling the predictable component of the aggregate analyst forecast errors, we find past stock market liquidity change loses its explanation power on the economy. Those results indicate that smart investors' informed trading is built on their information advantages over financial analysts. In the second essay we find aggregate stock price delay has a pro-cyclical pattern. Both market frictions and information production explanations fail to account for this phenomenon. We find only flight-to-quality behavior of investors is most responsible for this pro-cyclical aggregate stock price delay behavior. Investors move their wealth to safer assets such as more liquid stocks, Treasury securities, or even just cash when they feel very uncertain about the economy and when the economy is bad.

Since both aggregate analyst forecast errors and aggregate stock price delay highly correlate with the real GDP growth rate, innovations of both these two variables could be used as state variables to represent information risk factors in future asset pricing research. In addition, the correlation level between aggregate analyst forecast errors and the real GDP growth rate may signal the quality of analysts in different countries. Higher correlation between the aggregate analyst forecast errors and the real GDP growth rate may imply more informed trading and a less efficient market. Finally, we may also compare aggregate analyst forecast errors and aggregate stock price delay of different industries to know more about the differences among industries.

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