Bank Environment and the Investment Value of Analyst Recommendations

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We analyze the long-term performance of a large sample of analyst recommendations of bank stocks. We find that positive (negative) recommendations earn positive (negative) returns for at least three months following the recommendation. Thus, analyst recommendations in the banking industry are valuable for investors. Recommendations deliver greater value for banks with greater degree of information asymmetry. Similarly, regulations that decrease information asymmetry in the banking industry also decrease the investment value of analyst recommendations. Positive recommendations create greater value when they are issued in low-risk environments, while negative recommendations create greater value when they are issued in high-risk environments. We conclude that analysts add investment value when there is higher information asymmetry, while negative recommendations are particularly valuable when bank risk is higher.

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1. Introduction

Analysts assist investors in their investment decisions by synthesizing complex information into simple Buy, Hold, or Sell recommendations. Several studies have shown that analyst recommendations provide useful information about the rated firms and elicit a significant immediate price reaction (Givoly and Lakonishok, 1979; Lys and Sohn, 1990; Francis and Soffer, 1997; Moshirian, Ng, and Wu, 2009; Loh and Stulz, 2011).

Although these studies show that analyst recommendations provide new information that affects the rated firms, less attention has been paid to whether and how analyst recommendations create value for long term investors. Kim, Lin, and Slovin (1997) find that, on average, it takes five minutes for NYSE/AMEX stocks and 15 minutes for NASDAQ stocks to reflect the private information of analyst recommendations. Similarly, Busse and Green (2002) find that profit opportunities dissipate a few seconds after the televised broadcast of the recommendation. Given

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the speed in which recommendations are reflected into prices, it is unclear whether the typical long-term investor can benefit from analyst recommendations.

A few studies have measured the impact of analyst recommendations on the wealth of the long-term shareholders; however, they have either focused solely on whether analyst recommendations create investment value (Womack, 1996; Barber, Lehavy, McNichols, and Trueman, 2001), or on which analyst characteristics create greater value for the long-term shareholders (Stickel, 1995; Michaely and Womack, 1999; Mikhail, Walther, and Willis, 2004; Sorescu and Subrahmanyam, 2006).

We hypothesize that the analyst's ability to create value for the long-term investor could depend not only on individual skill, but also on the information environment (degree of information asymmetry and risk). The information environment changes over time, causing information asymmetry and risk to be more pronounced in some periods than others. This allows for two opposing theories to be tested. A base theory is that when information asymmetry and risk are more pronounced, analysts have limited access to valuable information from which they could extract value. Therefore, they may be less capable of creating value for long-term shareholders under these conditions. On the other hand, when information asymmetry and risk are more pronounced, this complicates the valuation process not only for analysts but also for investors. In fact, analysts should be better equipped to extract value, because their comparative advantage over other market participants should be greater under these conditions. Thus, analyst recommendations should be more valuable for long-term investors when information asymmetry and risk are more pronounced.

The banking industry provides an ideal framework for examining the impact of the information environment on the analyst's ability to create value for long-term investors. First, Flannery, Kwan, and Nimalendran (2013) and Laeven, Ratnovski and Tong (2016) find that bank opacity and risk vary significantly among banks and over time, and partially attribute this to the changes in the information environment over time. Such changes allow us to test whether and how analyst abilities to extract long-term value are dependent on the information environment. Second, the focus on a single industry allows for a better measurement of analyst value that is not affected by variation in industry characteristics. Boni and Womack (2006) find that investment strategies based on analyst recommendations yield higher returns when focused on a single industry. They conclude that analysts offer valuable information for long-term investors by ranking stocks within industries. Lastly, the investment value of analyst recommendations on the banking industry has not been studied before[2]. Several studies show that the banking industry behaves differently (compared to other industries) to news regarding equity issues, restructuring

[2] Premti, Garcia-Feijoo, and Madura (2017) study the announcement return of the analyst recommendations in the banking industry, but they do not test whether analysts can extract long-term value in bank stocks.

activities, profit warnings, share repurchases, and dividend announcements[3].

We examine how the information environment (i.e., information asymmetry and risk) affects the analyst's ability to create value for long-term investors in the banking industry. After examining a sample of 32,451 analyst recommendations of US banks between 1993 and 2012, we find that analyst recommendations create value for investors for periods of at least three months; and, in some specifications, for up to a full year. Specifically, we find that Buy recommendations and upgrades are followed by positive buy and hold abnormal returns (BHAR), while Sell recommendations and downgrades are followed by negative BHARs. The announcement return makes up a large proportion of the post-recommendation performance; however, analyst recommendations continue to create value for investors in the days after the announcement period.

We also find that recommendations deliver greater value when they are issued for banks with greater degree of information asymmetry. In addition, regulatory events that decrease information asymmetry in the banking industry, such as Sarbanes Oxley Act, also decrease the investment value derived from analyst recommendations. Positive recommendations create greater value when they are issued in low-risk environments, while negative recommendations create greater value when they are issued in high-risk environments.

This paper contributes to the literature in several ways. First, to the best of our knowledge, this is the first study to examine how the information environment affects the analyst's ability to create value for long term investors. Second, we are the first to study the long term performance of the analyst recommendations in the banking industry, a highly opaque industry which has not been studied before. Third, we show that the time variation in the information environment along with changes in the regulatory environment significantly affect the value of analyst recommendations. Lastly, to the best of our knowledge, this is the first study to show that while the announcement return of analyst recommendations makes up a significant portion of the long term performance (analyst information is quickly reflected into prices), it is not a significant predictor of the returns past the announcement window.

2. Literature Review

A strand of studies has assessed bank opacity. For example, Morgan (2002) and Iannotta (2006), Hirtle (2006), Haggard and Howe (2007), Bannier, Behr, and Guttler (2010), Morgan, Peristiani, and Savino (2010), and Jones, Lee, and Yeager (2012) show that banks are significantly more opaque than non-banks. Laeven, Ratnovski and Tong (2016) find that bank risk varies significantly depending on bank

[3] For example, see Polonchek, Slovin, and Sushka (1989), Wansley and Dhillon (1989), Slovin, Sushka and Polonchek (1991), Slovin, Sushka and Polonchek (1992), Vanna and Szewczyk (1993), Filbeck and Mullineaux (1993), Akhigbe and Madura (1999), Filbeck and Mullineaux (1999), Jackson and Madura (2004), Cornett, Fayman, Marcus, and Tehranian (2011).

characteristics. These studies offer insight on how bank valuations may be influenced by the information environment, but they do not assess the ability of analysts to value bank stocks.

Several studies have measured the impact and information content of analyst recommendations by focusing on their announcement return (Stickel, 1995; Irvine, 2004; Ivkovic and Jegadeesh, 2004; Asquith, Mikhail and Au, 2005; Loh and Stulz, 2011). Although these studies generally show that, on average, analyst recommendations are informative, little is known on whether analyst recommendations can provide value to the long term investor. The announcement return is not useful in this respect for several reasons. First, investors could over-react to the recommendation's announcement. Barber and Loeffler (1993) find that part of the initial reaction to analyst recommendations changes is explained by price pressure created by naive investors and that the initial reaction is partially reversed within 25 days of the recommendation. Bagella, Becchetti, and Ciciretti (2007) observe substantial overreaction of investors to both downward and upward firm-specific forecast revisions. Similarly, Cliff (2007) finds that the market over-reacts to Buy recommendations from affiliated analysts, but under-reacts to their Hold or Sell recommendations. This over-reaction could also be fueled by the publicity of analyst recommendations (see Ramnath, Rock, and Shane, 2008). By focusing on the announcement return, it is difficult to distinguish whether the initial reaction is due to the value provided by the recommendation, or whether it is due to the publicity that the media affords to the recommendation and investor over-reaction. Second, analysts themselves could over-react to news about the firm. Cornell (2001) shows that analysts over-reacted to Intel's press release issued on September 21, 2000. Similarly, Hussain (1998) finds that UK analysts are prone to over-react when forecasting changes in corporate earnings. Third, as noted above, studies have shown that prices reflect the analysts' new information quickly and it is unclear whether the typical investors could benefit from this information.

Some studies have focused on the longer-term returns of analyst recommendations in general, without a focus on any particular industry. Stickel (1995) documents that analyst recommendations are associated with short-term and permanent effects on stock prices. Womack (1996) find the post-recommendation price drift of Buy recommendations is short-lived (only 1-month), while Sell recommendations are associated with a -9.1% price drift over a longer 6-month period post recommendation. Michaely and Womack (1999) find that Buy recommendations from affiliated analysts perform poorly compared to the recommendations from unaffiliated analysts. Barber, Lehavy, McNichols, and Trueman (2001) find that a strategy of taking a long (short) position on the stocks with the most (least) favorable consensus recommendations can yield abnormal returns greater than 4%. Mikhail, Walther, and Willis (2004) find that buy-and-hold excess returns following the recommendations of analysts with a good track record, outperform the excess returns of analysts with a poor track record.

