Information Content of Analyst Recommendations in the Banking Industry

Abstract

After analyzing a sample of 23,632 analyst recommendations of banks, we find that both, analyst recommendation levels and recommendation changes, trigger a significant immediate impact on bank values. This result extends the findings of Barber et al. (2010) and suggests that even in an industry that is characterized by a high degree of information asymmetry (such as banking), analysts are able to provide new information to the investors. Furthermore, we find that analyst recommendations are more informative for banks with a higher degree of information asymmetry and for riskier banks. Similarly, regulation that decreased the information asymmetry (Sarbanes-Oxley Act) or the risk (Dodd-Frank Act) of the banking industry also decreased the information content of analyst recommendations, and regulation that increased the risk of the banking industry (Gramm-Leach-Bliley Act) also increased the information content of analyst recommendations. These results hold for positive and negative recommendations. We also find that positive recommendations are less informative for complex banks. Our results are robust to several measures of the information content of analyst recommendations; several measures of information asymmetry, risk, and complexity; and different sample selection criteria.

1. Introduction

Numerous studies have documented that analyst recommendations convey valuable information to investors (Khorana, Mola, Rau, 2012; Womack, 1996; Givoly and Lakonishok, 1979; Lys and Sohn, 1990; Francis and Soffer, 1997; and Moshirian, Ng, and Wu, 2009). Analysts both provide new information and interpret public information (Asquith et al., 2005). These studies show that the investment value of analyst recommendations varies depending on the analyst's skills and characteristics. However, the analyst's ability to offer valuable information could also depend on the degree of difficulty that the analyst faces, which is influenced both by the opacity, complexity, and risk of the firm being analyzed and by time variation in the information environment in which the analyst operates. Little is known about how the level of difficulty affects the analyst's ability to provide new information or interpret previously released information.

In an environment in which investors face difficulty evaluating a firm (such as opaque, complex, or uncertain environments) the analyst's expertise could be very valuable for investors. A counter argument is that a highly opaque, complex, or uncertain environment could inhibit the analyst's ability to collect and process the information, and therefore provide valuable information to investors. Previous studies have found that analysts are more likely to follow firms that disclose more information or are more transparent, which facilitates analysts' task (e.g., Lang and Lundholm, 1996; Jiraporn et al., 2012); however, it is unclear whether firm opacity makes analysts recommendation more or less valuable.

We investigate the effect of uncertainty in the information environment on the information content of analyst recommendations in the banking industry. Specifically, we test how bank characteristics (information asymmetry, bank complexity and bank risk) and the regulatory environment affect the information content of analyst recommendations.

Boni and Womack (2006) find that analyst recommendations are particularly valuable to rank stocks within industries. We focus on the banking industry, which provides an ideal framework for examining the impact of the information environment on the content of analyst recommendations for the following reasons. First, numerous studies show that banks are significantly more opaque than non-banks (e.g., Jones, Lee, and Yeager, 2013). Studies by Polonchek, Slovin, and Sushka (1989), Cornett, Fayman, Marcus, and Tehranian (2011) and others find that banks react significantly different from other industries to news signals.

Second, bank opacity varies significantly among banks and over time (Flannery, Kwan, and Nimalendran, 2013). This variation is partially due to shifts in bank regulation, and motivates us to measure the effect of firm opacity and complexity on the information content of analyst recommendations over time. These regulatory reforms include the Riegle-Neal Act, the Gramm-Leach-Bliley Act, and the Dodd-Frank Act.

Third, due to the use of derivative products, banks have become very complex over the recent years, and the complexity issue is more severe in the larger banks. According to De Nicolo and Kwast (2002), the industry consolidation has made banking entities more complex. This cross-sectional and time-series variation in opacity and complexity allows us to measure the effect that the degree of difficulty has on the information content of analyst recommendations over time.

By focusing on analyst recommendations in the banking industry, we attempt to answer the following question: How does the degree of uncertainty in the bank's environment affect the analyst's ability to provide valuable information to the investors and influence the share price? To the best of our knowledge, no prior study has examined the impact of analyst recommendations in the banking industry.

We find that both, analyst recommendation levels and recommendation changes, provide new information to the banking industry and trigger a significant immediate impact on bank values. This is consistent and extends the findings of Barber et al. (2010). Additionally, we find that analyst recommendations are more informative for banks with a higher degree of information asymmetry (i.e., smaller banks with low analyst following). Furthermore, regulation that reduced the information asymmetry in the banking industry (such as Sarbanes-Oxley Act) also reduced the information content of analyst recommendations. These results suggest that analysts of the banking industry are able to produce what otherwise would be private information and pass it on to the investors through their recommendations, thus reducing the information asymmetry in the banking industry.

In addition, we find that positive and negative recommendations are more informative for riskier banks (banks with higher return volatility, higher beta, and lower capital ratios). Analyst recommendations are also more informative when they are issued in riskier periods (periods in which the implied market volatility is higher). Furthermore, positive and negative recommendations become more informative after regulation that increased the risk in the banking industry (Gramm-Leach-Bliley Act) and less informative after regulation that decreased the risk in the banking industry (Dodd-Frank Act). These results suggest that when risk is higher, investors rely more on analyst recommendations for their investment decisions.

The results mentioned above hold for positive and for negative recommendations. They are also robust to several proxies used to measure the bank's degree of information asymmetry and risk, several methods of measuring the information content of analyst recommendations[1], and to different methods of dividing the sample into positive and negative recommendations.

We also find that recommendations are less informative for complex banks (banks that rely more heavily on non-traditional banking activities such as insurance and investment banking; or banks with greater growth options); however this result only holds for the subsamples of positive

[1] Following Loh and Stulz (2011) we use the announcement return in the window (0,1) to proxy for the information content of analyst recommendations. Loh and Stulz argue that if a recommendation has a large impact on the stock price, it does so because it provides new information. We use three methods to measure the announcement return: the market model, the Fama-French three factor model, and the Fama-French-Carhart four factor model.

recommendations. This result suggests that when the bank is highly complex, even financial experts (such as analysts) face great difficulty in evaluating the banks, decreasing the value of their recommendations.

2. Literature review

2.1 Impact of analyst recommendations

Studies that examine the impact of analyst recommendations generally focus on analyst's characteristics. Mikhail, Walther and Willis (2004) find that recommendations by analysts who have outperformed in the past are more informative. Sorescu and Subrahmanyam (2006) find that experienced analysts from reputable brokerage firms issue superior recommendations. Cliff (2007) finds that positive (negative) recommendations of affiliated analysts have a smaller (greater) impact on prices compared to recommendations of independent analysts. Chang and Chan (2008) find that negative recommendations are more informative and that the magnitude of recommendation change and the reputation of the brokerage firm play a significant role in the price reaction following the recommendation.

Jegadeesh and Kim (2010) find that analysts that do not herd (and analysts from smaller brokerages) have a greater impact on stock prices. Brown, Chan, and Ho (2009) find that reputable analysts have a greater effect on stock prices. Emery and Li (2009) find that star analysts issue recommendations that are not better (and sometimes worse) than the recommendations of non-star analysts. Bradley, Clarke and Cooney (2012) find that strong buy recommendations issued by unaffiliated all-star analysts from reputable banks have a larger impact than recommendations issued by other unaffiliated analysts during high IPO underpricing periods. Loh and Stulz (2011) find that analyst recommendations are more influential if they are issued by a star, or one whose previous ratings were influential, and whose ratings were distinctly different from the consensus. Overall, these studies show that the information content of analyst recommendations depends on the skill and reputation of the analyst. However, little is known about how the analyst's ability to provide new information is affected by the difficulty of the task. In this paper, we investigate how firm characteristics related to opacity, complexity and risk affect the analyst's ability to provide new information to investors.

2.2 Impact of information asymmetry on the information content of analyst recommendations

Several studies find that analysts reduce a firm's information asymmetry. Brennan and Subrahmanyam (1995) and Roulstone (2003) find that financial analysts provide new information to market. Furthermore, their results show that firms with larger analyst following are more liquid and have lower information asymmetry. Similarly, Chung and Jo (1996) and Lang, Lins, and Miller (2004) find that analyst coverage increases firm transparency and that analysts reduce agency costs by monitoring management. Chava, Kumar, and Warga (2010) find that analysts provide high-quality information to the investors that reduce a firm's agency costs.

However, several other studies find opposing results in regards to the relation of analyst coverage and the degree of information asymmetry. Jiang, Kim, and Zhou (2011) find that firms with larger analyst following have wider spreads, lower market quality index, and larger price impact of trades. Dhiensiri and Akin (2010) find that analysts do not have an impact on the firm's level of information asymmetry, but they significantly increase a firm's liquidity. Chung, McInish, Wood, and Wyhowski (1995), and Van Ness, Van Ness, and Warr (2001) find that firms with larger analyst following exhibit lower liquidity levels. Easley, O'Hara and Paperman (1998) find that stocks with greater analyst following exhibit more informed trades; yet, they also exhibit even more uninformed trades. Analysts could pressure managers to meet the earnings forecasts (Fuller and Jensen, 2002; Michenaud, 2008) or could issue biased recommendations (Coffee, 2002; Dechow, Hutton, and Sloan, 2000; Dugar and

Nathan, 1995; Lin and McNichols, 1998; Michaely and Womack, 1999), which could increase the information asymmetry surrounding the firm.

One reason for the inconsistent results in the literature could be the unequal representation of different industries with different levels of information asymmetry. Chung, McInish, Wood and Wyhowski (1995) argue that more analysts would follow a firm with greater information asymmetry because the value of their information increases with informational asymmetry. Lobo, Song, Stanford (2012) find that firms with low quality accruals and high cash flow uncertainty attract more analysts. They argue that this environment provides an opportunity for analysts to benefit by generating private information. However, Hodgdon, Tondkar, Harless, and Adhikari (2008) suggest that analysts can provide more useful and accurate information when the degree of information asymmetry is lower. Lang and Lundholm (1996) find that firms with better disclosure policies have larger analyst coverage and more accurate earnings forecasts. Jiraporn, Chintrakarn, and Kim, (2012) find that a transparent firm environment facilitates the analyst's job, and transparent firms attract more analysts. In this paper, we seek to shed light on the relative merits of the opposing views in the literature.

