Do Star Analysts Shine in Opaque Industries? Evidence from European Banking*

Benoit d'Udekem†

Université Libre de Bruxelles (ULB), Solvay Brussels School of Economics and Management, Centre Emile Bernheim, Avenue Franklin Roosevelt 42, B-1050 Brussels, Belgium

Abstract

We assess the influence on stock prices of 5,150 changes in analyst recommendations on 80 European banks between 2005 and 2012. Unlike in other industries, recommendation changes made by skilled analysts are not likelier to influence stock prices; those made by star analysts induce sharp negative price revaluations. We conclude that opaqueness impedes the ability of analysts to influence investors and that stars contribute to uncovering hidden firm-specific bad news. Also, stars maintain an influence by focusing on selected large, complex institutions that generate disagreement among analysts and by being apt at identifying mispricings.

Keywords: analysts, skills, banks, agency costs.
JEL Classification Codes: G14, G21, G24.

*I thank Ariane Szafarz and Kim Oosterlinck for their precious guidance. I also thank Blanche de Pierpont for her helpful suggestions and comments on prior versions of this paper. I am grateful to the members of Centre Emile Bernheim for their support. This version: January 26, 2017. First version: January 26, 2017.

†*Email:* bdudekem@ulb.ac.be *Phone:* +32-479-253479 *Fax:* +32-2-3186802

1 Introduction

Banks are often considered by scholars as opaque. Their opaqueness stems from information-intensive lending assets and from ever-changing trading positions that banks may be unwilling or unable to disclose in a timely manner. In turn, without detailed information about these assets, investors have difficulty in appreciating the riskiness and in assessing the value of banks. However, the empirical evidence that backs the fact that assets are the primary source of opaqueness is mixed;[1] to our knowledge, the empirical evidence that shows that investment decisions may be affected by opaqueness is lacking.

In reality, investors may not care about opaque assets; they may be able to see through opaque financial statements or to pick up quality signals in the midst of complex bank disclosures, for example in the willingness of banks to pay dividends even in times of crisis.

Alternatively, investors may be prevented by opaqueness from discerning the good from the bad banks. They may run more risk when investing in the banking industry than in other industries; if so, investing in bank stocks should perhaps come with a warning sign. Bank regulators and credit rating agencies mitigate the investment risk of depositors and creditors, but not that of equity investors. In particular, regulators are formally mandated to protect senior creditors (including depositors), and ultimately, deposit insurers, against the consequences of bank default. Likewise, credit rating agencies monitor banks in the interest of bank creditors; they send signals to the market that may be of limited usefulness to equity investors.

Only professional sell-side analysts may be concerned about the fate of equity investors. However, unlike regulators and credit rating agencies, analysts have no access to private bank information. They have to rely on public disclosures; they may be affected by opaqueness

[1] Morgan (2002) and Iannotta (2006) assess differences in the credit ratings attributed by Standard & Poor's and Moody's to the same bonds at issuance and find that information-intensive or transient assets exacerbate these differences. They conclude that these assets are the source of bank opaqueness. Flannery *et al.* (2004) seek to relate evidence of investor uncertainty in market microstructure variables to bank assets, but fail to conclude that opaque bank assets affect these variables. Flannery *et al.* (2013) repeat their analysis during the financial crisis and find that bank balance sheets have a limited effect on market microstructure variables, without being to pinpoint specific assets.

as much as investors. If so, analysts may express opinions that have more limited value in banking than in other industries.

In the present paper, we attempt to establish the link between opaqueness and investment decisions; in doing so, we fill a gap in the literature. We consider that, if investors are prevented by opaqueness from discerning good from bad banks, sell-side analysts should face similar obstacles when making investment recommendations. In particular, even the most skilled or prescient analysts should struggle to see through banks. We posit that the difficulties faced by skilled analysts should impede their ability to influence stock prices. Nonetheless, we postulate that these analysts should conceive of alternative strategies to maintain an influence in the market, and we seek to uncover these strategies.

Using a sample of 5,150 recommendation revisions relating to 80 European banks over 2005-2012, we determine if recommendation changes made by the most skilled analysts – which we measure by their being ranked among All-Europe analysts by *Institutional Investor Europe*, and refer to as "stars" – and by analysts that previously made influential recommendation revisions are more likely to influence bank stock prices than those made by other analysts. We also assess whether the magnitude of the stock price impact of recommendation changes made by leading analysts differs from that of other analysts. Finally, we shed light on the strategies adopted by star analysts to cope with opaqueness and maintain an influence in the market by examining how the recommendation changes they make differs from those that other analysts make. In our empirical analysis, we exploit both the global financial crisis and the ensuing Eurozone crisis as natural experiments, since crises have been shown to exacerbate the influence of analyst recommendations (Loh and Stulz, 2016). Also, we exclude recommendation changes that come at the same time as confounding disclosures and we control for opaqueness, agency conflicts, the information environment and external market factors (including the intensity of the crises).

We find that star and previously influential analysts are no more likely to make recommendation changes that significantly impact stock prices than other analysts. We interpret this observation as skilled analysts being prevented by the opaqueness of banks, possibly magnified by crises (Flannery *et al.*, 2013), from making more insightful recommendations, or from making a decisive impression among investors. By contrast, agency conflicts, which we proxy with non-controlling interests, exacerbate the influence of recommendation changes; lower leverage, a larger balance sheet size and greater analyst coverage reduce this influence, consistent with expectations.

Second, we find that, on average, recommendations changes made by star analysts have a statistically and economically significant negative impact on bank stock prices. Jin and Myers (2006) predict and Hutton *et al.* (2009) find that firms with opaquer financial statements have stock that are more prone to crash risk. Firm opaqueness makes it possible for insiders to hide firm-specific bad news. When accumulated bad news becomes public, investors suddenly and significantly revalue their holdings and to trigger stock price crashes. We interpret our finding as star analysts being the early bearers of bad news about opaque firms, causing investors to reconsider the value of the recommended banks, and the stock price of these banks to drop. We compare recommendation revisions made by star analysts to those made by non-stars and find support for this interpretation: star analysts focus on a limited number of larger, more complex banks that generate greater disagreement among analysts; they time bold, negative recommendation revisions to temper streaks of positive market performance.