As seen above, most studies focus on whether analysts create value for investors, and on analyst characteristics that contribute to this value. Unlike prior studies, we assess how the firm environment affects the analyst's ability to create value through their recommendations. In addition, this study differs from prior literature in that it focuses on analyst recommendations of banks, a highly opaque industry that differs greatly from other industries, and one that has not been the focus of the prior literature.

3. Hypotheses

A. Investment value of analyst recommendations

The analyst's ability to create value for the investors depends on his/her personal skills and on the difficulty of the task that the analyst faces. Prior studies have focused exclusively on how analyst characteristics affect the investment value of their recommendations; however, little is known on how the difficulty of the task affects the ability of the analyst to deliver value to long term investors. In a difficult environment, such as the banking industry which suffers from high information asymmetry and high risk fluctuations, analysts could find it difficult to provide information, and therefore, their ability to deliver value to long term investors could be limited. This argument would suggest that analyst recommendations in the banking industry should not lead to abnormal returns for long term investors.

On the other hand, in difficult environments, such as banking, analysts may find an opportunity to generate private information and use their expertise to predict future bank prices. By passing this information to investors through their recommendations, they could offer greater investment value to investors. Similarly, investors also may face difficulty in evaluating banks and may rely heavily on analyst recommendations. These arguments would suggest that analyst recommendations in the banking industry should lead to abnormal returns for long term investors.

B. Investment value of analyst recommendations and bank characteristics.

Flannery, Kwan, and Nimalendran (2013) and Laeven, Ratnovski and Tong (2016) find that the degree of information asymmetry and risk in the banking industry varies significantly among banks and over time. If these characteristics affect the investment value of analyst recommendations (as argued above), we should expect that the investment value of analyst recommendations varies depending on bank and time-period characteristics related to information asymmetry and risk. To test these hypotheses we use the following variables:[4]

B.1. Information Asymmetry

The number of analysts that follow the bank (**AnalystFollowing**) is used as a proxy of information asymmetry (D'Mello and Ferris, 2000; Doukas, Kim, and Pantzalis, 2005; Lustgarten and Tang; 2008). Given that analysts help reduce

[4] Premti et al. (2017) use similar variables.

information asymmetry, as more analysts follow the bank, its degree of information asymmetry gets lower. AnalystFollowing is calculated as the number of analysts that have covered the bank during that year.

Bank size (**SIZE**) is a second proxy used to measure the bank's degree of information asymmetry. Small banks are not covered much in the news and have a higher degree of information asymmetry. Flannery, Kwan, and Nimalendran (2013) find smaller banks to be more opaque than larger banks. SIZE is measured as the natural logarithm of the bank's total assets.

The passing of the Sarbanes-Oxley Act (**SOX**) is a third proxy related to the information asymmetry. Akhigbe and Martin (2006) and Nejadmalayeri Nishikawa, and Rao (2013) show that SOX significantly reduced the information asymmetry of US companies. To measure the effect of SOX on the investment value of analyst recommendations, we use a dummy variable that takes the value of 1 after the passing of SOX on July 30, 2002, and 0 otherwise.

B.2. Risk

The bank's beta (**BETA**) captures the risk of the bank. Lustgarten and Tang (2008) use BETA as a measure of firm risk and find that analyst recommendations are less dispersed in firms with larger betas. We calculate BETA by using the market model in the year prior to the recommendation.

The Chicago Board Options Exchange Market Volatility Index (**VIX**), also known as the "fear index", captures the degree of uncertainty in the market. We use the level of the VIX index on the day the recommendation is issued.

B.3. Other Control Variables

In addition to variables related to our hypotheses, we control for several bank, period, and analyst characteristics that could affect the analyst's ability to create value for the investors. These variables are listed below.

The bank's Tobin's Q (**Q**) is a proxy that captures the bank's overvaluation. Following McConnell and Servaes (1990) and Lie (2000) we calculate Q as:

$$Tobin's\ Q = \frac{Market\ Value\ of\ Equity + Book\ Value\ of\ Debt}{Book\ Value\ of\ Assets} \qquad (1)$$

The bank's non-interest income (**NII**) is used as a proxy for the bank's participation in complex activities, such as investment banking and proprietary trading. We standardize NII by dividing it by total revenue.

The Global Analyst Research Settlement (**SETTLEMENT**) was an agreement that required a few large investment banks to pay penalties for their biased past recommendations, and forced them to improve the reliability of their recommendations. We capture the impact of the SETTLEMENT on the investment value of analyst recommendations by using a dummy variable that takes the value of 1 after April 29, 2003, and 0 otherwise.

Analyst experience (**AnalystExperience**) is a proxy used to capture analyst's knowledge. AnalystExperience is calculated as the log of the number of days that the analyst appears in the IBES database.

The number of industries that the analyst covers (**NrOfIndustries**) is a proxy used to capture the analyst's expertize in the banking industry. Analysts that cover a single industry (i.e. banking) should be more knowledgeable about that idustry. We measure NrOfIndustries as the number of SIC codes that the analyst covers.

The change from the prior recommendation (**RecChange**) captures the level of upgrade or downgrade from the same analyst. We code the recommendations by using the following scale (Strong Buy=5, Buy=4, Hold=3, Sell=2, Strong Sell=1) and calculate RecChange as the current recommendation minus the last recommendation by the same analyst. Additionally, we control for the recommendation level by using **StrongBuy** (**StrongSell**), which take the value of 1 if the recommendation is a Strong Buy (Strong Sell) and 0 otherwise.

Price momentum (**MOMENTUM**) captures the bank's recent price movements. Muslu and Xue (2013) find that recommendations that follow past returns contribute to the existing price momentum and generate larger short- and long-term returns. We calculate MOMENTUM as the bank's buy and hold return in the 6-month periods prior to the analyst's recommendation.

The announcement return (**CAR01**) captures the price reaction to the analyst's recommendation in the event days 0 and 1. Kim, Lin, and Slovin (1997) find that, on average, it takes five minutes for NYSE/AMEX stocks and 15 minutes for NASDAQ stocks to reflect the private information of analyst recommendations. Similarly, Busse and Green (2002) find that profit opportunities dissipate a few seconds after the televised broadcast of analyst recommendations. These studies suggest that CAR01 should capture a large portion of the information that analysts provide. Premti, Garcia-Feijoo, and Madura (2017) find that analyst recommendations result in a higher announcement return in banks with high degree of information asymmetry. We calculate CAR01 by using the estimated coefficients of the market model and standard event study methodology.

4. Sample Selection and Methodology Of Calculating Returns

We collect all analyst recommendations of all commercial banks (SIC code 602X) and savings institutions (SIC code 603X)[5] that are covered in IBES in the period 1994-2012. The data on bank financials and stock returns comes from COMPUSTAT and CRSP. Following Premti et al. (2017) and Loh and Stulz (2011), we remove from the sample all recommendations that fall within three-days of an earnings announcements or an earnings guidance, the 1% outlier recommendations based on their announcement return, and event days with multiple recommendations for the same bank. Loh and Stulz (2011) argue that these events are likely to be a result other news. Lastly, we also remove from the sample banks that had a stock price of $1 or less. After these exclusions, our sample results in 23,632 recommendations.

[5] Akhigbe and Martin (2006) use the same SIC codes for the banking industry.

To measure the value that recommendations deliver to investors, we use Buy and Hold Abnormal Returns (BHAR) over several time horizons following the recommendation: We calculate BHAR as:

$$BHAR_{i,t} = \prod_{t=1}^{t}(1+R_{i,t}) - \prod_{t=1}^{t}(1+Rm_t) \quad (2)$$

Where $R_{i,t}$ is the return of the bank and Rm_t is the return of a benchmark. As a benchmark we use the returns of the CRSP value-weighted index. Barber and Lyon (1997) outline several issues with BHARs and suggest that some of these issues can be addressed if the returns of a control firm are used as a benchmark. Gur-Gershgoren, Hughson, and Zender (2008) further improve on the suggestion of Barber and Lyon (1997) and suggest using as a benchmark a portfolio of multiple control firms that had a high correlation of prior returns with the event firm. As a robustness test, we follow Gur-Gershgoren, Hughson, and Zender (2008) and use an alternative measure of BHAR in which the returns of a portfolio of the top 10 competitor banks are used as a benchmark.[6] We refer to this measure as BHAR(C) throughout the paper.

To correct for survivorship bias we follow Shumway (1997) and Shumway and Warther (1999) and replace the delisting return for banks and competitors that delist for performance reasons (delisting code 500, and delisting codes from 505 to 588) with -55% for NASDAQ banks and -30% for NYSE/AMEX banks. We measure the long-term performance across 4 time horizons: 1-month, 3-month, 6-month, and 1-year.

Each performance measure is labeled by the number of days in which the performance is measured. For example, BHAR0to30 measures the abnormal performance in the first 30 days (1 month), starting from the announcement date; while BHAR2to182C uses the portfolio of competitors as a benchmark and measures the abnormal performance in the 182-day (6-month) period, starting from day 2 (excluding the announcement window).