2.3 Impact of regulation on the information content of analyst recommendations

Studies have shown that recent regulatory reforms (such as Sarbanes-Oxley Act, Regulation Fair Disclosure, and Global Analyst Research Settlement) have had an impact on the information content of analyst recommendations; however, these studies have yielded mixed results. Hovakimian and Saenyasiri (2010) find that both RegFD and Global Research Analyst Settlement have helped reduce analyst forecast bias. Goff, Hulburt, Keasler, and Walsh (2008) find that even in the post-RegFD period analyst recommendations are informative. Loh and Stulz (2011) find that in the post-RegFD period analyst recommendations have become more influential. Cornett, Tehranian, Yalcin (2007) find that recommendations of affiliated analysts have become less biased in the post-RegFD period. Yang and

Mensah (2006) find that the analyst forecast accuracy improved in the post-RegFD period. Jiang and Jang-Chul (2005) find that RegFD has improved the information environment of U.S. stocks.

In contrast, other studies find that the informativeness of analyst reports declined in the post-regulatory period. Gintschel and Markov (2004) find that the price impact of analyst reports declined in the post-RegFD period. Palmon and Yezegel (2011) find that after RegFD analyst recommendations lose their predictive power. Seung-Woog and Small (2007) find that the accuracy of analyst forecasts declines after RegFD and the forecasts become more optimistic. Findlay and Prem (2006) find that forecast accuracy declines after RegFD but the analysts that were less (more) accurate before RegFD become more (less) accurate in the post-RegFD period. Bailey, Li, Mao, Zhong (2003) find the analyst forecast dispersion increases in the post-RegFD period suggesting that it has become more difficult for analysts to form their forecasts. Kadan, Madureira, Wang, Zach (2009) and Boni and Womack (2006) find that the information content of analyst reports declined after Global Analyst Research Settlement.

Given the differences in conclusions derived from these prior studies, it is unclear how regulatory reforms have affected the information content of analyst reports in general. Furthermore, the banking industry has been subject to specific regulatory reforms in recent years whose impact on the information content of analyst recommendations has not been studied before. These regulatory reforms include: Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, which allowed bank holding companies to acquire banks nationwide after September 29, 1995 and allowed banks to branch nationwide after June 1, 1997; Gramm-Leach-Bliley Financial Services Modernization Act of 1999 repealed the Glass-Steagall Act of 1933 and allowed banks to expand their activities beyond traditional banking; Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 aimed at limiting banks' risk-taking abilities. These regulatory reforms could have important implications regarding the information content of analyst recommendations as they likely affected the complexity and risk of the banking industry.

3. Hypotheses

We investigate the effect of the information environment on the information content of analyst recommendations in the banking industry. Prior studies have focused exclusively on how analyst characteristics affect the accuracy of their recommendations; however, little is known about how the task's difficulty affects the investment value of analysts' recommendations. Our study attempts to fill this gap in the literature. Specifically, we test how bank characteristics (information asymmetry, bank complexity and bank risk), the regulatory environment, and changes in economic conditions affect the information content of analyst recommendations.

3.1 Impact of bank's degree of information asymmetry and opacity

Morgan (2002) and Iannotta (2006) find that the debt of banks is more likely to be split-rated than the debt of non-banks, and conclude that banks are more opaque than non-banks. Hirtle (2006), Howe (2007), Bannier, Behr, and Guttler (2010), Morgan, Peristiani, and Savino (2010), and Jones, Lee, and Yeager (2012) use different methodologies and reach the same conclusion. Oldfield and Santomero (1997) classify several types of firms based on their opacity and show that commercial banks are among the most opaque firms.

Jones, Lee, Yeager (2013) argue that bank opacity stems from i) the investors' lack of information regarding the characteristics of the loan contracts that the bank holds and the creditworthiness of its borrowers, and ii) the complexity of the banks' trading assets (e.g. credit derivatives). Furthermore, they argue that high opacity makes banks susceptible to bank runs because depositors cannot easily distinguish between healthy and sick banks. Similar arguments could be made on the role that bank opaqueness plays in the ability of investors and analysts to value banks.

Jin and Myers (2006) show that firms with high opacity are more likely to crash. Flannery, Kwan and Nimalendran (2013) show that the risk and opacity of the banking industry significantly increases during financial crises. If analysts experience more difficulty in evaluating banks with greater degree of information asymmetry and opaqueness, we hypothesize that their recommendations should be less informative. However, a counter hypothesis is that for banks with a high degree of information asymmetry and opaqueness, analysts are able to offer valuable information not available to other market participants and pass it to the investors through their recommendations. Given the absence of public information, this information could lead to a more pronounced price impact for recommendations of banks with higher degree of information asymmetry.

In our empirical analysis, we use the following variables to measure opacity and information asymmetry broadly considered:

Analyst Following. The number of analysts that follow the bank (AnalystFollowing) captures the amount of information that is available about the firm (Lustgarten and Tang; 2008, D'Mello and Ferris, 2000; Doukas, Kim, and Pantzalis, 2005). Imhoff and Lobo (2992), Atiase and Bamber (1994), Marquardt and Weidman (1998), and Womack (1996) use the number of the analysts that follow the firm as a proxy for the firm’s information asymmetry. Greater analyst following suggests that more information is available about the bank and a given analyst recommendation is expected to have a smaller marginal effect on the bank’s price. Similar to Cliff (2007) we measure **AnalystFollowing** as the number of analysts that have issued a recommendation for the bank in the same calendar year.

Bank Size. The bank’s size (**SIZE**) is another measure of the bank’s degree of information asymmetry and opacity. Lustgarten and Tang (2008) and Cliff (2007) use size as a measure of the firm’s information asymmetry. Larger banks tend to receive more news coverage which lowers their degree of information asymmetry; however, they tend to be more complex as they engage in more non-traditional banking activities. We measure SIZE as the natural logarithm of the bank’s total assets.

Time Elapsed Since the Last Analyst Recommendation. The time elapsed since the last recommendation **(TimeSinceLastRec)** is another variable that captures the information asymmetry about the firm. When a long time has passed since the last recommendation, the information asymmetry of the bank may increase because the investors haven't received any new information about the bank. Cliff (2007) argues that analyst recommendations that arrive shortly after another recommendation are likely to be less informative. He measures the time since the last recommendation as the natural logarithm of the number of days since the last recommendation and finds a positive relationship between the announcement return. Similar, we use a variable called TimeSinceLastRec, measured as the natural logarithm of the number of days since the last recommendation.

3.2 Impact of bank's degree of complexity

Investors and analysts may face greater difficulty in evaluating banks with greater degree of complexity, and therefore may be less likely to issue recommendations that are informative for investors. However, if investors of complex banks rely more on the analysts' recommendations, analysts could exert more influence, making the recommendations of complex banks more informative.

We use the following variables to measure the degree of complexity:

Non-Interest Income. The bank's non-interest income **(NII)** measures the bank's degree of involvement in other non-traditional banking activities. Banks that generate higher levels of non-interest income are likely to be involved in other non-traditional banking activities, which increase the complexity of the bank and make it more difficult to be evaluated by the analyst and by the investors. We measure NII as the bank's non-interest income divided by total sales.

Tobin's Q. The bank's Tobin's Q **(Q)** measures the bank's investment opportunities. Firms with greater investment opportunities have more growth options, which are subject to greater complexity and are more difficult to evaluate. Several studies have used book-to-market ratio as a proxy for firm's investment opportunities. Loh and Stulz (2011) find a negative relation between book-to-market and the announcement return of analyst recommendations. However, negative book equity values could make book-to-market an inaccurate measure of investment opportunities. To alleviate the problem with negative values of book-to-market ratios, we use Tobin's Q, which is also commonly used as a proxy for the firm's investment opportunities. Following McConnell and Sevaes (1990) and Lie (2000) we calculate Q as:

$$\text{Tobin's Q} = \frac{\text{Market Value of Equity + Book Value of Debt}}{\text{Book Value of Assets}}$$

3.3 Impact of risk

Investors and analysts may face greater difficulty in evaluating riskier banks. If analysts face greater degree of difficulty in assessing the bank's value, they may be less likely to issue recommendations that are informative for the investors. However, investors may be incapable of accurately valuing riskier banks and may rely more on the analysts' recommendations. In this respect, the analysts could exert more influence over a large number of investors, thus making the recommendations of complex banks more informative.

We use following variables to measure risk:

Capital Ratio. A bank's capital ratio **(CAPR)** is a measure of financial leverage and therefore captures the bank's risk-taking behavior. Several studies (Peura and Keppo (2003), Diamond and Rajan (2000), Berger and Bouwman (2009), and Mehran and Thakor (2009)) have argued that a bank's capital can help alleviate its risk-taking behavior and it reduces the bank's exposure to adverse economic conditions. Banks with lower capital are subject to higher risk and higher exposure to economic conditions. Conversely, since required capital is a function of risk-weighted assets, banks that take greater risk might be required to hold greater levels of capital. To the extent that bank's capital is closely related to the banks risk-taking behavior it could affect the difficulty that analysts face when evaluating banks and the interest that the investors have in the information content of analyst recommendations. Since CAPR is a variable that is only reported by banks and no prior study has examined the impact on analyst recommendations in the banking industry, it is unclear how this variable affects the information content of analyst recommendations. We measure CAPR as the sum of Tier 1 and Tier 2 capital.