Collectively these results suggest that banks, because of their opaqueness, present a challenge for sell-side analysts; the most skilled among them struggle to make a greater impression among investors. Stars adopt alternative strategies to maintain an influence in the market, by seeking to bring new and early insights on complex banking institutions. They appear to have a different influence than in other industries, by triggering stock revaluations of the stocks that they recommend.

The remainder of the paper is structured as follows. Section 2 reviews prior literature. Section 3 describes our sample and details the empirical approach. Section 4 presents our main results. Section 5 discusses the robustness checks we conducted. Section 6 concludes.

2 Related Literature and Hypothesis Development

A substantial part of the literature on bank opaqueness focuses on the uncertainty that this opaqueness causes among agents who have a vested interest in assessing bank risk.

Morgan (2002) expects the uncertainty associated with opaque balance sheets to make it harder for credit rating agencies to assess risk. Consequently, credit rating agencies should disagree more often when they rate new bond issuances in opaque rather than in transparent industries. Consistent with this hypothesis, Morgan (2002) finds that, between 1983 and 1993, credit ratings split more often in US banking and insurance than in other industries. In banking, he traces splits to opaque lending and transient trading assets and he shows that rating splits are exacerbated by bank leverage and mitigated by tangible assets. Iannotta (2006) comes to similar conclusions for a sample of bonds issued by European banks between 1993 and 2003, after controlling for the intrinsic risk of the issuers. He also finds that rating splits increase with balance sheet size, but are not mitigated by bank capital.

Similarly, Flannery *et al.* (2004) anticipate that opaqueness-driven uncertainty should affect investors or sell-side analysts. They compare the microstructure properties and earnings forecasts of a sample of listed US Bank Holding Companies (BHCs) with those of other non-banking firms of similar market capitalisation, stock price and market venue over the period 1990-97. They find no statistically significant difference between the BHCs and the other firms. By contrast, the same authors find limited evidence that bank balance sheet composition affects microstructure properties when they repeat their analysis during the global financial crisis (Flannery *et al.*, 2013).

Along the same line of reasoning, we expect that sell-side analysts, like investors, will be negatively affected by bank opaqueness. However, we consider a different channel than Flannery *et al.* (2004): we expect that the lack of transparency will cloud the ability of skilled analysts to make more influential stock recommendations than their peers. This reduced influence is the consequence of sell-side analysts being confounded by banks, or alternatively, of investors being unsure as to which voice they should listen to.

There is a broad literature that shows both the influence and the investment value of analyst recommendation across industries in general. Stickel (1995) documents that, in the US between 1988 and 1991, analyst recommendation changes have a short-term impact on stock prices, that the impact of multi-level changes is larger in absolute value than that of single-level changes, and that All-American star analysts and larger brokerage houses have a temporarily larger influence than others. Womack (1996) makes similar findings using a sample that spans 1989 and 1990 and provides evidence of significant drift after recommendation changes. Using an international sample of recommendations between 1993 and 2002, Jegadeesh and Kim (2006) show that price reactions to recommendation changes are significantly lower in the UK, Canada, France, Germany, Italy and Japan than in the US. They attribute this difference to skill.[2]

Turning to the determinants of this influence, Jegadeesh and Kim (2010) provide evidence that analysts herd when making recommendations and that the recommendation revisions that diverge from the consensus have a greater price impact than the others. Loh and Stulz (2011) distinguish the probability that recommendation changes should have an significant influence on stock prices (of the same sign as the changes) from the magnitude of this influence. They find, using US data between 1993 and 2006, that recommendation changes that diverge from the consensus, are made by All-American Research Team star analysts or by previously influential analysts or that come with concurrent earnings forecasts are more likely to be influential. Loh and Stulz (2016) find that both the probability of influential recommendation changes and the magnitude of price reactions to changes increase in times of crisis.

However, prior research also confirms the within-industry performance of recommendation revisions. In particular, Boni and Womack (2006) report that analysts often specialise by industry. Analysts take an industry perspective when forecasting earnings and making

[2] When using First Call or Thomson One data instead of I/B/E/S data like Jegadeesh and Kim (2006), Hoechle *et al.* (2015) find that most, but not all, of the difference between the price reactions to recommendation changes on German stocks is attributable to inaccurate timestamps in I/B/E/S.

stock recommendations; they create value by ranking stocks within industries. On average, investors who follow analyst recommendations can expect to earn positive market-adjusted returns. However, Boni and Womack (2006) observe substantial differences between industries and recommend that "comparisons or measurements also should control for the industry the analyst covers" (p. 106).

The present paper focuses on one single industry, banking. We do not anticipate that analyst recommendations will have no influence, but rather, that this influence will be muted. More specifically, we expect that analyst skills and expertise should contribute less decisively to the influence of recommendation changes in banking than in other industries.

We measure analysts skills in two different ways. First, we identify as skilled the star analysts who appear in the All-Europe Research Team ranking published by *Institutional Investor Europe* every year. This ranking is the European equivalent of the well-researched All-America (AA) Research Team ranking. AA analysts have been shown to have better earning forecasting skills, not to herd as much, and to have a greater influence on the market than others Stickel (1992). Consistent with having superior skills, AA analysts issue bolder forecasts that deviate more often from the consensus forecasts (Leone and Wu, 2007) and less favourable, bolder and more timely recommendations in adverse firm circumstances (Clarke *et al.*, 2006). These analysts enjoy above-average performance because "innate talent" (Leone and Wu, 2007); this performance is "not entirely due to luck, market access, or better access to company management" (Fang and Yasuda, 2014, p. 267).