5. Results

A. Description of Returns and Statistical Tests

Table 1 displays the average long-term performance across several performance measures for each recommendation level, and the results of a series of t-tests of whether each abnormal performance is significantly different from zero. The BHAR measure of performance is known to be positively skewed. As a robustness test, we also test the significance of BHAR by applying two skewness-adjusted t-tests as in Johnson (1978) and Chen (1995). These results have been omitted to conserve space; however, the results of the skewness-adjusted t-tests are consistent with the reported results.

In the first two panels of Table 1, the long-term performance is calculated starting from day zero (announcement day), while in the bottom two panels, the

[6] We also use a third BHAR measure in which the returns of the closest competitor are used as a benchmark, as Barber and Lyon (1997) suggest. The results of this measure are not shown to conserve space; however, they are consistent with the results of the other two measures.

long-term performance is measured starting from day 2 (i.e., excluding the announcement window). Panel 1 shows the results of the BHAR measure. Results indicate that Sell and Strong Sell recommendations earn significantly negative abnormal returns (ranging from -1.34% to -5.48%) in all measures, while Buy and Strong Buy recommendations earn significantly positive returns (ranging from 1.15% to 6.32%) in all measures. These results show that analyst recommendations in the banking industry offer investment value to long-term investors. If investors follow the advice of analysts in the banking industry, they would earn returns that exceed a value weighted market index.

Table 1. Abnormal Returns by Recommendation Level

RecLevel	BHAR0to30	BHAR0to91	BHAR0to182	BHAR0to365
Panel 1				
Strong Sell	-0.0134***	-0.0170**	-0.0302***	-0.0548***
Sell	-0.0174***	-0.0219***	-0.0335***	-0.0235**
Hold	-0.0050***	-0.0025*	0.0021	0.0084***
Buy	0.0115***	0.0257***	0.0409***	0.0632***
Strong Buy	0.0150***	0.0249***	0.0395***	0.0490***
RecLevel	BHAR0to30(C)	BHAR0to91(C)	BHAR0to182(C)	BHAR0to365(C)
Panel 2				
Strong Sell	-0.0200***	-0.0237***	-0.0324***	-0.0556***
Sell	-0.0168***	-0.0220***	-0.0317***	-0.0392***
Hold	-0.0068***	-0.0097***	-0.0138***	-0.0195***
Buy	0.0065***	0.0068***	0.0061***	0.0059*
Strong Buy	0.0132***	0.0115***	0.0094***	0.0030
RecLevel	BHAR2to30	BHAR2to91	BHAR2to182	BHAR2to365
Panel 3				
Strong Sell	-0.0038	-0.0063	-0.0183*	-0.0422***
Sell	-0.0055**	-0.0116**	-0.0205***	-0.0106
Hold	-0.0013*	0.0014	0.0062***	0.0121***
Buy	0.0062***	0.0213***	0.0361***	0.0572***
Strong Buy	0.0077***	0.0161***	0.0307***	0.0410***
RecLevel	BHAR2to30(C)	BHAR2to91(C)	BHAR2to182(C)	BHAR2to365(C)
Panel 4				
Strong Sell	-0.0099***	-0.0137**	-0.0222***	-0.0454***
Sell	-0.0083***	-0.0135***	-0.0233***	-0.0306***
Hold	-0.0036***	-0.0065***	-0.0106***	-0.0162***
Buy	0.0026***	0.0027*	0.0018	0.0014
Strong Buy	0.0065***	0.0045**	0.0022	-0.0045

Notes: This table displays the results of a series of t-tests which examine whether analyst recommendations result in long term returns that are significantly different from 0. The long term performance is measured for each recommendation level. For each recommendation level, the number displayed is the average abnormal return for the time period. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

Panels 1 and 2 display the results of the performance measure that calculates the returns starting from the announcement day, while bottom panels 3 and 4 display the results of the performance measure that calculates the returns starting from day 2. Panles 1 and 3 display the results of the BHAR measure, while panels 2 and 4 display the results of the BHAR(C) measure. In the name of each performance measure, the numbers 30, 91, 182, and 365 represent the length of time period (in days) in which the performance is measured.

Panel 2 shows the results of the BHAR(C) measure. Consistent with the results of the BHAR measure, we find that Sell and Strong Sell recommendations earn significantly negative abnormal returns (ranging from -1.68% to -5.56%) in all measures, while Buy and Strong Buy recommendations earn significantly positive returns (ranging from 0.65% to 1.32%) in seven out of the eight measures. These results confirm the results of the BHAR measure and suggest that analyst recommendations in the banking industry outperform a portfolio of the closest competitors and earn positive returns for investors for periods of up to 1 year.

Panels 3 and 4 display the results for abnormal returns calculated starting from day 2. These results are consistent with the results of the top two panels; however, they are smaller in magnitude (in absolute value terms). This difference suggests that the information content of analyst recommendation is quickly absorbed into prices and a large proportion of long-term performance is earned during the first two days following the announcement of the recommendation. However, on average, prices continue to drift in the direction of the recommendation; thus, investors can earn abnormal returns by following analyst recommendations in the banking industry even if they are unable to enter the market immediately after the recommendation is announced. Results of the BHAR(C) measure show that the abnormal performance only lasts three months for investors who follow Buy or Strong Buy recommendations and don't enter the market immediately

Table 2 shows abnormal returns by the level of upgrade or downgrade by the same analyst (RecChange). The top panel displays the results of the performance measure that calculates the returns starting from the announcement day. The first four columns display the results of the BHAR measure, while columns 5-8 display the results of the BHAR(C) measure. The top panel of Table 2 shows that 1-level, 2-level, and 3-level downgrades earn significantly negative returns. These BHARs range from -0.54% to -5.7%. Upgrades of level 1 and level 2 earn significantly positive returns for all eight measures. They range from 1.27% to 5.56%. These results are consistent with the results of Table 1 and suggest that recommendations in the banking industry generate positive returns for investors for periods up to one year. If investors act upon analyst recommendation changes in the banking industry they would earn returns that exceed a value weighted market index (or the returns of their top competitors) for periods of up to one year. In almost all measures, 4-level downgrades, and 3-level and 4-level upgrades earn insignificant returns. This is likely due to the low number of observations in these categories.

Table 2. Abnormal Returns by Recommendation Change

RecChange	BHAR0to30	BHAR0to91	BHAR0to182	BHAR0to365	BHAR0to30(C)	BHAR0to91(C)	BHAR0to182(C)	BHAR0to365(C)
-4	0.0052	0.0610	0.0677	0.0584	-0.0017	0.0404	0.0264	0.0393
-3	-0.0172	-0.0320	-0.0355	-0.0801**	-0.0294***	-0.0570***	-0.0488**	-0.1062***
-2	-0.0165***	-0.0196***	-0.0285***	-0.0276***	-0.0170***	-0.0228***	-0.0284***	-0.0401***
-1	-0.0107***	-0.0089***	-0.0054	0.0247***	-0.0137***	-0.0187***	-0.0231***	-0.0218***
0	0.0035***	0.0160***	0.0210***	0.0399***	0.0018	0.0034*	0.0005	-0.0029
1	0.0141***	0.0285***	0.0395***	0.0556***	0.0132***	0.0180***	0.0194***	0.0224***
2	0.0139***	0.0138***	0.0198***	0.0157*	0.0165***	0.0137***	0.0163***	0.0127*
3	0.0040	0.0004	-0.0074	0.0277	-0.0133	-0.0435**	-0.0342	-0.0442
4	0.0247	0.0434	0.0343	-0.0015	0.0292	0.0386	0.0225	-0.0224
RecChange	BHAR2to30	BHAR2to91	BHAR2to182	BHAR2to365	BHAR2to30(C)	BHAR2to91(C)	BHAR2to182(C)	BHAR2to365(C)
-4	0.0093	0.0636	0.0869	0.0719	0.0002	0.0442	0.0299	0.0485
-3	-0.0096	-0.0235	-0.0224	-0.0736*	-0.0186**	-0.0463**	-0.0387*	-0.0957***
-2	-0.0055***	-0.0096***	-0.0179***	-0.0177**	-0.0081***	-0.014***	-0.0194***	-0.0314***
-1	-0.0019	-0.0005	0.0032	0.0346***	-0.0068***	-0.0116***	-0.0159***	-0.0142***
0	0.0031**	0.0169***	0.0220***	0.0395***	0.0018	0.0034*	0.0006	-0.0029
1	0.0054***	0.0197***	0.0297***	0.0456***	0.0050***	0.0093***	0.0105***	0.0129***
2	0.0036*	0.0014	0.0085	0.0031	0.0055***	0.0023	0.0043	0.0002
3	-0.0181	-0.0156	-0.0084	0.0205	-0.0213	-0.0501**	-0.0412	-0.0520
4	0.0256	0.0193	0.0295	-0.0014	0.0157	0.0261	0.0103	-0.0346

Notes: This table displays the results of a series of t-tests which examine whether analyst recommendations result in long term returns that are significantly different from 0. The long term performance is measured for each change in recommendation level by the same analyst (RecChange). RecChange is calculated as the current recommendation level minus the last recommendation level by the same analyst. Positive numbers of RecChange represent upgrades, while negative numbers represent downgrades. For each level of RecChange, the number displayed is the average abnormal return for the time period. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively. The top panel displays the results of the performance measure that calculates the returns starting from the announcement day, while bottom panel displays the results of the performance measure that calculates the returns starting from day 2. The first four columns display the results of the BHAR measure. Columns 5-8 display the results of the BHAR(C) measure. In the name of each performance measure, the numbers 30, 91, 182, and 365 represent the length of time period (in days) in which the performance is measured.