Return Volatility. The bank's standard deviation of returns **(STDEV)** measures the bank's total risk prior to the analyst's recommendation. We compute STDEV as the standard deviation or bank's returns in the 6-month period prior the analyst's recommendation.

Beta. The bank's beta **(BETA)** measures the bank's degree of systematic risk. Similar to STDEV it is another proxy for the degree of uncertainty that surrounds the bank. We estimate BETA by using the market model in the event window (-365,-30) prior to the analyst recommendation.

Implied Market Volatility. In periods of greater uncertainty, analysts could face greater difficulty in evaluating banks and may be less able to provide new information to investors. However, in periods with greater uncertainty, the investors may rely more on information content of analyst recommendations and they may perceive these recommendations to be more informative. We measure implied stock market volatility based on the Chicago Board Options Exchange Market Volatility Index **(VIX)** on the day of the analyst's recommendation.

3.4 Regulatory regimes

Because banks are very opaque, maintain higher leverage, and are an important economic sector, the banking industry is subject to stricter regulation. The banking industry has been subject to several regulatory reforms which have dramatically changed the banking industry and could have had a significant impact on the information content of analyst recommendations. The focus on the banking industry gives us a unique opportunity to study the effects of these regulatory reforms on the information content resulting from analyst recommendations. We focus on the following reforms:

Riegle-Neal Act. The Riegle-Neal Interstate Banking and Branching Efficiency Act (**RIEGLE**) of 1994 passed on September 29, 1994 and enabled banks to branch in other states after June 1, 1997. Calomiris (1999) finds that the geographic restrictions prior to the act made banks more susceptible to economic downturns, bank runs, and portfolio shocks. This act allowed banks to diversify in other states and has had significant impact in the banking industry. Dick (2006) finds that, as banks became larger after this act, the risk of bank loans and the concentration in the banking industry decreased. Akhigbe and Whyte (2003) find a significant decline in both, systematic and total risk, following this act. Although these studies show that this act reduced bank's risk, it also made the banks larger and more complex. Furthermore it increased the geographic diversification of the banks which can increase the degree of difficulty that the analysts faces when evaluating them (Bae, Stulz, Tan (2008), Sonney (2009), Malloy (2005)). To measure the marginal impact of the Riegle Neal Act on the information content of analyst recommendation, we use an indicator variable called RIEGLE that takes the value of 1 after June 1, 1997 (the date that Riegle Neal Act took effect) and 0 otherwise.

Gramm-Leach-Bliley Act. The Gramm-Leach-Bliley Financial Services Modernization Act **(GRAMM)** was enacted on November 12, 1999 and repealed the Glass-Steagall Act of 1933. It allowed banks to diversify by being able to acquire investment firms and insurance companies. This act made banks more complex and allowed banks to earn income from other non-interest sources. DeYoung and Roland (2001) show that this act increased the banks' fee-generated income, and increased the banks' earnings and revenue volatility. Cebula (2010) finds that this act increased the bank's exposure to risk and uncertainty and induced an increase in the bank failure rates. Geyfman and Yeager (2009) show that the increased participation in the investment banking in the post-GRAMM era increased the total risk of the banks. This evidence clearly shows that banks became riskier after this act. Furthermore, their complexity also increased as they expanded into other non-banking activities. To measure the marginal impact of the Gramm-Leach-Bliley Act on the information content of analyst recommendations, we use an indicator variable called GRAMM that takes the value of 1 after November 12, 1999 and 0 otherwise.[2] Regulation Fair Disclosure (RegFD) was enacted August 15, 2000, a few months after the enactment of Gramm-Leach-Bliley Act. Thus, any effect found for the Gramm-Leach-Bliley Act could be partially attributed to RegFD.

Dodd Frank Act. The Dodd-Frank Wall Street Reform and Consumer Protection Act (**DODD**) was enacted on July 21, 2010. Its goal was to stabilize the banking industry and limit the banks' risk taking abilities. To measure the marginal impact of the Dodd-Frank Act on the information content of analyst recommendations, we use an indicator variable called DODD that takes the value of 1 after July 21, 2010 and 0 otherwise.

3.5 Recommendation levels and recommendation changes

In a departure from prior literature, Barber et al. (2010) find that both analysts' recommendation levels and recommendation changes provide valuable information to investors. They conclude that analysts are able to generate valuable private information. By contrast, Jegadeesh et al. (2004) find that recommendation levels do not provide valuable information after taking into the accounting the information conveyed by recommendation changes. In our regression analysis, we

[2] On August 15, 2000, Regulation FD (**RegFD**) was implemented by the SEC. It required that when a company discloses any non-public material information to certain individuals or entities (such as analysts) it must publicly disclose that information to the investors as well. The purpose of this rule was to eliminate the unfair advantage that was created when analysts and other individuals or entities received material non-public information ahead of the other investors. Regulation Fair Disclosure occurred only a few months after Gramm-Leach-Bliley Act and the variables indicating both events were highly correlated, thus resulting in the VIF of RegFD being as high as 20.98 in some models. To avoid problems with multicollinearity we have excluded RegFD from all models. The effect of the Gramm-Leach-Bliley Act could be partially due to the effect of RegFD.

separately include variables measuring recommendation levels and changes. The inclusion of the separate variables serves a dual purpose. First, they serve as control variables in our investigation of whether the degree of difficulty makes analyst recommendations more informative. Second, the inclusion of the separate variables will allow us to provide additional evidence for the banking industry regarding Barber et al.'s finding that both are informative.

We separate levels from changes using the following variables:

Change from the Prior Recommendation. We control for whether the analyst recommendation reflects a change in the prior recommendation by the same analyst. We use a variable **RecChange** that is calculated as current recommendation level minus the most recent recommendation level by the same analyst, based on the following codes: Strong Buy=5, Buy=4, Hold=3, Sell=2, Strong Sell=1. RecChange takes the value of 0 for the first recommendation by the analyst, and ranges from -4 to 4 with the positive numbers representing upgrades and negative numbers representing downgrades.

Recommendation level (RecLevel) is a variable that quantifies the current recommendation level. RecLevel ranges from 1 to 5 and we code the recommendations by using the following scale (Strong Buy=5, Buy=4, Hold=3, Sell=2, Strong Sell=1).

StrongBuy is a dummy variable that takes the value of 1 if the recommendation is a Strong Buy (Strong Sell) and 0 otherwise. This variable is used instead of the variable RecLevel only on select subsamples that include only Buy or Strong Buy recommendations.

3.6 Additional control variables

In the empirical regression analysis, we also control for the following characteristics, which could impact the announcement return of analyst's recommendation.

Analyst Experience. The experience of an analyst **(AnalystExperience)** can serve as a proxy for the quality of the recommendation provided by the analyst. Experienced analysts might not only provide more informative recommendations, but could also appeal to more investors. We measure AnalystExperience as the natural logarithm of the number of days that the analyst appears in IBES files.

Analyst Focus. Analysts that follow many industries may not be able to provide as much information as an analyst who focuses only on the banking industry. We use a variable **NrOfIndustries** that is measured as the number of 4-digit SIC codes that the analyst covers.

Sarbanes-Oxley Act (SOX). The Sarbanes-Oxley Act was enacted on July 30, 2002 to make firms more transparent and improve disclosure by increasing the reporting standards for US firms and the penalties for fraudulent activities by managers. Several studies have reported that it had significant effects for US firms. Akhigbe and Martin (2006) find firms in the financial services industry (except securities firms), because of their high opacity, benefited from SOX. Their results show that opaque firms benefitted the most supporting their hypothesis that SOX helped reduce the information asymmetry of financial firms. Nejadmalayeri, Nishikawa, and Rao, (2013) find that bond spreads declined after the passage of SOX. To measure the marginal impact of the Sarbanes-Oxley Act on the information content of analyst recommendations, we use an indicator variable called SOX that takes the value of 1 after July 30, 2002 and 0 otherwise.

Global Analyst Research Settlement (SETTLEMENT). On April 29, 2003, the Global Analyst Research Settlement was reached by the SEC and 12 of the US largest investment banks, in which the investment banks agreed to pay a large penalty for their biased past recommendations and separate their research departments from their investment banking operations in order to alleviate the clear conflicts of interest. The goal of this settlement was to improve the quality of analyst forecasts and recommendations. To measure the marginal impact of the Global Analyst Research Settlement on the information content of analyst recommendations, we use an indicator variable called SETTLEMENT that takes the value of 1 after April 29, 2003 and 0 otherwise.

4. Data, methods, and sample description

4.1 Data and methods

We retrieve the sample of banks from COMPUSTAT's bank file. Following Akhigbe and Martin (2006), we include in the sample all commercial banks (SIC code 602X) and savings institutions (SIC code 603X). To be included in the sample the bank must have continuous returns on CRSP in the 365 day period prior to the analyst's recommendation. For each of the sample bank, we obtain all of their analyst recommendations that are reported on the Thomson Financial's Institutional Brokers Estimate (I/B/E/S) U.S. Detail File in the time period 1994-2012. IBES quantifies each recommendation with a number ranging from 1 (Buy Strong Buy) to 5 (Sell Strong Sell). In order to properly classify upgrades (with a positive sign) and downgrades (with a negative sign), we reverse the IBES rating and we code the recommendations by using the following scale (Strong Buy=5, Buy=4, Hold=3, Sell=2, Strong Sell=1).

To measure the information content of analyst recommendations we follow Loh and Stulz (2011) and use the announcement return of that recommendation in the event window (0,1) with day 0 being the announcement date of the recommendation if the recommendation is made before 4:30pm, or the next trading day if the announcement was made after 4:30 pm. To calculate the model parameters we estimate the market model in the window (-365,-30). As a robustness test we also estimate the model parameters by using the Fama-French 3-factor model and the Fama-French-Carhart 4-factor model.