The literature on European analyst rankings is scarce. As yet, there is no robust published evidence that All-Europe Research Team have above-average skills or simply a better reputation. Gresse and Porteu de la Morandière (2014) document that being ranked among All-Europe analysts requires having made profitable recommendations in the past, whereas being ranked in Extel rankings is only a matter of visibility. However, Gresse and Porteu de la Morandière (2014) argue that skills are not required to remain in either rankings. Kerl and Ohlert (2015) review the performance of the recipients of the Thomson Reuters

StarMine awards and find that star analysts from the US, France, Germany, Italy, Spain, the UK, Switzerland and Japan exhibit persistence in their above-average earnings forecasting skills. However, they find no evidence that the market reacts differently to the reports of StarMine stars.[3]

Second, we flag as skilled analysts those who have previously made influential recommendations. Loh and Stulz (2011) show that influence tends to repeat itself. Previously influential analysts are likelier to make recommendation revisions that trigger significant price reactions. These analysts forecast earnings more accurately, are more likely to be ranked as stars and have greater experience than the others.

In robustness checks, we consider the greater timeliness of certain analysts as a skill, following Cooper *et al.* (2001). We distinguish timeliness leaders from followers and examine differences between the recommendation revisions of leaders, stars and other analysts.

3 Empirical Approach and Data

3.1 Sample

The paper focuses on European banks that are subject to sustained analyst following. Such following ensures the timeliness and relevance of analyst recommendations. The banks included in major stock market indexes typically meet such requirements. The initial sample therefore comprises all banking institutions included in the STOXX Europe 600 Banks index[4] at any time between 1st July 2004 and 30th June 2012, for a total of 85 banks from 17

[3]In unreported regressions, we replicate most of Loh and Stulz's (2011) conclusions, on a sample of 53,130 recommendations changes made between 2005 and 2012 by 5,651 analysts, relating to 841 European firms from industries other than banking that were part of STOXX Europe 600 at least once between 2004 and 2012. In particular, we find that star and previously influential analysts (on the same stock) are likelier to make influential recommendations than other analysts. We conclude that, at the very least that the reputation of these analysts affords them a greater influence in the market outside of banking.

[4]STOXX Europe 600 Banks is one of the most representative banking indexes in Europe. STOXX Europe 600 Banks is a subset of the STOXX Europe 600 Index including all companies categorized as "Banks" in FTSE's Industry Classification Benchmark (ICB). STOXX Europe 600 was created in 1991 and is one of the most comprehensive European indexes, with 600 components at all times. STOXX Europe 600 includes small, mid and large caps in equal proportion (200 each) from all industries across 18 Western European countries, including all core eurozone countries, the United Kingdom, and all Nordic countries.

European countries. Changes to indexes often reflect significant events such as acquisitions, demergers, bankruptcies, or major business shifts. By construction, the sample mitigates survivorship bias.

For all banks in the sample, we collect 15,223 analyst recommendations from the Thomson-Reuters Institutional Brokers Estimate System (I/B/E/S) International Historical Detail File database. We focus on recommendation changes that are as free as possible of (or do not piggyback on) confounding contemporaneous disclosures since recommendations changes have been shown to be more informative to investors (Boni and Womack, 2006; Jegadeesh and Kim, 2010). We reverse the I/B/E/S recommendation scale so that the highest score (5) corresponds to "strong buy" and the lowest (1), to "strong sell". We calculate recommendation changes as the difference between a broker's new and previous recommendations, unless analyst coverage is interrupted ("stopped" in I/B/E/S parlance), in which case we consider the new recommendation is unrelated to the previous one. We consider that recommendations, unless reaffirmed or renewed, lapse after 365 days and that recommendations flagged by I/B/E/S to be "stopped" lapse on their stop date.

Prior research shows that analysts tend to herd and that their herding behavior is amplified by how informed they are (Guttman, 2010; Jegadeesh and Kim, 2010). Altınkılıç and Hansen (2009) argue that analysts piggyback on recent news and events and that this creates an identification issue. In order to avoid contamination by firm-specific news and events, we exclude recommendation changes that fall on the same date, in a three trading-day period around the earnings announcement date and during the two-day trading period after the announcement of EU stress test results of 2010 and 2011 (Petrella and Resti, 2013). We gather earnings announcement dates from Bloomberg, which we check for consistency and hand complete as necessary with data from primary sources. In order to avoid microstructure-related issues, we eliminate recommendation changes made when the unadjusted stock price is less than 100 times the ticker size.[5] Finally, we exclude zero recommendation changes

[5] 1 EUR for eurozone banks, 100p in the UK, 1 CHF in Switzerland, 1 DKK in Denmark, 1 NOK in Norway, 1 SEK in Sweden, and 1 ISK in Iceland.

and we pool the extreme positive/negative recommendation revisions because of their small number (-4 and -3 together and 4 and 3 together).

After this process, we are left with a sample of 5,672 recommendation changes for 84 banks from 17 European countries. We match the recommendation changes with a measurement of their influence on stock prices calculated as the 2-day Cumulative Abnormal Return (CAR) over the period [0, 1], where 0 is the trading day during which a recommendation change is announced and 1 is the next trading day. [6] When recommendation changes are made on non-trading days or outside of trading hours, 0 is the next trading day. We determine this CAR using a common one-factor market model:

$$R_{it} - R_{ft} = \alpha_i + \beta_i \cdot (R_{mt} - R_{ft}) + \epsilon_{it} \tag{1}$$

where R_{it} is the observed return of stock i at time t, R_{ft} is the daily return on the risk-free asset, R_{mt} is the daily market return, α_i and β_i must be estimated and ϵ_{it} are residuals. To assess the influence of recommendation changes on day 0, we estimate market models over the period $[-69, -6]$. We collect stock prices and dividends for all sample banks from Bloomberg. We retain the 1-year German treasury bond as the risk-free asset. Consistent with recommended practice, we use an equal weight market index (STOXX Europe 600 Equal Weight) and logarithmic rather than arithmetic returns (Corrado, 2011).