The bottom panel of Table 2 displays the results of performance measures that are calculated by starting on day 2. These results are similar to the results of the top panel; however, as in Table 1, they are of lower magnitude, and in some cases, insignificant. This difference suggests that the information content of analyst recommendation is quickly absorbed into prices; however, on average, prices continue to drift in the direction of the recommendation change and investors can earn abnormal returns by following analyst recommendation.

Figures I to IV show graphs of the abnormal performance of analyst recommendations during the first year following the announcement. Figure I shows the performance of Buy and Sell recommendations using the BHAR measure, while Figure II shows the performance of Buy and Sell recommendations using the BHAR(C) measure. Similar to the results of Table 1, these figures show that Buy and Sell recommendations continue to earn abnormal returns in the direction suggested by the recommendation, throughout the year. However, Figure I shows that Sell recommendations generate most of the value in the first three months following the announcement; their performance is similar to the CRSP index for the rest of the year. Figure III shows the performance of upgrades and downgrades using the BHAR measure, while Figure IV shows the performance of upgrades and downgrades using the BHAR(C) measure. In Figure III, upgrades earn positive abnormal returns throughout the first year following their announcement. Downgrades earn negative returns for about 170 trading days following their announcement; however, the abnormal returns start reversing about 170 days after their announcement and towards the end of the first year the abnormal returns become positive. The results of Figure IV show that upgrades and downgrades outperform a portfolio of competitors for the 1-year period; however, for downgrades, most of the abnormal returns are earned in the first three months following the announcement. Overall, these results suggest that analyst recommendations in the banking industry create value for long term investors. Positive recommendations earn abnormal returns for the investors for periods up to one year, while negative recommendations earn abnormal returns for the investors for at least three months and up to one year.

Figure I. Long-Term Performance of Buy or Sell - Recommendations Using the BHAR Measure

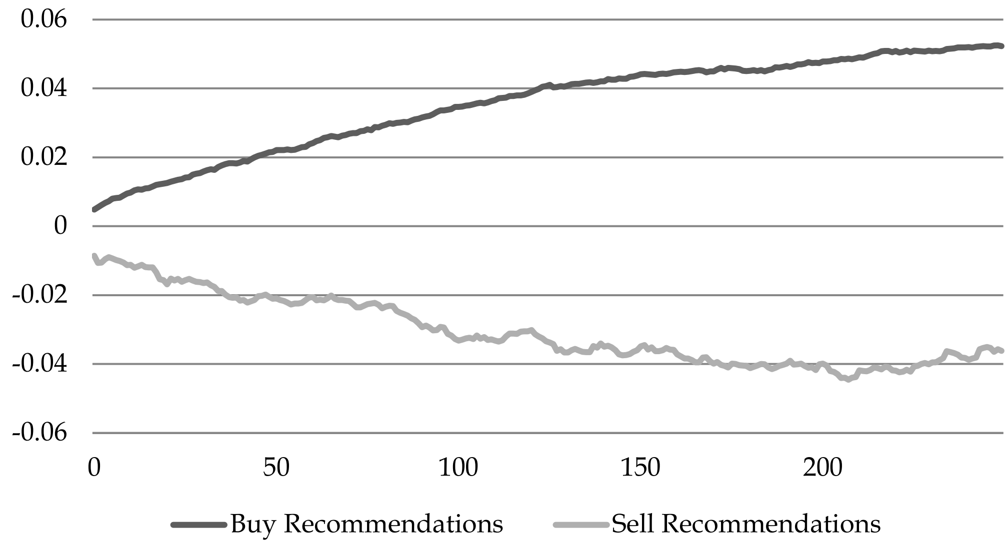


Figure II. Long-Term Performance of Buy or Sell - Recommendations Using the BHAR(C) Measure

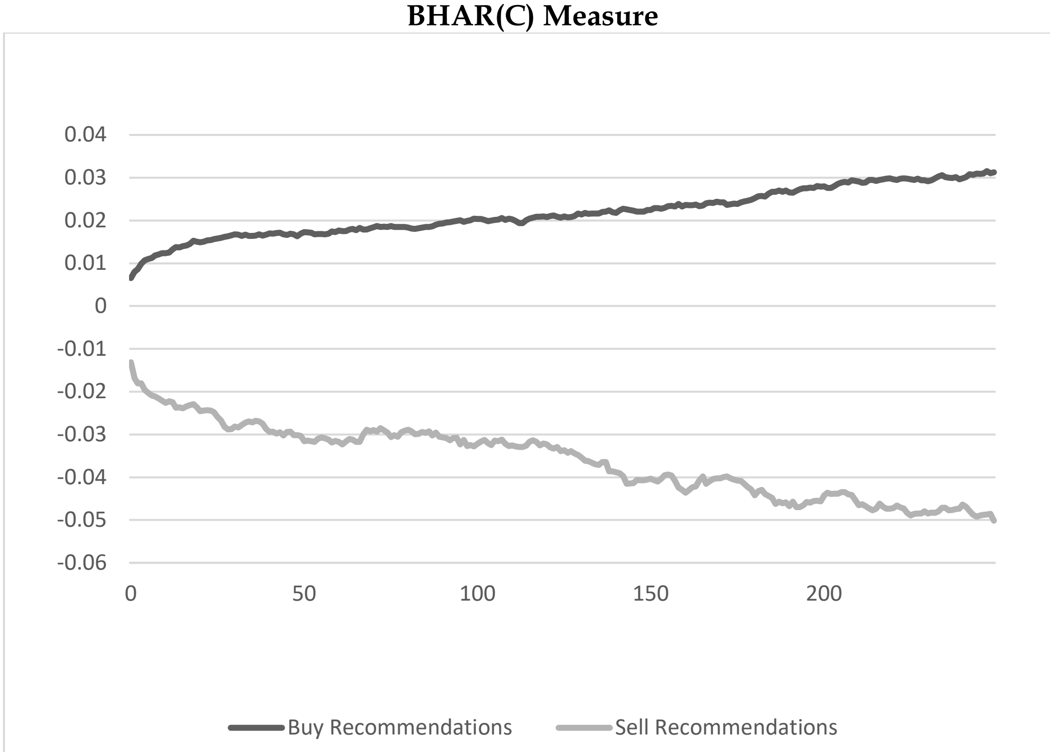


Figure III. Long-Term Performance of Upgrades and Downgrades - Using the BHAR Measure

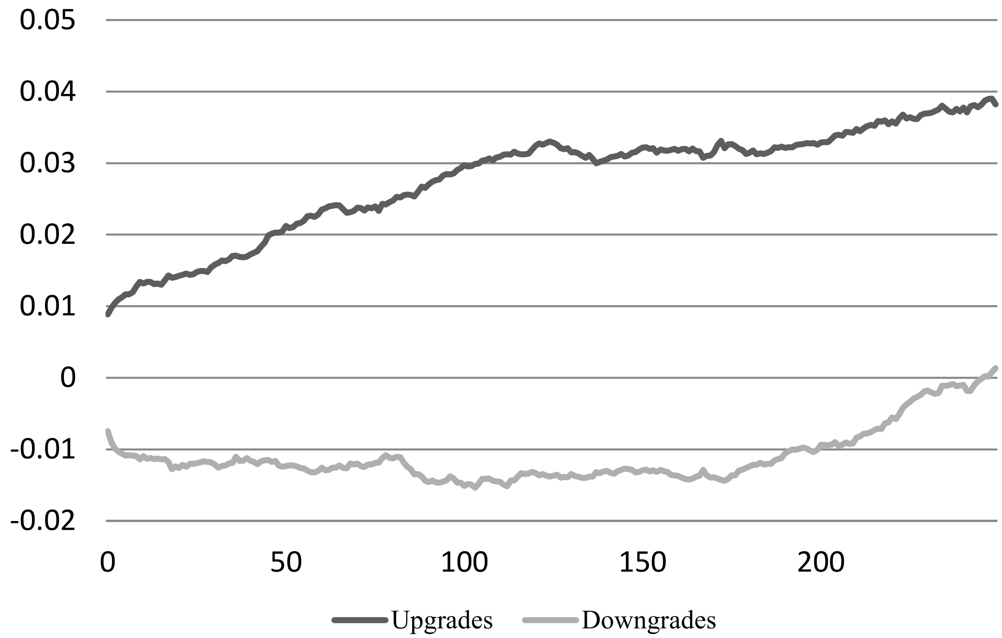
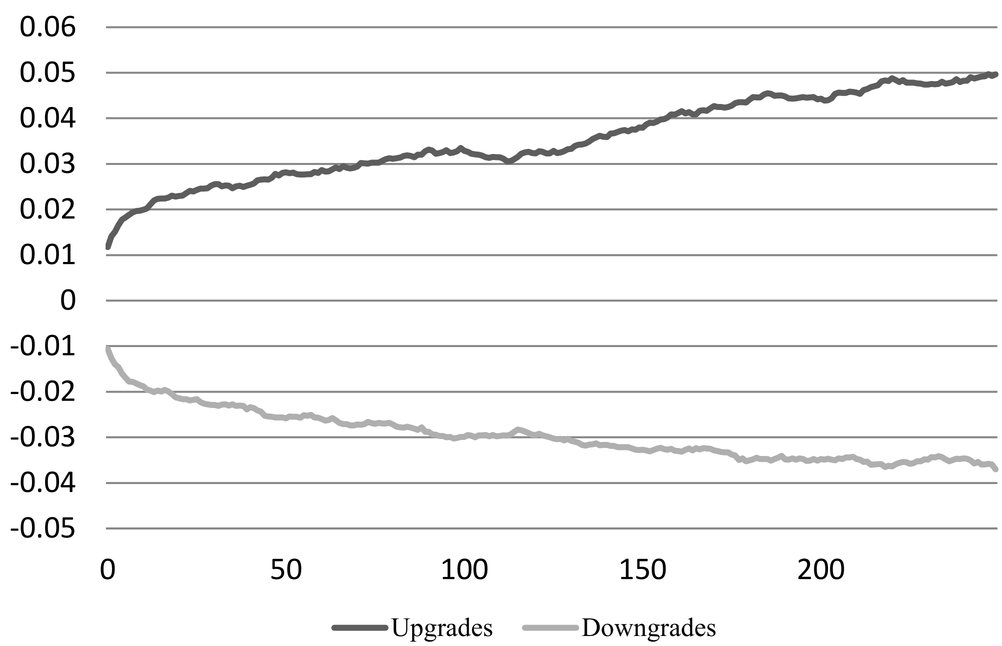