Loh and Stulz (2011) argue that if an analyst recommendation has a large impact on a bank's price; it does so because it contains much information about the bank. However, the announcement return could also capture other news about the firm. To ensure that we are not capturing the effect of other firm news, we remove from the sample all announcements that fall within a three-day window around earnings announcements and earnings guidance. In addition, similar to Loh and Stulz (2011), we also remove recommendations that elicit a market response in the top or bottom 1% of the sample, as well as event days with multiple recommendations for the same bank. Loh and Stulz (2011) argue that large announcement returns or multiple recommendations in the same day are likely to be triggered by other confounding events. To ensure that the results are not driven by lower priced stocks, we remove from the sample banks that had a share price less than $1 in the day prior to the announcement.

Our sample consists of 23,632 recommendations. Table 1 displays summary statistics for the variables used in the regression analysis. The average bank in our sample has $78.129 billion in assets, ranging from $44.53 million to $2.8 trillion. The average bank in our sample is followed by 7.62 analysts, ranging from 1 to 28. On average, banks receive a recommendation every 73.69 days.

The average Q for the banks in the sample is 1.077. The average bank generates 21.19% of its income from non-interest sources. The standard deviation of returns in the 6-month period prior to analyst recommendations averages 0.02. Banks in the sample have a beta of 0.98 on average, and an average capital ratio of 13.97%.

About 80% of analyst recommendations in the sample occur after the Riegle-Neal Act; 67 % of analyst recommendations in the sample occur after the Gramm-Leach-Bliley Act and 11% of analyst recommendations in the sample occur after the Dodd-Frank Act. About 53% of analyst recommendations in the sample occur after the Sarbanes-Oxley Act and 47 % of analyst recommendations in the sample occur after the Global Analyst Research Settlement. On average, analysts in the sample have 1,629 days of experience and cover 3.31 industries.

4.2. Recommendation levels and recommendation changes

In Table 2, we display the average announcement return (CAR01) and the number of observations broken down by the level of the current recommendation (Panel 1),change in recommendation (Panel 2), and by recommendation levels and changes conditional on one another (Panel 3). For each category, we also run a t-test to determine whether the average CAR01 is significantly different from 0. The t-statistics have been omitted to conserve space; however the results of the t-test are displayed by the asterisks: *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

Panel 1 shows that Strong Sell recommendations elicit a negative and significant CAR01 of -1.09%. Strong Sell recommendations elicit the lowest CAR01 and they are closely followed by Sell recommendations which elicit a CAR01 of -0.99%. Hold, Buy and Strong Buy recommendations elicit a CAR01 of -0.42%, 0.38%, and 0.71%, respectively. The average abnormal return in each category is statistically different from 0 at the 1% significance level. Thus, CARs increase monotonically from Strong Sell to Strong Buy recommendations. These results are consistent with prior research: negative recommendations are more credible and elicit a larger price reaction compared to positive recommendations.

Panel 2 summarizes the CAR01 by the change in recommendation level by the same analyst (ChangeRec). ChangeRec takes values from -4 to 4 with negative numbers representing downgrades and positive numbers representing upgrades. Panel 2 shows that 4-level and 3-level downgrades are rare events (11 and 49 observations respectively) and elicit a negative CAR01 (-0.47% and -0.89% respectively). 2-level and 1-level downgrades are much more common and elicit a more pronounced price response. The average CAR01 is -1.06% for 2-level downgrades and -0.92% for 1-level downgrades. The average returns for 1-level, 2-level, and 3-level downgrades are negative and significantly different from 0.

The 1-level and 2-level upgrades represent a large portion of the sample with 3,131 and 1,519 observations. 1-level upgrades elicit a CAR01 of 0.83% on average while 2-level upgrades elicit a CAR01 of 1.20% on average. These returns are significantly different from 0 at the 1% significance level. The 3-

level and 4-level upgrades are rare events and, on average, elicit a smaller price response compared to 1-level and 2-level upgrades, and their average return is not statistically different from 0. Our unconditional results for downgrades and upgrades in the banking industry are consistent with the general patterns previously found across all industries (e.g., Barber et al. (2010))

In Panel 3, we present results for recommendation levels and changes conditional on one another. This panel summarizes the analyst recommendations in the sample by their current rating and the prior rating by the same analyst. The numbers shown in Italics represent all analyst downgrades; the numbers shown in Bold represent all analyst upgrades; and the numbers across the left-right diagonal represent all reiterations.

Panel 3 can be used to provide evidence for the banking industry on whether recommendation levels provide valuable information controlling for recommendation changes. In each and every column, CAR01 monotonically increase from Strong Sell to Strong Buy recommendations, indicating recommendation levels are informative irrespective of changes.

Similarly, Panel 3 also indicates that recommendation changes convey valuable information irrespective of levels. Upgrades always earn higher CARs than downgrades, and CARs are larger (in absolute value), the bigger the change.

Almost all analyst upgrades elicit a positive CAR01 on average; however, upgrades from Strong Sell to Sell and upgrades from Strong Sell to Buy on average elicit a negative CAR01. Upgrades from Sell to Strong Buy elicit the largest CAR01 of 1.4% on average. Upgrades from Hold to Strong Buy and upgrades from Hold to Buy also elicit a large CAR01 on average (1.31% and 1.07% respectively).

Overall, the univariate results suggest that the CAR01 depends not only on the level of the upgrade or downgrade, but also on the level of the current recommendation. These results also suggest that on average, analyst recommendations in the banking industry do provide valuable information and result in abnormal returns that are significantly different from 0. These results confirm for the banking industry the findings of Barber et al. (2010). However, these results do not offer any insight on how the firm environment affects the analyst's ability to generate valuable private information about the banks. In the rest of the paper, we provide evidence on the impact of the environment on the information content of analyst recommendations and revisions.

5. The information content of analyst recommendation and revisions: Regression analysis

5.1. Subsample definition

To measure the effect of the firm environment on the magnitude of the announcement return we run the following regression model:

$$CAR01 = \alpha + \beta_1 SIZE(\text{or AnalystFollowing}) + \beta_2 TimeSinceLastRec + \beta_3 Q + \beta_4 NII + \beta_5 STDEV + \beta_6 BETA + \beta_7 CAPR + \beta_8 VIX + \beta_9 RIEGLE + \beta_{10} GRAMM + \beta_{11} DODD + CONTROLS + \varepsilon_i$$

Due to the high correlation between AnalystFollowing and SIZE, we run two versions of the model which include only one of these two variables. Additionally, to avoid any problems cause by heteroskedasticity, all models are run with robust standard errors as in White (1980).

Several studies have documented the analysts' propensity to issue positive recommendations (Bradley, Clarke, Cooney, 2012; Xu and Tang, 2012; Hovakimian and Saenyasiri, 2010; Mokoaleli-Mokoteli, Taffler, and Agarwal, 2009). Due to this analyst bias, negative recommendations send a more credible signal and elicit a greater price reaction. In addition, our hypotheses make opposite predictions for positive and negative recommendations. For these reasons, we separate the subsamples that contain only positive or only negative recommendations.

However, as mentioned, Barber et al. (2010) find that both rating levels and rating changes provide new information and affect the market reaction. Accordingly, we also take into account whether a given recommendation is an upgrade, which would convey positive information, or a downgrade, which would convey negative information. That is, we attempt to use a classification process that properly isolates positive analyst signals from negative analyst signals. To ensure that positive (negative) recommendation subsamples are not confounded by opposite simultaneous signals, we require that the share price response (CAR01) at the time of the recommendation be positive (negative).[3] We also consider subsets of the main sample (Sample 1) as described below separately for positive recommendations and negative recommendations:

Positive Recommendations	**Negative Recommendations**
Sample 1) Recommendations that are either a Buy, a Strong Buy, or an Upgrade	Sample 1) Recommendations that are either a Sell, a Strong Sell, or a Downgrade
Sample 2) Upgrades to a Buy or Upgrades to a Strong Buy	Sample 2) Downgrades to a Sell or Downgrades to a Strong Sell
Sample 3) Buy or Strong Buy Recommendations	Sample 3) Hold, Sell, or Strong Sell Recommendations

5.2 Results for positive recommendations: buy, strong buy, or an upgrade

Table 3 displays the results of the multivariate models for the subsample that includes only recommendations that are a Buy, a Strong Buy, or an Upgrade. The first three models include SIZE as a measure of information asymmetry and they differ only in the manner by which the dependent variable (cumulative abnormal return) is measured. In the first model, it is estimated by using the market model (CAR01); in the second, by using the Fama-French 3-factor model (CAR01FF); and in the third, by using the Fama-French-Carhart 4-factor model (CAR01FFC). In models 4 through 6 we substitute SIZE with

[3] While we do take several precautions to isolate our sample from any confounding effects (as outlined in the Data and Methodology section), we acknowledge that our sample could still be subject to some confounding effects.

AnalystFollowing as a measure of information asymmetry. All the remaining tables in the paper are organized in the same fashion.

Table 3 shows that the coefficient of SIZE is negative and significant in all three models. This result suggests that analyst recommendations elicit a stronger market response when assigned to smaller banks, thus supporting the hypothesis that analyst recommendations are more informative for banks with a greater degree of information asymmetry. Similarly, the coefficient of AnalystFollowing is negative and significant in all three models. This result further supports the hypothesis that analyst recommendations are more informative for banks with a greater degree of information asymmetry.

The coefficient of NII is negative and significant only in models with AnalystFollowing. The coefficient of Q is negative and significant in two out of six models. These results weakly suggests that analyst recommendations provide less information for complex banks.

The coefficient of STDEV is positive and significant in all six models, while the coefficient of BETA is positive and significant in two out of the six models. Similarly, the coefficient of CAPR is negative and significant in all six models. These results further support the notion that analyst recommendations of riskier banks are more informative. The coefficient of VIX is positive and significant in all six models. Consistent with the other variables related to risk, this result suggests that analyst recommendations issued in riskier periods (periods with higher VIX) provide more information to investors.