We then flag analysts that make influential recommendations on any bank stock or on each specific stock. We also identify star analysts in the All-Europe annual rankings of *Institutional Investor Europe* (first, second, third or runner-up teams covering any industry or geography); these analysts are selected based on polls conducted by the magazine *Institu-*

[6] Bradley *et al.* (2014) report that I/B/E/S timestamps in US files are systematically delayed compared newswire sources. Hoechle *et al.* (2015) conclude similarly after comparing I/B/E/S timestamps to those of First Call or Thomson One. The latter authors document mean delays of approximately 0.4 days for Britain, France and Germany for the period 2004-2010 and find that announcement CARs tend to be underestimated. However, they also note that I/B/E/S timestamps are "significantly more precise for large companies, for recommendations and forecasts of large brokerage firms, and for recommendations and forecasts of more experienced and star analysts". In order to assess how timestamp errors affect our results, we shift all announcements by 10 hours ($0.4 \cdot 24$ hours). We find that our conclusions are essentially unchanged.

tional Investor Europe, announced in February of each year and maintain their status for one year. We also collect quarterly IFRS accounting data for each bank from Bloomberg, which we hand complete as necessary with data from annual reports and quarterly disclosures; we exclude observations prior to 2004 annual earnings disclosures because they are reported under local accounting standards, and those for which relevant accounting data is missing.

Our final sample includes 5,150 recommendation changes made by 655 analysts for 80 banks from 17 European countries.

We use proxies for a bank's information environment and agency costs, as well as analyst skills as the main regressors to assess the factors that are associated with the influence of recommendation changes. We also use independent variables typically found in the analyst forecasting literature, and which Loh and Stulz (2011) report to be both statistically and economically significant to explain the influential character of recommendation changes. The regression variables are summarized in Table 1.

[Table 1 about here.]

Bank opaqueness and agency costs. In our setting, bank opaqueness may translate into the composition of a bank balance sheet inducing greater difficulty for analysts to make impactful forecasts or recommendations. Accordingly, we test the effect of this composition on the influence of changes in recommendations. However, in a similar way to Iannotta (2006), we are limited to accounting variables that are reported regularly (i.e. on a half-yearly or quarterly basis) and consistently by the banks in our sample, especially in the early years of our sample. We retain the ratio of loans to assets (LOAN_TO_ASSETS), and leverage, measured as the ratio of common equity to assets (EQUITY_TO_ASSETS), as independent variables that evidence balance sheet composition.

We incorporate an inflation-adjusted measurement of EUR total assets (LOG_ASSETS) to assess how bank size affects the influence of recommendation changes. On the one hand, information about small firms only gets out slowly (Hong *et al.*, 2000). Analysts may have more incentives to cover larger than smaller banks in a timely manner; also, the information environment of banks may become richer with the size of their balance sheet, making it easier for analysts to be insightful. Also, larger, more diversified banks may be induced to take additional risk (Demsetz and Strahan, 1997), possibly because their size affords them an implicit government safety net. Recommendation changes may be more, or more often, influential for larger banks. On the other hand, the complexity of banking institutions grows with the size of their balance sheet, together with their asset diversification. With a greater size come more opportunities to hide information in general, and bad new in particular. Consequently, recommendation changes may be less often, or less influential for larger banks.

We also test the influence of analyst coverage on the influence of recommendation changes (NUM_ANALYSTS). Analyst coverage can be interpreted in different ways. First, in their work, the analysts compete for the attention of investors in the same way as the brokers that employ them compete for the investors' transactions. Opportunities for recommendation changes to be influential may be "competed away" as analyst coverage increases. Second, many, rather than few, analysts may be more effective in monitoring agency costs (Chen *et al.*, 2015) and in exercising pressure on management to disclose bad news (Hong *et al.*, 2000). Under these two interpretations, greater analyst coverage may reduce the likelihood that recommendation changes should be influential.

We use minority interests reported in bank balance sheets as a proxy for agency costs. Such agency costs stem from the ability of non-controlling shareholders, who exert de facto control over corporate resources, either on their own or in coalition with other minority shareholders, to expropriate majority shareholders (Zwiebel, 1995).[7] In fact, minority shareholders may have more to gain from wealth-redistributing activities than their majority counterparts, and therefore greater incentives to engage in expropriation and tunneling: Atanasov *et al.*

[7] The Royal Bank of Scotland (RBS), a British bank, provides a vivid example of such agency costs. In 2007, RBS acquired Dutch bank ABN AMRO together with Spanish Santander and Belgian-Dutch Fortis. After the acquisition, RBS consolidated ABN AMRO in its financial statements despite owning only approximately 38% of the Dutch bank, but faced two substantial non-controlling shareholders that, in coalition, may have exerted de facto control over ABN AMRO.

(2010, p. 2) argue that "the net gain a blockholder stands to realize from expropriation is inversely related to that blockholder's level of ownership". Lang *et al.* (2004, p. 594) provide evidence that, in such situations, analyst monitoring makes it "more difficult for managers to engage in asset transfers, excessive perquisite consumption or outright theft of earnings". Accordingly, we posit that recommendation changes will be more often, or more, influential when the ratio of non-controlling interests to total equity (MINORITIES_TO_EQUITY) is more elevated.

Analyst skill. Loh and Stulz (2011) find that skilled analysts are more likely to make influential recommendation changes. However, if bank opaqueness presents a hurdle to analysts, we expect a muted impact of analyst skill on the likelihood of recommendation changes to be influential. We use two distinct proxies for analyst skills.

First, we determine whether analysts have issued prior influential recommendation changes either on any stock (INFLUENTIAL_BEFORE_ANY), or on the same stock (INFLUENTIAL_BEFORE_SAME). Because analysts tend to specialise in certain industries or geographies, the first case (any stock) suggests that analysts gain industry insights through read across (Boni and Womack, 2006). The second case (same stock) hints that the forecasting abilities of analysts increase with the depth of knowledge they gain about the companies they cover. If banks present special challenges for analysts, read across from one bank to another should be difficult and deeper knowledge of a bank may not be significantly helpful.

Second, we identify the analysts being listed in annual All-Europe rankings (STAR), similar to All-American (AA) rankings in the United States. The insightfulness of the analysts that feature in these rankings is recognised ex post by institutional investors in annual polls organised by *Institutional Investor Europe*. Fang and Yasuda (2014) find that AA-rankings of analysts predicts their future performance and conclude that "skill differences among analysts exist and at least partially explain star analysts' outperformance" (p. 238). If the opaqueness of banks is an obstacle for analysts, the ex post recognition as a star analyst may not contribute ex ante to issuing more influential recommendations, unlike in more transparent industries.