Figure IV. Long-Term Performance of Upgrades and Downgrades - Using the BHAR(C) Measure



There are several reasons that could explain why the investment value of negative recommendations declines in the post 3-month period. First, the greater the amount of time following the recommendation, the greater the probability that unforeseen confounding events that dictate the bank's performance could occur. Second, the greater the amount of time following the recommendation, the lower the probability that an analyst could foresee such events and issue the appropriate recommendation. Third, it is difficult to clearly classify recommendations into positive ones and negative ones as some recommendations could send mixed signals. For example, a downgrade from a Strong Buy to a Buy could send negative signals because it is a downgrade; however, it is still a Buy recommendation which sends a positive signal. Fourth, many analysts issue recommendations frequently (usually quarterly), and as such, many recommendations may not be intended to guide investors' decisions for periods of longer than three months. Hobbs, Kovacs, and Sharma (2012) find that analysts who frequently revise their recommendations outperform those who do not. Given that most of the value from analyst recommendations (especially negative recommendations) is created in the first three months, and to conserve space, we only focus on the 1-month and 3-month performance measures for the remainder of this paper.

B. Zero-Cost Portfolio Formation and Results

To further investigate whether analysts are able to provide recommendations that create value for long-term investors in the banking industry, we perform an additional test. Following the methodology of Boni and Womack (2006), we construct zero-cost investment portfolios at the end of every month. The portfolios are formed based on analyst recommendations issued in month t-1 (data are collected at the end of month t-1) and each portfolio is held for one month (month t). The portfolios are constructed using two methods: 1) based on the consensus level of all recommendations in month t-1; and 2) based on the recommendation changes in month t-1 (net upgrades and net downgrades). In each strategy, the investor buys the most favorably recommended banks by short-selling the least favorably recommended banks. In the consensus level strategy, the investor takes a long position on the top 10% banks with the highest consensus recommendation (or the bank with the highest consensus recommendations)[7] and a short position on the 10% of the banks with the lowest consensus recommendation (or the bank with the lowest consensus recommendation). We calculate the consensus recommendation as the average of all recommendations that the bank receives in the month t-1. Similarly, in the aggregate recommendation change strategy the investor takes a long position on the top 10% banks with the highest aggregate recommendation change (or the bank with the highest aggregate recommendation change) and a short position on the 10% of the banks with the lowest aggregate recommendation change (or the bank with the lowest aggregate recommendation change). The aggregate recommendation change is calculated as the average of the current recommendation level minus the prior recommendation level by the same analyst.

[7] If 2 or more banks tie in the highest (lowest) consensus recommendation, one of these banks is chosen at random.

All observations that are either analyst coverage initiations or cannot be matched to a prior analyst rating are excluded from the calculations of aggregate recommendation change. The portfolios are created as equally-weighted portfolios.

Table 3. Results of the Zero-Cost Investment Strategy that Goes Long the Top 10% Recommended Banks and Short the Bottom 10% Recommended Banks

	Strategy Based on Recommendation Levels			
	Top & Bottom 10% of Banks		Top & Bottom Bank	
	Portfolio Excess Return		Portfolio Excess Return	
Constant	0.0106***	0.0106***	0.0175*	0.0168*
mktrf	-0.0918	-0.0916	-0.1840	-0.1430
smb	-0.0362	-0.0362	-0.4770	-0.4940*
hml	0.1180	0.1180	-0.1060	-0.0716
umd		0.0004		0.1050
N	230	230	230	230
R-sq	0.028	0.028	0.022	0.024
	Strategy Based on Recommendation Changes			
	Top & Bottom 10% of Banks		Top & Bottom Bank	
	Portfolio Excess Return		Portfolio Excess Return	
Constant	0.0118***	0.0117***	0.0174*	0.0192*
mktrf	-0.1380*	-0.1350	0.1440	0.0393
smb	-0.1290	-0.1310	0.0493	0.0873
hml	0.1430	0.1460	0.0422	-0.0392
umd		0.0084		-0.255
N	230	230	230	230
R-sq	0.046	0.046	0.002	0.01

Notes: This table displays the results of the Fama-French regressions of the returns of portfolios formed based on the $0 cost trading strategy. The top panel displays the results of the portfolios formed based on the recommendation levels, while the bottom panel displays the results of the portfolios formed based on the recommendation changes. In each panel, the left two columns display the results of portfolios formed by selecting the top and botton 10% of banks, while the right two columns display the results of portfolios formed by selecting the top and botton bank. The dependent variable is the portfolio excess return. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively.

To examine whether analyst recommendations in the banking industry are valuable to long-term investors, we regress the excess returns of each month's portfolio on the Fama and French (1993) factors: the market excess return ($Rm - Rf$), the size factor (SMB), and the value factor (HML). Additionally, we also include in the model the momentum factor (UMD) as in Carhart (1997). The intercept of these models (ALPHA) captures the average monthly abnormal return derived from this strategy.

Table 3 displays the results of the Fama-French regressions of the returns of portfolios formed based on the zero-cost investment strategy. The top panel displays the results of the portfolios formed based on the recommendation levels, while the bottom panel displays the results of the portfolios formed based on the recommendation changes. In each panel, the left two columns display the results of portfolios formed by selecting the top and bottom 10% of banks, while the right two columns display the results of portfolios formed by selecting the top and bottom bank. In each model, the dependent variable is the portfolio excess return. Results of Table 3 show that each investments strategy results in positive and significant abnormal returns, as measured by the Alpha (i.e., the intercept) of the regression models. The alpha indicates that the strategy would result in abnormal returns ranging from 1.06% to 1.92% per month, after we account for the Fama, French, and Carhart risk factors. These results further confirm that analyst recommendations in the banking industry create investment value for long term investors.

C. Cross-Sectional Determinants of Investment Value

To determine how the firm environment affects the investment value of analyst recommendations, we run a regression model controlling for several bank and analyst characteristics that could affect the value of analyst recommendations. For every recommendation we calculate the 1-month and 3-month abnormal returns following each recommendation. As above, we calculate the abnormal returns by using BHAR and BHAR(C). To test our hypotheses we run the following cross-sectional regression model:

$$BHAR \text{ (or } BHAR(C)) = a + \beta_1 AnalystFollowing \text{ (or } SIZE) + \beta_2 SOX + \beta_3 BETA + \beta_4 VIX + \beta_5 Q + \beta_6 NII + \beta_7 SETTLEMENT + \beta_8 AnalystExperience + \beta_9 NrOfIndustries + \beta_{10} RecChange + \beta_{11} StrongBuy \text{ (or } StrongSell) + \beta_{12} Momentum + \beta_{13} CAR01 + \varepsilon_I \quad (3)$$

Because AnalystFollowing and SIZE are highly correlated, we run two versions of the model in which we include only one of these variables.