The coefficient of GRAMM is positive and significant in all six models. This result suggests that the analyst recommendations became more informative after the enactment of the Gramm-Leach-Bliley Act. Given the evidence provided by DeYoung and Roland (2001), Geyfman and Yeager (2009), and Cebula (2010) which show that bank risk increased after the enactment of Gramm-Leach-Bliley Act, this result provides further evidence that analyst recommendations become more informative with the increase in bank risk.

The coefficient of DODD is negative and significant in all six models, which suggests that analyst recommendations became less informative in the post-Dodd-Frank period. Given that the Dodd-Frank Act was intended to reduce the risk of the banking industry, this result is consistent with the previous results showing that analyst recommendations are more informative for riskier banks.

The coefficient of SOX is negative and significant in all six models. This result shows that analyst recommendations became less informative after the enactment of Sarbanes-Oxley Act. This result could be due to the increase in public disclosure in the post-SOX period, which decreased the information asymmetry of banks. This result further supports the hypothesis that analyst recommendations are more informative in firms with higher degree of information asymmetry.

The coefficient of SETTLEMENT is positive and significant in all six models. This result shows that analyst recommendations became more informative in the post-Settlement period. This result is consistent with the results of Hovakimian and Saenyasiri (2010) and Muslu and Xue (2013) who show that Global Research Analyst Settlement achieved its goal of reducing analysts' bias.

Consistent with Barber et al. (2010) and the earlier evidence from our univariate analysis (2010), both RecChange and RecLevel are positive and significant in all six models, which suggests that both recommendation levels and changes provide valuable information in the banking industry. Overall, the R-square of the models ranges from 0.11 to 0.13.

In summary, the results from Table 3 strongly suggest that analyst recommendations are more informative for riskier banks and for banks with greater degree of information asymmetry. Furthermore, regulatory events that reduced the information asymmetry of the banking industry (such as SOX) or decreased the risk of the banking industry (such as DODD) resulted in less informative recommendations; and regulations such as GRAMM that increased the risk of the banking industry resulted in more informative recommendations. However, results suggest that analyst recommendations of more complex banks are less informative.

Table 4 present the results of the models applied to the subsample that includes only upgrades to a Buy or to a Strong Buy. The results of Table 4 are fully consistent with the results of Table 3, with one relevant exception: The coefficient of CAPR is insignificant in all models. The coefficients of RecChange and StrongBuy (i.e., recommendation level) are insignificant in this subsample, likely because there is not enough variability in the subsample. Overall, the R-square of the models in Table 4 ranges from 0.11 to 0.14.

Table 5 displays the results of the models applied to the subsample which includes only Buy or Strong Buy recommendations. The results of Table 5 are fully consistent with the results of Table 3, and very similar to results shown in Table 5. The R-square of the models in Table 5 ranges from 0.108 to 0.131.

5.3 Results for negative recommendations: sell, strong sell, or a downgrade

In this section, we focus on negative recommendations. Thus, before proceeding, we note that the interpretation of model coefficients differs from the interpretation of coefficients in the positive recommendation subsamples in Tables 3-5. In the positive subsamples, a more informative recommendation would result in a higher announcement return, while in the negative subsamples, a more informative recommendation would result in a lower (more negative) announcement return.

Table 6 shows the results of the regression analysis in the subsample that includes only recommendations that are a Sell, a Strong Sell, or a Downgrade. The coefficient of SIZE is positive and significant in all three models. Consistent with the results found in the positive subsamples, this result suggests that analyst recommendations provide more information for banks with greater asymmetry. The negative recommendations of smaller banks (which suffer from greater information asymmetry) result in lower (more negative) abnormal returns. Similarly, the coefficient of AnalystFollowing is positive and significant in all three models. These results support the results found in the positive subsamples and suggest that negative recommendations are more informative when they are issued for banks with greater information asymmetry.

The variables related to bank complexity yield inconclusive results. The coefficient of Q is negative and significant in three models, which suggests that negative recommendations are more informative for complex banks. However, the coefficient of NII is positive and significant in four models, which suggests that negative recommendations are less informative for complex banks.

The coefficients of STDEV and BETA are negative and significant in all six models. Consistent with the results found in the positive subsamples, these results suggest that negative recommendations of riskier banks are more informative. The coefficient of CAPR is mostly insignificant.

The coefficient of VIX is negative and significant in three out of the six models, which suggests that negative recommendations are more informative during riskier periods. This result is consistent with the results of the other risk-related variables and consistent with the results found in the positive subsamples.

The coefficient of RIEGLE is negative and significant in four out of the six models. This result provides some evidence that negative recommendations became more informative after the enactment of Riegle-Neal Act. The coefficient of GRAMM is negative and significant in all six models. Consistent with the results found in the positive subsamples, this result suggests that negative recommendations became more informative after the enactment of Gramm-Leach-Bliley Act. This result also further supports the results found in the risk related variables. As the risk of the banking industry increased after GRAMM (see DeYoung and Roland, 2001; Geyfman and Yeager, 2009; and Cebula, 2010), analyst recommendations became more informative.

The coefficient of DODD is positive and significant in four out of the six models. This result further supports the results found for the risk related variables and suggests that as the risk of the banking industry declined after the enactment of the Dodd-Frank Act, negative recommendations became less informative. This result is also consistent with the results found in the positive subsamples.

The coefficient of SOX is positive and significant in all six models. This result suggests that negative recommendations became less informative after the inception of Sarbanes-Oxley Act. This result further supports the results found in the coefficients of SIZE and AnalystFollowing and suggests that as the information asymmetry of the banking industry decreased after SOX, negative recommendations became less informative. This result is also consistent with the results found in the positive subsamples.

The coefficient of SETTLEMENT is negative and significant in three out of the six models. Consistent with the findings of prior literature, this result suggests that negative recommendations became more informative after the Global Settlement, which intended to make recommendations more reliable.

The coefficient of RecChange is positive and significant in all six models, which confirms that greater downgrades elicit a significantly lower announcement returns. Similarly, the coefficient of RecLevel is positive and significant in five out of the six models. This result suggests that lower recommendation levels elicit a significantly lower announcement return, consistent with expectations, and with the results found in the positive subsamples.

Overall, the R-square of the models ranges from 0.08 to 0.17. In summary, the results Table 6 suggest that negative analyst recommendations are more informative for banks with greater degree of information asymmetry and riskier banks. Furthermore, regulatory events that reduced the information asymmetry of the banking industry (such as SOX) or decreased the risk of the banking industry (such as DODD) resulted in less informative recommendations; and regulations such as GRAMM that increased the risk of the banking industry resulted in more informative recommendations. These results are fully consistent with the results found in the positive subsamples.

Table 7 displays the results of the models applied to the subsample which includes downgrades to a Hold, downgrades to a Sell, or downgrades to a Strong Sell. Finger and Landsman (2003) find that investors interpret Hold recommendations as negative news, therefore we include downgrades to a Hold in this negative subsample. The results of Table 7 are fully consistent with the results of Table 6, except that the coefficient of RIEGLE is negative and significant in only one out of the six models. The coefficient of RecLevel is also insignificant in all models. Overall, the R-square of the models in Table 7 ranges from 0.07 to 0.13.

Table 8 displays the results of the models applied to the subsample which includes only Hold, Sell, or Strong Sell recommendations. The results of Table 8 are fully consistent with the results of Table 6, except that the coefficient of RecLevel is positive and significant in only one out of the six models. Overall, the R-square of the models in Table 8 ranges from 0.06 to 0.13.

6. Conclusions

Based on our assessment of 23,632 analyst recommendations in the banking industry, we find that analyst recommendations provide valuable information and have a significant impact on bank prices. Additionally, we find that the bank's information environment has a significant impact on the information content of analyst recommendations. Analyst recommendations issued for banks with a high degree of information asymmetry are significantly more informative for the investors. Furthermore, regulatory events that decreased the information asymmetry of the banking industry (such as SOX) also decreased the information content of analyst recommendations. These results suggest that in an environment that suffers from lack of information, analysts are able to generate private information and pass it through to the investors through their recommendations.

We also find that analyst recommendations issued for riskier banks or during riskier periods are significantly more informative for the investors. In addition, analyst recommendations are also more informative after regulatory events that increased the risk in the banking industry (such as GRAMM). Regulatory events that reduced the risk of the banking industry (such as DODD) also reduced the information content of analyst recommendations. These results suggest that, when faced with a high degree of risk and uncertainty, investors pay closer attention to analyst recommendations.

We also find weak evidence that positive recommendations issued for more complex banks are significantly less informative for the investors. This result suggests that when the difficulty of evaluating the bank increases, analysts are less able to provide useful information for the investors. In the negative subsamples we do not observe a conclusive relationship between bank complexity and the information content of analyst recommendations.

Table 1. Sample Description

This table displays the summary statistics for all variables used in the regression models. Results are shown for the full sample which includes all recommendations issued in the banking industry during the period 1994-2012. Total Assets is shown in millions (in the regression models we use SIZE which is calculated as the natural logarithm of the bank's total assets). AnalysFollowing is the number of analysts that have issued a recommendation for the bank in the same calendar year. Nr. Of Days Since Last Rec. is the number of days that have passed since the bank received its last recommendation (in the regression models we use TimeSinceLastRec which is calculated as the natural logarithm of the number of days since the last recommendation). Q is the bank's Tobin's Q calculated as:

$\frac{\text{Market Value of Equity} + \text{Book Value of Debt}}{\text{Book Value of Assets}}$. NII is the bank's non-interest income divided by total sales. STDEV is the standard deviation or bank's returns in the 6-month period prior the analyst's recommendation. BETA is estimated by using the market model in the event window (-365,-30) prior to the analyst recommendation. CAPR is the sum of Tier 1 and Tier 2 capital. All the regulatory variables (RIEGLE, GRAMM, DODD, SOX, SETTLEMENT,) are dummy variables that equal 1 after the regulation has been enacted, and 0 otherwise. VIX is the level of the VIX index in the day of the analyst's recommendation. AnalystExperience is the number of days that the analyst appears in IBES files (in the regression models we use the natural logarithm of the number of days that the analyst appears in IBES files). NrOfIndustries is the number of 4-digit SIC codes that the analyst covers.