In doing so, we control for the breadth of coverage of the recommending broker over the preceding 365 days (BROKER_COVERAGE). Jacob *et al.* (1999) report that analysts employed by larger brokerage houses issue more accurate earnings forecasts. They argue that larger brokerage houses are provide for a better infrastructure to analysts, for more opportunities of information exchange between analysts and possibly for better access to the management of covered firms; also, they are in a position to attract the better analysts thanks to more advantageous compensation.

Recommendations and other controls. Other control variables include variables indicative of industry-wide and bank-specific uncertainty. The regressions control for the spread between the Overnight Indexed Swap (OIS) and 3-month EURIBOR, which is a common gauge of stress in the European banking industry (EUR_OIS_SPREAD). Following Loh and Stulz (2016), we expect the influence of recommendation changes to increase with this stress metric, as investors seek more guidance from analysts in uncertain times. The regressions also control for the idiosyncratic stock volatility (VOLATILITY) of the recommended banks, measured as the standard deviation of market model residuals (over the period [-69, -6]), and a measurement of the prior absolute performance of the recommended bank stocks (PRIOR_PERFORMANCE) measured over the same period. Excess stock-specific volatility should lead to overreactions to recommendation changes and to confounding disclosures, which would be excluded as outliers in our processing of recommendation changes. Significant recent changes in value should reduce the probability that analysts should cause a sudden stock revaluation. We therefore expect the influence of recommendation changes to be muted at high levels of stock-specific volatility and after significant absolute prior performance of bank stocks.

Finally, we incorporate into the regressions the presence of concurrent forecasts together with the recommendation changes (CONCURRENT_FORECAST), the relative level of bank-specific uncertainty felt by analysts, measured as the standard deviation of analyst recommendation levels (REC_SD), the level of recommendation change, and therefore of the signal sent by an analyst (CHANGE_REC), for the recommendation levels after recommendation changes (REC_LEVEL).

3.2 Descriptive statistics

[Figure 1 about here.]

Figures 1(a), 1(b) respectively plot the fraction of recommendation changes that are influential and that are made by star analysts. Figures 1(c) and 1(d) contrast these proportions with the percentage of negative recommendation changes and the mean 3-month EURIBOR - OIS spread during each sample period quarter. The first figure shows that the proportion of influential recommendations increased monotonically between the third quarter of 2006 until it peaked in the third quarter of 2007; it remained elevated until the end of 2009, dropped and increased again together with the Eurozone crisis. This pattern is consistent with Loh and Stulz's (2016) observation that analyst influence increases in periods of stress. The proportion of influential recommendation changes and the mean indicator of banking stress are significantly correlated (0.45).

The second figure shows that star analysts made more recommendation changes in the midst of both the global financial crisis and the Eurozone crisis, but also in mid-2006. These periods coincide with those during which analysts issued a larger proportion of downgrades than upgrades, as the third figure illustrates. There is an economically and statistically significant correlation (0.527) between the proportion of negative recommendation changes and the 3-month EURIBOR - OIS spread. This observation suggests that the boom before the global financial crisis and the subsequent two crises prompted analysts to review their perspectives on the banks they covered; in turn, this may have exacerbated the level of stress perceived by market participants.

Table 2 reports statistics on recommendation changes in the sample, grouped by recommendation change level. The reported percentages are contrasted with comparable statistics documented by Loh and Stulz (2011), reported in the last column. These statistics show that the frequencies of recommendation change levels are broadly comparable, although our sample appears to be somewhat more balanced between upgrades and downgrades. By contrast, the overall proportion of influential recommendation changes in our sample (7.7%) is much lower than that reported by these authors (11.7%). Jegadeesh and Kim (2006) find that the influence of recommendation changes on stock prices is lower in non-US G7 countries than in the US. This finding may partly explain the lower proportion of influential recommendation changes that we observe, since our sample includes 4 non-US G7 countries. However, this lower proportion may also translate the difficulty of making influential recommendations in an opaque industry such as banking or during crises.

[Table 2 about here.]

Table 4 provides summary statistics for the whole sample (column 1). These statistics show that on average, across recommendation changes, the banks in the sample have average assets of close to EUR 300 billion, small non-controlling interests (6.2% of equity), a leverage ratio of 19.2, and 53.6% of assets invested in loans. They are covered by a mean of 25.8 analysts. Recommendation changes come from sizeable brokerage houses that cover a mean of 212.7 STOXX 600 Europe firms. 42.2% of recommendation changes are made by analysts that were influential before on any bank stock, 10.9% by analysts that were influential on the same bank stock and 1.8% by star analysts. By contrast Loh and Stulz (2011) document that 57.4% of recommendation changes are made by previously influential analysts on any stock, 16.4% on the same stock and 10.4% by All-American star analysts. The difference in the proportion of recommendation changes issued by star analysts is particularly striking, but it can largely be explained by the very small number of distinct banking analysts that have received the award, as shown in Table 3: out of 37 banking analysts that received the All-Europe accolade between 2005 and 2012, 9 (out of which 3 distinct analysts) belonged to

Merrill Lynch or Lehman Brothers and do not appear in the version of I/B/E/S distributed to academics (Zitzewitz, 2012), 15 received multiple awards, and 2 transferred out of Merrill Lynch and Lehman Brothers, leaving a total of 14 individual star banking analysts in the I/B/E/S sample (2.2% of all analysts in our sample).

[Table 3 about here.]

Table 4 also contrasts four subsamples: a subsample of influential versus one of non-influential recommendation changes (columns 2 and 3) and a subsample of recommendation changes made by star and non-star analysts (columns 4 and 5). The table provide univariate tests of differences between the means of the four subsamples, two by two. The test statistics suggest that there are only few differences between influential and non-influential subsamples and only subtle differences between the star and non-star subsamples.