Table 4 displays summary statistics for the variables used in the regression analysis. On average, banks in our sample have $78 billion in assets and are followed by 7.6 analysts. 53% of our recommendations occur after the enactment of SOX. The average bank beta is 0.97 and the average VIX index for our sample period is 20.92. Tobin's Q has an average of 1.08. The NII has a mean of 0.21, which suggests that banks in our sample generate 21% of their income from non-traditional banking activities. 47% of our recommendations occur after the Global Analyst Research Settlement was reached. The average analyst has worked in the industry for about 1,630 days and covers 3.31 SIC codes. The average RecChange is -0.05 and about 19% of our recommendations are Strong Buys, while only about 2% are Strong Sells. The average announcement return (CAR01) of the recommendations in our sample is 0.

Table 4 Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Total Assets	23,264	78,129.34	238,212.70	44.53	2,807,491.00
AnalystFollowing	23,632	7.62	5.51	1.00	28.00
SOX	23,632	0.53	0.50	0.00	1.00
BETA	22,549	0.97	0.53	-3.34	4.89
VIX	23,632	20.92	8.14	9.31	80.86
Q	22,528	1.08	0.12	0.80	4.74
NII	19,884	0.21	0.14	0.00	0.98
SETTLEMENT	23,632	0.47	0.50	0.00	1.00
AnalystExperience	32,451	1,629.78	1,482.92	1.00	6,971.00
NrOfIndustries	32,451	3.31	4.95	1.00	153.00
RecChange	23,632	-0.05	0.96	-4.00	4.00
StrongBuy	23,632	0.19	0.39	0.00	1.00
StrongSell	23,632	0.02	0.15	0.00	1.00
Momentum	22,829	0.08	0.24	-0.94	6.31
CAR01	22,828	0.00	0.03	-0.10	0.10

Notes: This table describes the variables used in our study. Total Assets represents the bank's total assets.[8] AnalysFollowing is the number of analysts that follow the bank. SOX is a dummy variable that equals 1 after the SOX was enacted, and 0 otherwise. BETA is the bank's beta prior to the recommendation. VIX is value of the VIX index on the day the recommendation is issued. Q represents Tobin's Q and it is 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 as a percentage of revenue. SETTLEMENT is dummy variable that equals 1 after the Global Analyst Research Settlement was reached, and 0 otherwise. AnalystExperience is the log of the number of days that the analyst has appeared in the IBES database prior to the recommendation. NrOfIndustries is the number of SIC codes that the analyst covers. RecChange is calculated as the current recommendation level minus the last recommendation level by the same analyst. StrongBuy (StrongSell) are dummy variables that take the value of 1 if the recommendation is a Strong Buy (Strong Sell) and 0 otherwise. Mometum is the bank's buy and hold return in the 6-month periods prior to the analyst's recommendation. CAR01 is the announcement return of the recommendation measured by using the market model.

Our hypotheses make opposite predictions for positive and negative recommendations. For example, if analyst recommendations deliver greater investment value for banks with high degree of information asymmetry, we should observe greater abnormal returns for positive recommendations of opaque banks, and lower abnormal returns for negative recommendations of opaque banks. Therefore, it is important that we run our model separately in subsamples that contain only positive or only negative recommendations. This task requires some attention because some recommendations can send mixed signals. For example, a Buy recommendation sends a positive signal; however, it could also be a downgrade

[8] In our regression models, we use SIZE, which is the natural log of the bank's total assets.

from a Strong Buy, which sends a negative signal. Similarly, an upgrade from a Strong Sell to a Sell could send mixed messages to the investors. These mixed signals make it difficult to split the sample into positive and negative subsamples. Cliff (2007) runs his model separately for subsamples of only Buy or only Sell recommendations. Similarly, Loh and Stulz (2011) run their model in subsamples of only upgrades or only downgrades. Similar to Cliff (2007), we originally split the sample into two subsamples: a Positive Subsample with only Buy or Strong Buy recommendations and a Negative Subsample with only Sell or Strong Sell recommendations. To ensure that our subsamples contain strictly positive (negative) recommendations, we maintain in the Positive (Negative) subsample only the recommendations that have a positive (negative) CAR01. As a robustness test we also use a more restrictive criteria that combines the methodologies used in Cliff (2007) and in Loh and Stulz (2011) in splitting the sample: we maintain in the Positive Subsample the recommendations that are an upgrade to a Buy or an upgrade to a StrongBuy and in the Negative Subsample the recommendations that are a downgrade to a Sell or a downgrade to a StrongSell. Premti et al. (2017) use similar subsamples of positive and negative recommendations. In addition, to minimize the period-specific effects that could impact the performance of the analyst recommendations, all the models are run with year fixed effects.

D. Results of the Regression Model Applied to the Positive Subsamples

Table 5 displays the results of our models applied to the subsample that contains only Buy or Strong Buy recommendations. In this table, as well as in all the following tables, the left panel displays the results of the models with BHAR as the dependent variable, while the right panel displays the results of the models with BHAR(C) as the dependent variable. In each panel, the first two models use AnalystFollowing as a proxy for information asymmetry, while the right two models display the results of the models that include SIZE as a proxy for information asymmetry.

Table 5 shows that the coefficient of AnalystFollowing is negative and significant in all four models. This result suggests that analyst recommendations provide greater value in banks with lower analyst following (which have a greater degree of information asymmetry). This result suggests that in banks with higher degree of information asymmetry, analysts are able to generate private information that can help to guide investors' decisions.

Similarly, the coefficient of SIZE is negative and significant in all four models. This result reinforces the results of the AnalystFollowing coefficient and suggests that, for similar reasons, analyst recommendations provide greater investment value for smaller banks (which have a greater degree of information asymmetry).

The coefficient of SOX is negative and significant in all models with BHAR as the dependent variable. This result suggests that the investment value of analyst recommendations declined after the passage of the Sarbanes-Oxley Act. The Sarbanes-Oxley Act increased the reporting standards and helped reduce the information asymmetry in all industries. This result complements the results found for AnalystFollowing and SIZE and suggests that analyst recommendations provide greater investment value in periods with greater degree of information asymmetry (like the pre-SOX period). The coefficient of SOX is also economically significant. It ranges from -0.0233 to -0.0567 and it suggests that recommendations that were issued in the post-SOX period would result in a BHAR that is about 2.33% to 5.67% lower in a 1 to 3 month period, compared to the recommendations that were issued in the pre-SOX period. In the models with BHAR(C) as the dependent variable, the coefficient of SOX is insignificant.

The coefficient of BETA is negative and significant in all eight models. This result suggests that positive recommendations of riskier banks provide lesser value for the investors. Similarly, the coefficient of VIX is negative and significant in six out of the eight models. This result suggests that positive recommendations deliver smaller value to the investors in riskier periods (periods with high VIX). Combined, these results show that positive recommendations create lesser value when they are issued in a high-risk environment. These results suggest that in a risky environment analyst face a challenge in predicting future prices, or that investors rely less on (or discount) positive recommendations issued in risky environments.

The coefficient of Q is negative and significant in five out of the eight models. This result suggests that positive recommendations provide smaller investment value for overvalued banks. When the stock is overvalued, investors may be less willing to act upon positive recommendations as the upside potential is low.

The coefficient of MOMENTUM is negative and significant in all models. This result suggests that positive recommendations of banks deliver greater value when issued for banks that have had lower returns in the past six months. It contradicts the results of Muslu and Xue (2013) who find that analyst recommendations contribute to the current momentum and push prices further in the same direction.

The coefficient of CAR01 is positive and significant in all eight models, suggesting that analyst recommendations that elicit a large immediate price response also provide a greater investment value in the 1-month and 3-month periods. The coefficient of CAR01 is also economically significant. It ranges from 0.763 to 1.075 and it suggests that a 1% increase in the announcement return results in an increase of 0.763% to 1.075% in BHAR in a 1 to 3-month period.

Table 6 displays the results of our models applied to the subsample that contains only recommendations that are an upgrade to a Buy or an upgrade to a Strong Buy. Results of Table 6 are consistent with the results of Table 5.

After analyzing different subsamples of positive recommendations, we find that positive analyst recommendations deliver greater investment value to investors when they are issued for banks with higher degree of information asymmetry or if they are issued prior to regulatory events that decreased the information asymmetry in the banking industry, such as Sarbanes Oxley Act. In addition, we find that positive recommendations deliver smaller value when they are issued in risky environments or issued for overvalued banks.

E. Results of the Regression Model Applied to the Negative Subsamples

Tables 7 and 8 display the results of the regression models applied to the negative subsamples. In these subsamples, the interpretation of the coefficients differs from the interpretation of the coefficients in the positive subsamples. When an analyst issues a positive recommendation, investors expect an upward price movement, and the higher the upward price movement (the higher the abnormal return), the greater the value that the investor derives by following the analyst's positive recommendation. Therefore, in the positive subsamples, a positive coefficient suggests that an increase in the corresponding variable results in a higher abnormal return and a higher value for the investor. When an analyst issues a negative recommendation, investors expect a downward price movement. An investor would act upon the negative recommendation by shorting (or selling) the stock. By taking a short position on the stock, the investor benefits when there is a large downward movement in the stock, and the larger the downward price movement (the more negative the abnormal return), the greater the value that the investor derives by following the analyst's negative recommendation.