Variable	N	Mean	Std. Dev.	Min	Max
Total Assets	23264	78129.34	238212.70	44.53	2807491.00
AnalystFollowing	23632	7.62	5.51	1.00	28.00
Nr. Of Days Since Last Rec.	22650	73.69	153.39	1.00	5622.00
Q	22528	1.08	0.12	0.80	4.74
NII	19884	0.21	0.14	0.00	0.98
STDEV	22828	0.02	0.01	0.00	0.21
BETA	22828	0.99	0.54	-1.35	5.23
CAPR	21601	13.97	4.17	-1.44	147.80
VIX	23632	20.92	8.14	9.31	80.86
RIEGLE	23632	0.80	0.40	0.00	1.00
GRAMM	23632	0.67	0.47	0.00	1.00
DODD	23632	0.11	0.31	0.00	1.00
SOX	23632	0.53	0.50	0.00	1.00
SETTLEMENT	23632	0.47	0.50	0.00	1.00
AnalystExperience	32451	1629.78	1482.92	1.00	6971.00
NrOfIndustries	32451	3.31	4.95	1.00	153.00

Table 2. Announcement Return Summary

This table summarizes the announcement return of analyst recommendations. Panel 1l summarizes the announcement return by the recommendation level. Panel 2 summarizes the announcement return by the change in the recommendation level from the prior recommendation level by the same analyst. The change in the recommendation level by the same analyst is represented by the variable RecChange which is calculated as current recommendation minus the most recent recommendation by the same analyst. RecChange ranges from -4 to 4 with the positive numbers representing upgrades and negative numbers representing downgrades. Panel 3 displays the results partitioned by the current recommendation level and by the previous recommendation level by the same analyst. The downward-slopping diagonal represents all analyst reiterations. The numbers above the downward-slopping diagonal (in italics) represent all analyst downgrades, while the numbers below the downward-slopping diagonal (in bold) represent all analyst upgrades. In each category, the top number represents the average CAR01 for that category, while the bottom number represents the number of observations in that category. . For each category, we run a t-test to determine whether the average CAR01 is significantly different from 0. The t-statistics have been omitted to conserve space; however the results of the t-test are displayed by the asterisks: *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

Panel 1

RecLevel	CAR01/N
Strong Sell	-0.0109***
	518
Sell	-0.0099***
	1278
Hold	-0.0043***
	10350
Buy	0.0038***
	6379
Strong Buy	0.0071***
	4276
Total	-0.0003
	22801

Panel 2

RecChange	CAR01/N
-4	-0.0047
	11
-3	-0.0089*
	49
-2	-0.0106**
	1798
-1	-0.0092***
	3754
0	-0.0004
	3513
1	0.0083***
	3131
2	0.0120***
	1519
3	0.0067
	26
4	0.0071
	11
Total	-0.00081
	13812

Panel 3

	Previous Recommendation				
Current Rec.	Strong Sell	Sell	Hold	Buy	Strong Buy
Strong Sell	-0.0089*	*-0.0108*	*-0.0155****	*-0.0071*	*-0.0033*
	32	*17*	*285*	*29*	*12*
Sell	**-0.0024**	-0.0020	*-0.0128****	*-0.0089****	*-0.0100*
	21	148	*665*	*121*	*22*
Hold	**0.0075*****	**0.0049*****	-0.0011*	*-0.0093****	*-0.0097****
	269	**629**	1633	*2276*	*1425*
Buy	**-0.0032**	**0.0063*****	**0.0107***.**	0.0017*	*-0.0052****
	13	**103**	**1769**	858	*898*
Strong Buy	**0.0071**	**0.0138**	**0.0132*****	**0.0054*****	-0.0010
	11	**16**	**1171**	**779**	424

Table 3. Results of the Regression Model Applied to the Subsample that Contains only Recommendations that Are a Buy, a Strong Buy, or an Upgrade

This table displays the results of the regression models applied to the subsample that contains only recommendations that are a Buy, a Strong Buy, or an upgrade. The numbers in brackets represent the t-statistics of the coefficients. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

	CAR01	CAR01FF	CAR01FFC	CAR01	CAR01FF	CAR01FFC
CONSTANT	0.0194***	0.0308***	0.0320***	0.00184	0.00734	0.00788
	(3.27)	(5.11)	(5.35)	(0.38)	(1.43)	(1.53)
SIZE	-0.00142***	-0.00190***	-0.00198***			
	(-8.08)	(-10.35)	(-10.85)			
AnalystFollowing				-0.000348***	-0.000516***	-0.000566***
				(-5.35)	(-7.40)	(-8.11)
TimeSinceLastRec	0.000113	0.0001	0.000227	0.000155	0.0000872	0.00017
	(0.54)	(0.46)	(1.02)	(0.70)	(0.38)	(0.73)
Q	-0.00606	-0.0123***	-0.0122***	0.000313	-0.00366	-0.00323
	(-1.39)	(-2.83)	(-2.83)	(0.08)	(-0.91)	(-0.79)
NII	-0.00218	-0.000828	0.00037	-0.00714***	-0.00693***	-0.00561**
	(-0.90)	(-0.33)	(0.15)	(-3.27)	(-2.99)	(-2.37)
STDEV	0.279***	0.281***	0.306***	0.312***	0.324***	0.350***
	(7.43)	(6.73)	(7.49)	(8.50)	(7.87)	(8.69)
BETA	0.00283***	0.00117	0.000661	0.00261***	0.000991	0.000552
	(4.01)	(1.51)	(0.88)	(3.62)	(1.24)	(0.71)
CAPR	-0.000270***	-0.000214***	-0.000232***	-0.000207***	-0.000133*	-0.000150**
	(-3.74)	(-2.77)	(-3.11)	(-2.95)	(-1.78)	(-2.07)
VIX	0.000366***	0.000358***	0.000260***	0.000356***	0.000347***	0.000250***
	(6.44)	(5.61)	(4.20)	(6.25)	(5.45)	(4.05)
RIEGLE	-0.00155	-0.000868	-0.00000365	-0.00231*	-0.0019	-0.00107
	(-1.21)	(-0.64)	(-0.00)	(-1.82)	(-1.41)	(-0.80)
GRAMM	0.00430***	0.00232**	0.00203*	0.00424***	0.00234**	0.00212*
	(4.09)	(2.10)	(1.82)	(4.00)	(2.09)	(1.87)
DODD	-0.00392***	-0.00416***	-0.00372***	-0.00337***	-0.00338***	-0.00288***
	(-4.45)	(-4.53)	(-4.05)	(-3.83)	(-3.64)	(-3.09)
SOX	-0.00825***	-0.00499***	-0.00446***	-0.00769***	-0.00428***	-0.00374***
	(-6.57)	(-3.88)	(-3.34)	(-6.14)	(-3.35)	(-2.82)
SETTLEMENT	0.00928***	0.00809***	0.00663***	0.00863***	0.00716***	0.00562***
	(7.24)	(6.08)	(4.89)	(6.71)	(5.39)	(4.16)
AnalystExperience	-0.0000092	-0.0000314	-0.000007	-0.0000209	-0.0000396	-0.000011
	(-0.06)	(-0.20)	(-0.05)	(-0.14)	(-0.25)	(-0.07)
NrOfIndustries	0.00000313	-0.0000102	-0.0000129	-0.0000104	-0.0000293	-0.0000333
	(0.05)	(-0.20)	(-0.26)	(-0.18)	(-0.57)	(-0.66)
RecChange	0.00229***	0.00234***	0.00245***	0.00232***	0.00236***	0.00247***
	(6.75)	(6.52)	(6.58)	(6.78)	(6.55)	(6.61)
RecLevel	0.00168***	0.00136***	0.00140***	0.00190***	0.00166***	0.00172***
	(3.96)	(3.03)	(3.10)	(4.46)	(3.68)	(3.79)
N	5296	5296	5296	5296	5296	5296
R-sq	0.133	0.128	0.118	0.127	0.121	0.111

Table 4. Results of the Regression Model Applied to the Subsample that Contains only Recommendations that Are Upgrades to a Buy or Upgrades to a Strong Buy

This table displays the results of the regression models applied to the subsample that contains only recommendations that are upgrades to a Buy or upgrades to a Strong Buy. The numbers in brackets represent the t-statistics of the coefficients. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