On average, influential recommendation changes are made by brokers with a broader analyst coverage, which suggests that larger brokerage houses exert more influence on the market. Also, these recommendations relate to smaller banks, consistent with opaqueness increasing with bank size, and to banks that are covered by fewer analysts, consistent with opportunities for analysts to be influential being competed away and/or with monitoring improving with the number of analysts; they diverge from consensus recommendations, consistent with Jegadeesh and Kim's (2010) findings. Finally, they are associated with a lower idiosyncratic volatility, consistent with our expectations. Strikingly, influential recommendation are not more often made by star analysts or by previously influential analysts, consistent with our hypothesis.

By contrast with those made by non-stars, recommendation changes made by star analysts trigger a substantial negative revaluation of the recommended stocks. Together with the fact that star analysts issue more negative recommendation changes and justify all changes with concurrent earnings forecasts, this finding suggests that star analysts are the bearers of bad news, more often than non stars. Also, the star analysts make recommendation changes that relate to larger banks with more diversified balance sheets, in which loans feature less prominently, perhaps because such banks are less opaque or because their greater diversification makes them more predictable. The stars come from larger brokerage houses, with substantial coverage, consistent with these brokers attracting the best analysts thanks to better compensation (Jacob *et al.*, 1999). The stocks that they recommend suffer from a lower underperformance than the other stocks in the sample, as if stars issued recommendations at other times than non-stars or selected higher quality banks that were less affected by negative market conditions.

[Table 4 about here.]

3.3 Empirical Approach

Our empirical focus is on the influence of analyst recommendation changes on bank stock prices. We adopt three different regression specifications to assess this influence.

First, we determine the extent to which opaqueness and agency costs may affect the influence of recommendation changes on stock prices. We expect opaqueness to inhibit the usual factors associated with greater influence, such as analyst skills, and heightened agency costs to exacerbate this influence. Following Loh and Stulz (2011), we model the influence of changes in analyst recommendations as binary outcomes. The binary INFLUENTIAL dependent variable takes the value one when the 2-day CAR is statistically significant and has the same sign as the change in recommendation with which the CAR is associated. Like Loh and Stulz (2011), we conclude that a 2-day CAR is statistically significant if it exceeds $1.96 \cdot \sqrt{2} \cdot \epsilon_{MM}$ where ϵ_{MM} is the standard deviation of the market model residuals.

Several of our main variables of interest, including minority interests, loans to assets and bank size, typically evolve only slowly. Fixed effects models do not adequately estimate the effects of sluggish variables. We estimate pooled probit regressions and we cluster standard errors by calendar day:

$$Prob\left(INFLUENTIAL_{ijt} \mid X_{iq}, A_{jt}, T_t\right) = \Phi\left(\alpha + \beta \cdot X'_{iq} + \gamma \cdot A'_{jt} + \tau \cdot T_t + \epsilon_{it}\right) \qquad (2)$$

for a recommendation change relating to bank i made by analyst j at time t in quarter q, where $Prob$ is the probability operator; X_{iq} is a vector of bank characteristics in quarter q disclosed prior to the recommendation change; A_{jt} is a vector of analyst characteristics at time t; T_t is a vector of bank-independent control variables at time t; Φ is the cumulative distribution function of the standard normal distribution; α (the intercept), τ, β, and γ are the regression parameters to be estimated; and ϵ_{it} is an error term.

Hong *et al.* (2000) observe that stocks subject to low analyst coverage react more slowly to bad news than to good news, contrary to high coverage stocks. The authors posit that analysts play a significant role in the dissemination of bad news. If anything, the opaqueness of banking should exacerbate this role, and the asymmetry of the stock price impact of recommendation changes. Accordingly, we should observe differentiated results for recommendation changes that have a positive and a negative influence on bank stock prices. We assess this asymmetry by estimating the same regression in two distinct sub-samples with recommendation changes that have had a positive and a negative influence (measured with the 2-day CAR) on stock prices. In doing so, we recognise that, because of their smaller size, the two sub-samples afford more limited statistical inferences than the full sample.

Second, we assess whether opaqueness and agency costs affect the magnitude of the impact of recommendation changes on stock prices. In the opaque, information-intensive banking industry, management should be in a position to hide bad news for extended periods of time (Hutton *et al.*, 2009). We expect recommendation changes to be catalysts of information revelation, and the impact of recommendation changes on stock prices to be greater for skilled analysts and in the presence of heightened agency conflicts. To test this, we estimate linear regressions in which the dependent variable is the 2-day CAR, which we divide by the standard deviation of market model residuals to increase (resp. reduce) the weight of less volatile, more reliable (resp. more volatile, noisier) observations (Campbell *et al.*, 1997, p. 160), which is especially important during crises; the independent variables are identical to those above:

$$Standardized\ CAR_{ijt} = \alpha + \beta \cdot X'_{iq} + \gamma \cdot A'_{jt} + \tau \cdot T_t + \epsilon_{it} \tag{3}$$

Third, after observing that recommendation changes made by All-Europe star analysts differ from those made by non-star analysts, we evaluate the differences between recommendation changes made by the former and by the latter, by means of a probit regression, similar to (2) above:

$$Prob\left(STAR_{ijt} \mid X_{iq}, A_{jt}, T_t\right) = \Phi\left(\alpha + \beta \cdot X'_{iq} + \gamma \cdot A'_{jt} + \tau \cdot T_t + \epsilon_{it}\right) \tag{4}$$

where $STAR_{ijt}$ is a binary variable that takes the value one for recommendation changes made by star analysts, and zero otherwise.

4 Empirical Results

Table 5 reports estimates of the pooled probit models to assess when recommendation changes are influential, for the whole sample (first column) and for subsamples of recommendation changes associated with positive (second column) and with negative (third column) CARs. Similarly, Table 6 reports estimates of pooled OLS regressions of standardized 2-day CARs associated with recommendation changes, for the whole sample, and for subsamples of recommendations changes with positive and negative CARs.

We discuss our results by describing what the regressions tell us about our hypotheses.

[Table 5 about here.]

[Table 6 about here.]