Table 7 shows the results of our models applied to the subsample that contains only Sell or Strong Sell recommendations. The coefficient of AnalystFollowing is positive and significant in all four models. This result suggests that an increase in the bank's analyst following would results in a higher abnormal return, and therefore a smaller value for the investors acting upon negative recommendations. Negative analyst recommendations provide greater investment value in banks with lower analyst following (which have a greater degree of information asymmetry). This result is consistent with the result found in the positive subsamples. The coefficient of SIZE is positive and significant in all four models. This result suggests that negative recommendations provide greater investment value in smaller banks (which have a greater degree of information asymmetry). Lastly, the coefficient of SOX is positive and significant in seven out of the eight models. This result is consistent with the results found in the positive subsamples and provides further support for the hypothesis that that analyst recommendations provide greater investment value in an periods with a high degree of information asymmetry (like the pre-SOX period). The coefficient of SOX is also economically significant. It ranges from 0.0377 to 0.095 and it suggests that recommendations that were issued in the post-SOX period would result in a BHAR that is about 3.77% to 9.5% higher, compared to the recommendations that were issued in the pre-SOX period. Overall, the results from positive and negative subsamples suggest that in an environment

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

	Using CRSP VW Index				Using a Portfolio of Close Competitors			
	BHAR	BHAR	BHAR	BHAR	BHAR(C)	BHAR(C)	BHAR(C)	BHAR(C)
	1 Month	3 Months	1 Month	3 Months	1 Month	3 Months	1 Month	3 Months
Constant	0.06820***	0.20800***	0.08870***	0.26400***	0.00622	0.04480**	0.03150**	0.0804***
AnalystFollowing	-0.00083***	-0.00254***			-0.00104***	-0.00192***		
SIZE			-0.00202***	-0.00551***			-0.00249***	-0.00346***
SOX	-0.0233***	-0.05670***	-0.02280***	-0.05510***	0.01040	0.00652	0.01110	0.00786
BETA	-0.00980***	-0.01390***	-0.01060***	-0.01700***	-0.00663***	-0.00720*	-0.00765***	-0.01020**
VIX	-0.00166***	-0.00325***	-0.00166***	-0.00325***	-0.00061***	-0.00004	-0.00061***	-0.00001
Q	-0.01150	-0.06260***	-0.01900*	-0.08350***	0.00040	-0.03460**	-0.00881	-0.04840***
NII	0.00984	0.02660	0.01200	0.02880	0.01870**	0.02780*	0.02110**	0.02490
SETTLEMENT	-0.00677	0.00038	-0.00743	-0.00155	0.00737	0.01960	0.00654	0.01830
AnalystExperience	0.00215***	0.00117	0.00216***	0.00113	0.00152**	0.00085	0.00152**	0.00077
NRofIndustries	0.000533	0.00074	0.00055	0.00080	0.00025	-0.00012	0.00027	-0.00007
RecChange	-0.000422	0.00276	-0.00041	0.00276	0.00217	0.00149	0.00218	0.00145
StrongBuy	0.00212	-0.00431	0.00183	-0.00509	0.00377	0.00001	0.00342	-0.00046
Momentum	-0.02190***	-0.03960***	-0.02100***	-0.0371***	-0.01960***	-0.04190***	-0.01850***	-0.04010***
CAR01	1.00400***	1.07500***	1.00000***	1.06900***	0.76800***	0.80100***	0.76300***	0.80400***
N	4994	4992	4994	4992	4994	4992	4994	4992
R-sq	0.07600	0.05800	0.07500	0.05600	0.05700	0.03200	0.05600	0.0300

Notes: This table displays the results of the regression models applied to the subsample that contains only Buy or Strong Buy recommendations. In this table all the performance measures are calculated by starting from the announcement day. The first four models display the results of the model with the dependent variable being the BHAR measure that uses the CRSP index as a benchmark. The last four models display the results of the model with the dependent variable being the BHAR(C) measure that uses the portfolio of competitors as a benchmark. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively. For a detailed explanation of the independent variables please refer to the description of Table 4.

Table 6. 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

	Using CRSP VW Index				Using a Portfolio of Close Competitors			
	BHAR	BHAR	BHAR	BHAR	BHAR(C)	BHAR(C)	BHAR(C)	BHAR(C)
	1 Month	3 Months	1 Month	3 Months	1 Month	3 Months	1 Month	3 Months
Constant	0.03490	0.18700***	0.06740**	0.22300***	-0.02430	-0.01840	0.01410	0.00832
AnalystFollowing	-0.00133***	-0.00268***			-0.00123***	-0.00190***		
SIZE			-0.00340***	-0.00374*			-0.00400***	-0.00282*
SOX	-0.03030**	-0.02900	-0.02960**	-0.02760	0.00317	0.01590	0.00381	0.01700
BETA	-0.00788*	-0.01000	-0.01010**	-0.01660**	-0.00376	-0.00213	-0.00525	-0.00665
VIX	-0.00162***	-0.00399***	-0.00162***	-0.00400***	-0.00046*	0.00002	-0.00045*	0.00001
Q	0.01720	-0.02840	0.00613	-0.03930	0.02750*	0.04240	0.01410	0.03410
NII	0.02060	0.04580*	0.02470	0.03300	0.03010**	0.01740	0.03980***	0.00943
SETTLEMENT	0.00427	0.01410	0.00437	0.01380	0.01600	0.02870	0.01630	0.02850
AnalystExperience	0.00168	-0.00328	0.00192	-0.00353	0.00068	-0.00328	0.00112	-0.00342
NRofIndustries	-0.00028	-0.00165	-0.00030	-0.00168	-0.00078	-0.00245**	-0.00080	-0.00247**
RecChange	0.00613	0.00910	0.00613	0.00934	0.00337	0.00447	0.00331	0.00463
StrongBuy	-0.00283	-0.01940**	-0.00328	-0.02020**	-0.00085	-0.01240*	-0.00132	-0.01290*
Momentum	-0.01630**	-0.05140***	-0.01460*	-0.04990***	-0.01680**	-0.03730***	-0.01480**	-0.03610***
CAR01	0.97200***	1.22500***	0.95600***	1.23500***	0.79900***	0.79400***	0.77300***	0.79900***
N	2135	2135	2135	2135	2135	2135	2135	2135
R-sq	0.08900	0.08200	0.08800	0.07600	0.07000	0.04000	0.07200	0.03600

Notes: 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. In this table all the performance measures are calculated by starting from the announcement day. The first four models display the results of the model with the dependent variable being the BHAR measure that uses the CRSP index as a benchmark. The last four models display the results of the model with the dependent variable being the BHAR(C) measure that uses the portfolio of competitors as a benchmark. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively. For a detailed explanation of the independent variables please refer to the description of Table 4.

Table 7. Results of the Regression Model Applied to the Subsample that Contains only Sell or Strong Sell Recommendations

	Using CRSP VW Index				Using a Portfolio of Close Competitors			
	BHAR	BHAR	BHAR	BHAR	BHAR(C)	BHAR(C)	BHAR(C)	BHAR(C)
	1 Month	3 Months	1 Month	3 Months	1 Month	3 Months	1 Month	3 Months
Constant	0.06030	0.16500**	0.02330	0.04460	0.02430	0.07330	-0.00007	-0.00854
AnalystFollowing	0.00179***	0.00228**			0.00171***	0.00302***		
SIZE			0.00418**	0.01210***			0.00298*	0.00886***
SOX	0.03860*	0.06640*	0.03770	0.07060*	0.07350***	0.09500***	0.07190***	0.09490***
BETA	-0.00791	-0.02620**	-0.00517	-0.02480**	-0.01350**	-0.03000***	-0.01050*	-0.02590***
VIX	-0.00069	-0.00292***	-0.00077	-0.00297***	-0.00052	-0.00001	-0.00060	-0.00013
Q	-0.08520***	-0.15700***	-0.07610***	-0.13300***	-0.06940***	-0.14900***	-0.06270**	-0.13000***
NII	0.05140*	0.10600**	0.05040*	0.05800	0.05800**	0.11500***	0.06400***	0.10000**
SETTLEMENT	0.00358	0.01590	0.00448	0.01770	0.00120	0.01600	0.00196	0.01770
AnalystExperience	-0.00167	-0.00607*	-0.00161	-0.00617*	-0.00290*	-0.00654**	-0.00282*	-0.00649**
NRofIndustries	-0.00024	0.00197	-0.00035	0.00174	0.00085	0.00049	0.00076	0.00029
RecChange	0.00033	0.00032	0.00019	-0.00122	0.00210	0.00554	0.00218	0.00494
StrongSell	0.00550	0.00518	0.00643	0.00484	-0.00574	0.00229	-0.00463	0.00346
Momentum	-0.00152	0.02990	-0.00229	0.02940	0.00531	0.04410***	0.00450	0.04300**
CAR01	0.97400***	0.72700***	0.96800***	0.65200**	0.70900***	0.39600*	0.71400***	0.36800
N	1034	1034	1034	1034	1034	1034	1034	1034
R-sq	0.08900	0.06400	0.08600	0.07100	0.09100	0.06200	0.08500	0.06000

Notes: This table displays the results of the regression models applied to the subsample that contains only Sell or Strong Sell recommendations. In this table all the performance measures are calculated by starting from the announcement day. The first four models display the results of the model with the dependent variable being the BHAR measure that uses the CRSP index as a benchmark. The last four models display the results of the model with the dependent variable being the BHAR(C) measure that uses the portfolio of competitors as a benchmark. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively. For a detailed explanation of the independent variables please refer to the description of Table 4.