	CAR01	CAR01FF	CAR01FFC	CAR01	CAR01FF	CAR01FFC
CONSTANT	0.0527***	0.0565***	0.0582***	0.0189**	0.0183**	0.0200**
	(4.95)	(5.37)	(5.08)	(2.11)	(1.97)	(2.07)
SIZE	-0.00240***	-0.00277***	-0.00279***			
	(-7.55)	(-8.09)	(-8.41)			
AnalystFollowing				-0.000359***	-0.000542***	-0.000579***
				(-3.13)	(-4.45)	(-4.91)
TimeSinceLastRec	-0.000118	-0.000312	-0.000144	0.000249	-0.000066	0.0000572
	(-0.30)	(-0.76)	(-0.34)	(0.59)	(-0.15)	(0.13)
Q	-0.0223***	-0.0228***	-0.0238***	-0.00795	-0.00659	-0.00765
	(-2.95)	(-3.05)	(-2.92)	(-1.13)	(-0.91)	(-1.01)
NII	-0.00109	0.0014	0.000795	-0.0126***	-0.0103**	-0.0105**
	(-0.26)	(0.30)	(0.18)	(-3.27)	(-2.49)	(-2.54)
STDEV	0.183***	0.256***	0.275***	0.238***	0.320***	0.340***
	(3.15)	(5.20)	(4.56)	(4.12)	(5.06)	(5.74)
BETA	0.00363***	0.00102	0.00114	0.00320**	0.000825	0.00102
	(2.99)	(0.86)	(0.91)	(2.53)	(0.63)	(0.79)
CAPR	-0.000149	-0.000189	-0.000199	-0.0000319	-0.0000591	-0.0000697
	(-0.91)	(-1.22)	(-1.20)	(-0.21)	(-0.36)	(-0.45)
VIX	0.000353***	0.000301***	0.000230**	0.000339***	0.000288***	0.000218**
	(4.06)	(4.24)	(2.36)	(3.90)	(3.00)	(2.26)
RIEGLE	0.0032	0.00322	0.00366	0.00219	0.00206	0.00249
	(1.01)	(1.00)	(1.11)	(0.68)	(0.62)	(0.74)
GRAMM	0.00717***	0.00448*	0.00236	0.00630**	0.00377	0.00172
	(2.71)	(1.81)	(0.84)	(2.37)	(1.33)	(0.60)
DODD	-0.00563***	-0.00430***	-0.00474***	-0.00471***	-0.00311**	-0.00351**
	(-4.09)	(-2.79)	(-3.26)	(-3.40)	(-2.14)	(-2.40)
SOX	-0.0112***	-0.00789***	-0.00556*	-0.0101***	-0.00686**	-0.00457
	(-3.89)	(-2.71)	(-1.94)	(-3.48)	(-2.37)	(-1.57)
SETTLEMENT	0.0103***	0.00968***	0.00902***	0.00973***	0.00888***	0.00817***
	(4.06)	(3.63)	(3.63)	(3.76)	(3.53)	(3.25)
AnalystExperience	-0.000505	-0.000289	-0.0000978	-0.000602	-0.000354	-0.00015
	(-1.09)	(-0.56)	(-0.20)	(-1.24)	(-0.69)	(-0.29)
NrOfIndustries	0.000265*	0.000188	0.00023	0.000241*	0.000162	0.000203
	(1.80)	(0.88)	(1.48)	(1.65)	(1.07)	(1.37)
RecChange	0.00179	0.00196	0.000745	0.00184	0.00203	0.000821
	(0.74)	(0.80)	(0.35)	(0.74)	(0.92)	(0.38)
StrongBuy	-0.000109	-0.00047	0.000264	0.000321	-0.0000099	0.000718
	(-0.04)	(-0.18)	(0.11)	(0.12)	(-0.00)	(0.31)
N	1750	1750	1750	1750	1750	1750
R-sq	0.139	0.133	0.132	0.118	0.111	0.111

Table 5. Results of the Regression Model Applied to the Subsample that Contains only Buy or Strong Buy Recommendations

This table displays the results of the regression models applied to the subsample that contains only Buy or Strong Buy recommendations. The numbers in brackets represent the t-statistics of the coefficients. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

	CAR01	CAR01FF	CAR01FFC	CAR01	CAR01FF	CAR01FFC
CONSTANT	0.0250***	0.0382***	0.0398***	0.00870*	0.0160***	0.0172***
	(4.30)	(6.39)	(6.68)	(1.84)	(3.15)	(3.35)
SIZE	-0.00142***	-0.00196***	-0.00200***			
	(-7.63)	(-10.06)	(-10.35)			
AnalystFollowing				-0.000339***	-0.000528***	-0.000564***
				(-4.83)	(-7.16)	(-7.66)
TimeSinceLastRec	0.000129	0.0000826	0.00019	0.000189	0.0000807	0.000154
	(0.58)	(0.36)	(0.81)	(0.81)	(0.34)	(0.63)
Q	-0.00519	-0.0130***	-0.0132***	0.000851	-0.0046	-0.00457
	(-1.18)	(-2.88)	(-2.93)	(0.22)	(-1.08)	(-1.06)
NII	-0.00324	-0.00193	-0.00114	-0.00832***	-0.00827***	-0.00736***
	(-1.28)	(-0.72)	(-0.42)	(-3.58)	(-3.33)	(-2.92)
STDEV	0.315***	0.310***	0.332***	0.348***	0.355***	0.378***
	(7.84)	(7.06)	(7.78)	(8.87)	(8.19)	(8.96)
BETA	0.00269***	0.00128	0.000908	0.00236***	0.000977	0.000662
	(3.60)	(1.56)	(1.15)	(3.09)	(1.16)	(0.81)
CAPR	-0.000257***	-0.000206***	-0.000240***	-0.000199***	-0.000131*	-0.000165**
	(-3.48)	(-2.59)	(-3.11)	(-2.77)	(-1.70)	(-2.21)
VIX	0.000348***	0.000280***	0.000198***	0.000340***	0.000272***	0.000191***
	(5.82)	(4.16)	(2.99)	(5.67)	(4.06)	(2.90)
RIEGLE	-0.00131	0.000111	0.000773	-0.00205	-0.00091	-0.000271
	(-0.99)	(0.08)	(0.55)	(-1.56)	(-0.65)	(-0.19)
GRAMM	0.00454***	0.00257**	0.00230**	0.00440***	0.00252**	0.00230**
	(4.21)	(2.26)	(2.01)	(4.04)	(2.19)	(1.98)
DODD	-0.00384***	-0.00383***	-0.00362***	-0.00330***	-0.00303***	-0.00278***
	(-4.09)	(-3.91)	(-3.68)	(-3.51)	(-3.05)	(-2.78)
SOX	-0.00835***	-0.00457***	-0.00432***	-0.00777***	-0.00382***	-0.00357**
	(-6.13)	(-3.29)	(-3.01)	(-5.72)	(-2.77)	(-2.51)
SETTLEMENT	0.00962***	0.00747***	0.00648***	0.00902***	0.00656***	0.00552***
	(6.79)	(5.10)	(4.34)	(6.34)	(4.48)	(3.70)
AnalystExperience	-0.0000615	-0.0000815	-0.0000316	-0.0000742	-0.00009	-0.0000368
	(-0.39)	(-0.49)	(-0.19)	(-0.48)	(-0.54)	(-0.22)
NrOfIndustries	0.000125	0.0000692	0.0000569	0.00011	0.0000458	0.0000317
	(1.31)	(0.71)	(0.61)	(1.13)	(0.46)	(0.33)
RecChange	0.00272***	0.00262***	0.00257***	0.00273***	0.00262***	0.00256***
	(6.85)	(6.46)	(6.28)	(6.83)	(6.43)	(6.24)
StrongBuy	0.000055	0.0000855	-0.0000124	0.000304	0.000427	0.000336
	(0.09)	(0.13)	(-0.02)	(0.48)	(0.66)	(0.52)
N	4637	4637	4637	4637	4637	4637
R-sq	0.131	0.123	0.116	0.125	0.115	0.108

Table 6. Results of the Regression Model Applied to the Subsample that Contains only Recommendations that Are a Sell, a Strong Sell, or a Downgrade

This table displays the results of the regression models applied to the subsample that contains only recommendations that are a Sell, a strong Sell, or a downgrade. The numbers in brackets represent the t-statistics of the coefficients. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

	CAR01	CAR01FF	CAR01FFC	CAR01	CAR01FF	CAR01FFC
CONSTANT	-0.000673	-0.0166**	-0.0147**	0.00806**	-0.00272	0.000804
	(-0.15)	(-2.32)	(-2.26)	(2.20)	(-0.51)	(0.17)
SIZE	0.000845***	0.00133***	0.00152***			
	(5.24)	(7.12)	(8.08)			
AnalystFollowing				0.000242***	0.000367***	0.000457***
				(4.13)	(5.54)	(6.72)
TimeSinceLastRec	-0.000145	-0.000377*	-0.000289	-0.0000878	-0.000307	-0.000155
	(-0.80)	(-1.84)	(-1.36)	(-0.46)	(-1.45)	(-0.71)
Q	-0.00675**	0.000942	-0.00177	-0.00970***	-0.00371	-0.00705*
	(-2.56)	(0.17)	(-0.36)	(-3.98)	(-0.86)	(-1.92)
NII	0.00522***	0.00358	0.00255	0.00774***	0.00770***	0.00685***
	(2.66)	(1.51)	(1.09)	(4.24)	(3.70)	(3.28)
STDEV	-0.342***	-0.250***	-0.265***	-0.362***	-0.281***	-0.302***
	(-11.31)	(-6.06)	(-5.30)	(-12.16)	(-7.12)	(-6.23)
BETA	-0.00281***	-0.00233***	-0.00170**	-0.00273***	-0.00217***	-0.00158*
	(-4.51)	(-3.22)	(-2.09)	(-4.33)	(-2.96)	(-1.95)
CAPR	-0.0000736	-0.000138	-0.000124	-0.000096	-0.000174*	-0.000164
	(-0.76)	(-1.39)	(-1.25)	(-1.00)	(-1.78)	(-1.62)
VIX	-0.000311***	-0.0000513	-0.000126*	-0.000298***	-0.0000299	-0.000102
	(-5.79)	(-0.80)	(-1.88)	(-5.57)	(-0.47)	(-1.55)
RIEGLE	-0.000912	-0.00408***	-0.00339**	-0.000565	-0.00353**	-0.00277*
	(-0.67)	(-2.77)	(-2.34)	(-0.42)	(-2.43)	(-1.94)
GRAMM	-0.00392***	-0.00327**	-0.00315**	-0.00385***	-0.00314**	-0.00306**
	(-3.24)	(-2.54)	(-2.41)	(-3.18)	(-2.43)	(-2.33)
DODD	0.00327***	0.00196**	0.00112	0.00298***	0.00152*	0.000579
	(4.57)	(2.30)	(1.26)	(4.13)	(1.84)	(0.67)
SOX	0.00472***	0.00324**	0.00465***	0.00426***	0.00250*	0.00384***
	(3.88)	(2.49)	(3.44)	(3.53)	(1.95)	(2.88)
SETTLEMENT	-0.00321***	-0.000508	-0.00228*	-0.00273**	0.000233	-0.00139
	(-2.87)	(-0.42)	(-1.85)	(-2.45)	(0.19)	(-1.14)
AnalystExperience	-0.000366***	-0.000214	-0.000128	-0.000350***	-0.000187	-0.0001
	(-2.91)	(-1.56)	(-0.91)	(-2.79)	(-1.36)	(-0.71)
NrOfIndustries	0.0000289*	0.0000302	0.0000223	0.0000320*	0.0000352*	0.0000278
	(1.78)	(1.62)	(1.18)	(1.92)	(1.92)	(1.50)
RecChange	0.00321***	0.00327***	0.00337***	0.00325***	0.00334***	0.00345***
	(11.05)	(9.99)	(10.00)	(11.17)	(10.18)	(10.19)
RecLevel	0.00113**	0.00122**	0.00115**	0.000998*	0.00100*	0.000916
	(2.18)	(2.14)	(1.99)	(1.92)	(1.76)	(1.59)
N	5922	5922	5922	5922	5922	5922
R-sq	0.172	0.089	0.096	0.17	0.086	0.093