Bank opaqueness and agency costs. The regressions suggest that bank balance sheets matter. In particular, bank leverage affects analyst influence. On the one hand, low levels of leverage (high levels of equity to assets) reduce the likelihood that recommendation changes should be influential. On the other hand, low levels of leverage mitigate extreme stock returns. These observations are consistent with the (probability and magnitude of the) influence of recommendation changes increasing with the likelihood of bank-specific stress. Beyond the findings of of Loh and Stulz (2016), it therefore appears that firm-specific crises also induce greater analyst influence.

Also, balance sheet size reduces the probability that recommendation changes should be influential, although the effect is not significant at usual confidence levels (p-value of 0.15). The complexity and asset diversity that come with balance sheet size appear to dominate the insights that analysts can gain from broader information environments and the risk-shifting opportunities that a larger size offer.

By contrast, loans do not affect the probability that recommendation changes should be influential; but loans exacerbate the magnitude of the changes induced by recommendation changes, although their effect is only statistically significant at conventional levels in the positive CAR subsample. This finding is consistent with loans being the source of unexpected good or bad surprises, possibly induced by their opaqueness. Alternatively, this observation may relate to the business models of banks: for example, more traditional banks with a greater share of loans in their balance sheet may have been voted up by analysts during the crisis.

Although we are unable to evaluate many asset types, our results hint that assets may not matter as much as agency conflicts: the regressions show that the influence, and the magnitude of negative CARs associated with recommendation changes increase with agency conflicts. Analysts play the role of delegated monitors and their recommendations appear to respond to investors' demand for monitoring (Moyer *et al.*, 1989). The sign and statistical significance of analyst coverage in influence regressions concur with this explanation: the more numerous they are, the better able they are to pressure management into disgorging bad news early. Alternatively, the more numerous analysts are the harder it becomes for any of them to issue influential recommendation changes: their opportunity to make an impression decreases as competition increases.

Analyst skill. Whereas in most industries, recommendation changes made by star and previously influential analysts are likelier to impact the recommended stock prices, we find no such effect in European banking between 2005 and 2012. On the contrary, analysts that issued influential new recommendations on a given bank stock had a lower influence later on; those that issued influential new recommendations on any stock were no more likely to influence bank stock prices again than other analysts. Neither the depth of knowledge, nor read across appear to help analysts in making an impression, consistent with bank opaqueness being a hurdle for analysts themselves, and possibly for investors to grasp the investment value of the recommendations that they receive.

Even All-Europe star analysts are unable to beat other analysts to issue more frequent influential recommendations. Where they do have an edge is in the mean impact of their recommendations, which is significantly negative and economically meaningful: over the full sample, star analysts have a negative influence that is approximately equivalent to a recommendation change level of -1.6; over the sub-sample of negative recommendations, their influence nearly equals a recommendation change level of -3.[8] Star analysts appear to be listened to by investors as the bearers of bad news; their recommendation changes act as the catalysts of their influence: they trigger negative revaluations of bank stocks. However, these recommendation changes may have distinct characteristics that confer them their influence. These characteristics are likely to reflect the way that stars influence investors in an opaque industry.

We assess these characteristics using a multivariate probit regression. Table 7 reports regression estimates as well as the marginal effects for each dependent variable. We calculate marginal effects for continuous variables (resp. for binary variables) as the decreases

[8]This effect is preserved if we remove outliers by identifying zero-weighted observations in least trimmed square regressions of returns against a constant at each recommendation change level. In fact, the effect is muted by our exclusion of small-price stocks.

in probability when the variables decrease from their mean value by one standard deviation (resp. when they decrease from 1 to 0). The base probability for the average bank in our sample (and with binary variables set to one) is 2.2%. The regression highlights that recommendation revisions made by stars differ from those of other analysts in various respects.

First, star analysts focus on larger, highly capitalised banks that they rate highly. The banks have a lower proportion of loans, presumably because larger banks are more diversified, or alternatively, because stars seek diversified balance sheets. The banks are covered by fewer analysts, although analyst coverage is not statistically significant, and they generate disagreement among analysts. Star analysts may create value by focusing on complex banks that other analysts find hard to assess and may be reluctant to cover. Or, alternatively, that stars may cater to the demand of institutional investors for monitoring complex institutions. The banks also have smaller non-controlling interests, consistent with stars distancing themselves from agency conflicts, as predicted in general by Lang *et al.* (2004).

Second, stars belong to larger brokerage houses, with higher coverage, consistent with brokers seeking to employ the best analysts and with high-quality analysts competing for jobs at high-status brokerage houses (Fang and Yasuda, 2014). These analysts are more likely to have made influential recommendations on the recommended bank and less likely to have made influential recommendations on other banks. We infer from this result that star analysts focus their efforts on a limited number of banks, which they select based on certain criteria.

Third, the recommendation changes made by star analysts are always anchored in earnings forecasts revisions, often negative and multi-levels, and tend to diverge from the consensus.[9] With greater (lower) probability, they come after a streak of good (bad) performance, suggesting that star analysts may react to, and that their recommendations may temper, valuations that they consider excessive. Stars appear to be especially apt to identify industry

[9] AWAY is close to statistical significance at conventional levels, with a p-value of 0.14.

mispricings (Boni and Womack, 2006). Stars appear to position themselves as the bearers of the bad news, and are appreciated as such by the market that revalues the stocks that stars express an opinion on.

[Table 7 about here.]

Larger brokerage houses with greater firm coverage do exert greater influence, both in terms of probability and magnitude. However, this influence appears to be mostly positive, as if our independent variable captured the optimism biases that larger brokers may instil among their analysts (Carleton *et al.*, 1998).

Recommendations and other controls. Consistent with prior literature, the regressions indicate that recommendation changes that diverge from the consensus and relating to banks that generate greater disagreement among analysts, have a greater probability of being influential. The joint announcement of earnings forecasts does not affect the influence of recommendation changes. But unlike in the US, nearly all recommendation changes come with revised earnings forecasts; revised earnings factors are not substantial differentiating factors.

Also, "signal strength", measured as recommendation change levels, exacerbates both the probability and magnitude of the influence of recommendation changes. Recommendation levels attained after revisions of recommendations have a statistically and economically significant impact on 2-day CARs, consistent with the signal value of recommendation changes.