Table 8. Results of the Regression Model Applied to the Subsample that Contains Recommendations that Are Downgrades to a Sell or Downgrades to a Strong Sell

	Using CRSP VW Index				Using a Portfolio of Close Competitors			
	BHAR	BHAR	BHAR	BHAR	BHAR(C)	BHAR(C)	BHAR(C)	BHAR(C)
	1 Month	3 Months	1 Month	3 Months	1 Month	3 Months	1 Month	3 Months
Constant	-0.05620	-0.09720	-0.10900	-0.278**	-0.17600***	-0.24400**	-0.24400***	-0.42700***
AnalystFollowing	0.00241***	0.00281**			0.00236***	0.00429***		
SIZE			0.00511**	0.01430***			0.00612***	0.0153***
SOX	-0.00769	-0.01030	-0.00945	-0.00750	0.04770*	0.03950	0.04660*	0.0400
BETA	0.00533	-0.00029	0.00952	0.00336	-0.00207	-0.00379	0.00186	0.00274
VIX	-0.00182***	-0.00233**	-0.00189***	-0.00225**	-0.00088	0.00051	-0.00093*	0.00050
Q	-0.00727	-0.01990	0.01350	0.05330	0.10100**	0.13300	0.12800***	0.20600**
NII	0.01330	0.05000	0.01360	-0.00994	0.01530	0.03950	0.00746	-0.00519
SETTLEMENT	-0.00949	0.01190	-0.00965	0.01010	-0.01040	0.00499	-0.01080	0.00352
AnalystExperience	0.01370***	0.01470**	0.01370***	0.01350*	0.00412	0.00073	0.00399	-0.00008
NRofIndustries	0.00047	0.00585*	0.00021	0.00540	0.00153	0.00260	0.00126	0.00203
RecChange	0.01830*	0.00948	0.01850*	0.00725	0.00680	0.01750	0.00669	0.01600
StrongSell	0.02150*	0.01700	0.02370**	0.01770	-0.00289	0.01280	-0.00094	0.01530
Momentum	-0.01630	-0.00019	-0.01680	0.00552	-0.00288	0.02550	-0.00248	0.02940
CAR01	0.82100***	0.90100***	0.81700***	0.81100***	0.65100***	0.63900**	0.63600***	0.56900**
N	686	686	686	686	686	686	686	686
R-sq	0.10500	0.06700	0.09800	0.07900	0.09000	0.05900	0.08500	0.06600

Notes: This table displays the results of the regression models applied to the subsample that contains only recommendations that are downgrades to a Sell or downgrades to a Strong Sell. In this table all the performance measures are calculated by starting from the announcement day. The first four models display the results of the model with the dependent variable being the BHAR measure that uses the CRSP index as a benchmark. The last four models display the results of the model with the dependent variable being the BHAR(C) measure that uses the portfolio of competitors as a benchmark. *, **, and *** represent the level of significance at the 10%, 5%, and 1%, respectively. For a detailed explanation of the independent variables please refer to the description of Table 4.

with higher degree of information asymmetry, analysts are able to generate private information, and, when passed to the investors, this information creates greater value.

The coefficient of BETA is negative and significant in six out of the eight models, while the coefficient of VIX is always negative; however, it is significant in only two out of the eight models. These results are consistent with the results of Loh and Stulz (2017) who find that analysts work harder and investors rely more on analysts during bad (uncertain) times. Unlike the results found in the positive subsamples,[9] these results suggest that negative recommendations deliver greater value to investors in riskier environments. Overall, we believe that the results of positive and negative subsamples suggest that, in riskier environments, when investors worry about the future of their investment, investors view negative recommendations as more credible and act more upon them, while they may not view the positive recommendations as credible, or they may be reluctant to pursue them, given the risk involved.

In an alternate version of the model, we also substituted VIX with a dummy variable called CreditCrisis[10], which took the value of 1 from December 2007 to June 2009 (the official recession dates as reported by the National Bureau of Economic Research), and 0 otherwise. The coefficient of CreditCrisis is insignificant in the positive subsamples, and negative and significant in the negative subsamples. This result further supports our finding that during high risk periods, investors rely more on the negative recommendations, and do not rely on the positive recommendations. However, this result needs to be interpreted with caution. Given that our model is run with year fixed effects, the majority of the effect for year 2008 (the main year of the Credit Crisis) would be captured in that year's fixed effect, and not in the CreditCrisis dummy. For this reason, we believe that the VIX index is a better measure to capture the effect of the Credit Crisis, and only report the results of the model with the VIX index.

The coefficient of Q is negative and significant in all the eight models. This result suggests that negative recommendations provide greater investment value for overvalued banks. When the stock is overvalued, investors may be more willing to act upon negative recommendations as the downside potential is greater.

The coefficient of AnalystExperience is negative and significant in six out of the eight models. This result suggests that experienced analysts create greater value for investors when issuing negative recommendations.

The coefficient of CAR01 is positive and significant in seven out of the eight models. Consistent with results of the positive subsamples, this result suggests that negative recommendations that elicit a lower (more negative) CAR01 continue to generate lower (more negative) abnormal returns in the 1-month and 3-month

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[9] The results of positive subsamples showed that positive recommendations deliver lower value to the investors, when issued in riskier environments.

[10] VIX and CreditCrisis were highly correlated, as VIX was very high during the Credit Crisis period.

periods and result in greater value of the investors. The coefficient of CAR01 is also economically significant. It ranges from 0.368 to 0.974 and it suggests that a 1% decrease in the announcement return results in a decrease of 0.368% to 0.974% in BHAR in a 1 to 3 month period.

Table 8 displays the results of the multivariate models in the subsample that contains only recommendations that are a downgrade to a Sell or a downgrade to a Strong Sell. Results are consistent with the results of Table 7, except for the coefficient of BETA and Q, which are mainly insignificant in this subsample.

As a robustness test, we also run our regression models for all subsamples by using BHAR measures computed from day +2 as the dependent variable. Results are consistent with those of Tables 5-8. The only difference is that while CAR01 is positive and significant in the tables in which the dependent variable is abnormal performance calculated from day 0 (Tables 5-8); it is insignificant in the tables in which the dependent variable is abnormal performance calculated from day 2 (unreported tables). These results suggest that while CAR01 makes up a significant proportion of the long-term performance (analyst information is reflected quickly into prices), CAR01 does not predict the price movement in post announcement period. Given their consistency, and in order to conserve space, the tables in which the dependent variable is BHAR calculated from day 2, have been omitted.

Overall, the results of our regression models suggest that analyst recommendations deliver greater value to the investors when they are issued in an environment of heightened degree of information asymmetry. These results suggest that analysts are able to generate valuable information when investors need it the most (in environments with high degree of information asymmetry), and this information leads to higher long term returns for investors. We also find that in an environment with higher risk, positive recommendations deliver lower value for the investors, while negative recommendations deliver greater value. We interpret this result to mean that in riskier environments, investors view negative recommendations as more credible and act more upon them, while they may not view the positive recommendations as credible, or they may be reluctant to pursue them, given the risk involved. Lastly, our results show that while CAR01 makes up a significant proportion of the long-term performance (analyst information is reflected quickly into prices); however, CAR01 does not predict the price movement in post announcement period.

6. Conclusion

We analyze a large sample of analyst recommendations in the banking industry. We argue that generalizations about analyst abilities to offer valuable recommendations for shareholders are subject to error, because the analyst abilities might be conditioned on the information environment. We propose that analysts might possess a greater comparative advantage over other investors in an industry subject to higher information asymmetry. Prior literature notes the banking industry is subject to more information asymmetry, so we believe it serves as a useful experiment to assess analyst abilities.

We find that analysts are able to create value for long term investors for periods up to one year. While most of the value is realized in the first few days, or in the first 3 months, prices generally continue to drift in the direction that the recommendation suggests for periods of 1 year. These results are robust to several measures of abnormal performance, including several BHAR measures, and a zero-investment strategy that simulates a long position on the banks with the highest aggregate recommendation and a short position on the banks with the lowest aggregate recommendation (as in Boni and Womack (2006).

Moreover, we find that analysts are able to create the greatest value for investors when their recommendations are issued in environments with high degree of information asymmetry (e.g., before Sarbanes Oxley Act), or on banks characterized by higher information asymmetry (e.g., smaller, or with lower analyst following). Overall, our results are consistent with the notion that analyst recommendations create greater value for investors when issued in a highly opaque environment.

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