Table 7. Results of the Regression Model Applied to the Subsample that Contains only Recommendations that Are Downgrades to a Hold, Downgrades to a Sell, or Downgrades to a Strong Sell

This table displays the results of the regression models applied to the subsample that contains only recommendations that are downgrades to a Hold, downgrades to a Sell, or downgrades to a Strong Sell. The numbers in brackets represent the t-statistics of the coefficients. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

	CAR01	CAR01FF	CAR01FFC	CAR01	CAR01FF	CAR01FFC
CONSTANT	-0.0105	-0.0429***	-0.0384***	0.00766	-0.0155*	-0.00803
	(-1.25)	(-4.68)	(-4.16)	(1.05)	(-1.95)	(-1.00)
SIZE	0.00137***	0.00208***	0.00235***			
	(5.29)	(7.29)	(8.05)			
AnalystFollowing				0.000273***	0.000434***	0.000563***
				(3.01)	(4.22)	(5.39)
TimeSinceLastRec	-0.000169	-0.000286	-0.0000974	-0.000282	-0.000432	-0.000166
	(-0.58)	(-0.87)	(-0.28)	(-0.93)	(-1.27)	(-0.47)
Q	-0.00248	0.0169***	0.0132**	-0.0108**	0.00433	-0.000848
	(-0.44)	(2.69)	(2.09)	(-2.03)	(0.73)	(-0.14)
NII	0.00248	-0.00082	-0.00216	0.00792***	0.00718**	0.00603**
	(0.81)	(-0.25)	(-0.64)	(2.85)	(2.41)	(2.00)
STDEV	-0.258***	-0.165***	-0.186***	-0.301***	-0.230***	-0.260***
	(-5.27)	(-2.66)	(-2.87)	(-6.28)	(-3.86)	(-4.16)
BETA	-0.00405***	-0.00342***	-0.00285***	-0.00377***	-0.00303***	-0.00254**
	(-4.24)	(-3.16)	(-2.68)	(-3.89)	(-2.74)	(-2.33)
CAPR	0.0000604	0.0000631	0.0000839	0.0000124	-0.0000088	0.00000584
	(0.55)	(0.56)	(0.72)	(0.11)	(-0.08)	(0.05)
VIX	-0.000350***	-0.0000622	-0.000155*	-0.000323***	-0.0000219	-0.000113
	(-4.61)	(-0.68)	(-1.72)	(-4.24)	(-0.24)	(-1.27)
RIEGLE	-0.000456	-0.00395*	-0.00332	0.000379	-0.00269	-0.00188
	(-0.21)	(-1.72)	(-1.49)	(0.17)	(-1.17)	(-0.84)
GRAMM	-0.00729***	-0.00640***	-0.00602***	-0.00726***	-0.00638***	-0.00612***
	(-3.65)	(-3.12)	(-2.90)	(-3.63)	(-3.09)	(-2.92)
DODD	0.00485***	0.00521***	0.00414***	0.00427***	0.00431***	0.00308**
	(4.28)	(4.27)	(3.29)	(3.71)	(3.46)	(2.40)
SOX	0.00546***	0.00306	0.00441**	0.00470**	0.00191	0.00314
	(2.75)	(1.45)	(2.06)	(2.37)	(0.91)	(1.47)
SETTLEMENT	-0.00410**	-0.00139	-0.00328*	-0.00348**	-0.000423	-0.00211
	(-2.38)	(-0.73)	(-1.74)	(-2.01)	(-0.22)	(-1.11)
AnalystExperience	-0.000582	-0.000203	-0.000224	-0.000363	0.000122	0.000115
	(-1.34)	(-0.42)	(-0.46)	(-0.84)	(0.25)	(0.24)
NrOfIndustries	0.000210*	0.000206	0.000173	0.000233*	0.000241*	0.000211*
	(1.69)	(1.63)	(1.43)	(1.82)	(1.80)	(1.69)
RecChange	0.000942	0.00104	0.00142	0.00123	0.00147*	0.00188**
	(1.22)	(1.23)	(1.62)	(1.59)	(1.73)	(2.15)
RecLevel	0.000809	0.000544	0.000191	0.00062	0.000262	-0.000113
	(1.19)	(0.73)	(0.26)	(0.91)	(0.35)	(-0.15)
N	2724	2724	2724	2724	2724	2724
R-sq	0.129	0.073	0.082	0.123	0.062	0.071

Table 8. Results of the Regression Model Applied to the Subsample that Contains only Hold, Sell, or Strong Sell Recommendations

This table displays the results of the regression models applied to the subsample that contains only Hold, Sell, or Strong Sell recommendations. The numbers in brackets represent the t-statistics of the coefficients. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

	CAR01	CAR01FF	CAR01FFC	CAR01	CAR01FF	CAR01FFC
CONSTANT	-0.00195	-0.0162**	-0.0145**	0.00834**	-0.00141	0.00154
	(-0.43)	(-2.10)	(-2.03)	(2.30)	(-0.25)	(0.31)
SIZE	0.000960***	0.00139***	0.00155***			
	(5.34)	(6.66)	(7.43)			
AnalystFollowing				0.000233***	0.000346***	0.000443***
				(3.58)	(4.78)	(5.96)
TimeSinceLastRec	-0.00011	-0.000353	-0.000222	-0.000106	-0.000334	-0.00012
	(-0.50)	(-1.45)	(-0.88)	(-0.47)	(-1.34)	(-0.47)
Q	-0.00507*	0.00207	0.00015	-0.00856***	-0.00296	-0.00545
	(-1.84)	(0.34)	(0.03)	(-3.61)	(-0.65)	(-1.36)
NII	0.00356	0.00231	0.0015	0.00693***	0.00707***	0.00620***
	(1.56)	(0.84)	(0.55)	(3.28)	(2.97)	(2.60)
STDEV	-0.316***	-0.243***	-0.265***	-0.340***	-0.277***	-0.303***
	(-8.97)	(-5.19)	(-4.44)	(-9.84)	(-6.24)	(-5.29)
BETA	-0.00310***	-0.00265***	-0.00203**	-0.00286***	-0.00233***	-0.00180*
	(-4.27)	(-3.14)	(-2.12)	(-3.90)	(-2.74)	(-1.89)
CAPR	-0.0000548	-0.000111	-0.00011	-0.0000847	-0.000154	-0.000155
	(-0.50)	(-1.00)	(-0.99)	(-0.78)	(-1.40)	(-1.41)
VIX	-0.000334***	-0.0000885	-0.000170**	-0.000318***	-0.000066	-0.000146**
	(-5.63)	(-1.25)	(-2.28)	(-5.39)	(-0.94)	(-2.00)
RIEGLE	-0.00139	-0.00429***	-0.00355**	-0.000989	-0.00371**	-0.00290*
	(-0.99)	(-2.79)	(-2.32)	(-0.70)	(-2.45)	(-1.92)
GRAMM	-0.00423***	-0.00288**	-0.00274**	-0.00408***	-0.00269**	-0.00264**
	(-3.45)	(-2.24)	(-2.09)	(-3.32)	(-2.08)	(-2.01)
DODD	0.00329***	0.00241**	0.00167	0.00293***	0.00188*	0.00104
	(3.89)	(2.40)	(1.60)	(3.46)	(1.95)	(1.02)
SOX	0.00587***	0.00327**	0.00493***	0.00536***	0.00253*	0.00413***
	(4.43)	(2.32)	(3.36)	(4.06)	(1.81)	(2.85)
SETTLEMENT	-0.00385***	-0.000995	-0.00294**	-0.00336***	-0.000273	-0.00206
	(-3.05)	(-0.72)	(-2.10)	(-2.65)	(-0.20)	(-1.47)
AnalystExperience	-0.000517***	-0.000332*	-0.000295*	-0.000494***	-0.000301*	-0.000269
	(-3.31)	(-1.95)	(-1.78)	(-3.17)	(-1.77)	(-1.62)
NrOfIndustries	0.0000728	0.0000774*	0.0000672	0.0000809	0.0000889*	0.0000799*
	(1.50)	(1.70)	(1.47)	(1.62)	(1.84)	(1.65)
RecChange	0.00279***	0.00286***	0.00299***	0.00286***	0.00295***	0.00306***
	(8.19)	(7.46)	(7.48)	(8.38)	(7.68)	(7.64)
RecLevel	0.000753*	0.000692	0.000684	0.000637	0.000527	0.000513
	(1.81)	(1.55)	(1.51)	(1.54)	(1.19)	(1.14)
N	4831	4831	4831	4831	4831	4831
R-sq	0.144	0.081	0.091	0.142	0.077	0.087

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