The intensity of crises, prior performance (or momentum) and idiosyncratic volatility all have the expected significance and signs. The level of distrust between banks that accompanies crises exacerbates both the probability that recommendation revisions should be influential and their impact on stock prices, consistent with Loh and Stulz's (2016) conclusions. When it is positive, the recent performance of a recommended stock mutes the influence (both in probability and magnitude) of recommendation changes; when it is negative, this performance exacerbates the influence of recommendation revisions. Excess idiosyncratic volatility reduces the probability that recommendation changes should be influential and mutes their stock impact.

5 Robustness check

As yet, the published evidence that All-Europe Research Team analysts are skilled rather than lucky is limited. Despite the evidence above, star analysts may have more clout in the market because of a reputation they gained from past bold gambles, or from the prestigious brokerage houses they work for. As Gresse and Porteu de la Morandière (2014) argue, their past performance may have afforded these analysts to join the club of stars, but their later performance may no longer justify their continued membership.

We address potential biases in analyst rankings and the concerns that may arise from our interpretation of the star attribute in two ways. First, we note that our other proxies for analyst skills (binary variables that flag analysts that were influential before on any stock or on the same stock) are constructed empirically from our sample and do not suffer from ranking biases. Second, we replace the three skill proxies with a measurement of analyst quality that is endogenous to analyst coverage. We calculate the perfect foresight Leader-Follower Ratio for each analyst in our sample (Cooper *et al.*, 2001), as the ratio of the sum of the time differences between this analyst's recommendations and each of the previous two recommendations made by other analysts, to the sum of the time differences between this analyst's recommendations and each of the next two recommendations made by other analysts. The Leader-Follower Ratio measures the extent to which analysts regularly provide timely recommendations; it identifies timeliness leaders that trigger herding among followers.

Like Cooper *et al.* (2001), we only retain those analysts that provide at least 5 recommendations, which causes the sample size to drop to 4,895. We identify as leaders the analysts whose Leader-Follower Ratio are in the top decile of the distribution. We flag the recommendation revisions made by leaders with a binary variable (LEADER) set to one, and those made by followers with the same binary variable set to zero. Unreported regressions suggest that lead analysts have an influence similar to stars: they are no more likely to have a greater influence than other analysts, but they also seem to induce negative stock revaluations (although this effect is only visible in the negative CAR subsample).

[Table 8 about here.]

Similar to stars' recommendation revisions, we assess the characteristics of the recommendation revisions of timeliness leaders with a probit regression whose parameter estimates and marginal effects are reported in Table 8 (base probability: 5.4%). The timeliness leaders' recommendation changes appear to be strikingly different from those of stars: leaders focus on smaller banks with high leverage, that may be more likely to experience difficulties during crisis periods; they time their recommendations when the uncertainty in the European banking sector is higher. These results suggest that the sources of leader's influence may be opportunism and a lack of timely coverage by other analysts. The stark differences between star and timeliness leader recommendation revisions comfort us in our interpretation that stars actively strategise to maintain an influence in the market despite the inherent opaqueness of banking institutions.

6 Conclusion

Sell-side analysts play two crucial roles in the market: they gather, process and disseminate news and information to investors and they monitor and mitigate agency conflicts. In doing so, analysts contribute to making markets more efficient and to reducing the cost of capital of the firms they cover, among others through the discipline that analysts instil. However, for analysts to effectively perform their role, firms must be transparent enough that analysts can see through firms' activities and exposures and identify and follow potential agency problems.

Banks are often considered as opaque, although decisive empirical evidence remains elusive. The opaqueness of banks may affect the ability of analysts to process information and to monitor agency costs, and may impede their capacity to make insightful recommendations. In this paper, we examine the relation between the skills of analysts and the price impact on bank stocks of their recommendation revisions. We posit that, if banks are opaque, even the most skilled analysts will struggle to make recommendations impactful on bank stocks. We use a dataset on 5,150 stock recommendations relating to 80 European banks between 2005 and 2012, a period that encompasses two crises. We proxy analyst skills in two different ways: we identify *Institutional Investor* All-Europe Research Team (star) analysts and we flag previously influential analysts.

We find that, unlike in other industries, the recommendation revisions made by the most skilled analysts are no more likely than others to significantly impact bank stock prices. We interpret this finding as analysts facing difficulty in making insightful recommendations or in being recognised by investors as valuable. By contrast, the recommendation changes coming from star analysts induce sharp negative revaluations of bank stock prices. This observation suggests that bank opaqueness enables managers to hide firm-specific bad news, and that analysts maintain an influence in the market by uncovering bad news.

Stars focus on selected larger, well-capitalised banks with a diversified asset base that generate disagreement among analysts. In doing so, stars may cater to demand of institutional investors; or, alternatively, they may have special insights about complex banks that other analysts find hard to assess and may be reluctant to cover. Also, stars often make negative, multi-level recommendation changes that tend to diverge from the consensus. They time their recommendation revisions after a streak of good stock performance, consistent with their being especially apt to identify mispricings. Stars appear to articulate a strategy to maintain an influence in the market despite the opaqueness of the industry they deal with.

In robustness checks, we also single out with perfect foresight the analysts that are among the first to make new recommendations that are followed by other analysts. These timeliness leaders have an influence similar to stars but for seemingly different reasons: they appear to behave opportunistically, at times of high uncertainty and by focusing on weaker banks and to benefit from a lack of timely coverage by other analysts. Hence, timeliness leaders may have a fortuitous influence on stock price that may have little to do with skills.

Collectively, the results in this paper suggest that sell-side analysts face challenges when assessing opaque firms. The most skilled analysts cope with opaqueness by devising strategies to maintain an influence in the market, which includes uncovering bad news early. To the extent that sell-side analysts are representative of investors, our results suggest that investors face considerable uncertainty when investing in the banking industry, as they may be hindered by opaqueness from discerning good from bad banks.

References

Altınkılıç, O., Hansen, R. S., 2009. On the information role of stock recommendation revisions. Journal of Accounting and Economics 48 (1), 17–36.

Atanasov, V., Boone, A., Haushalter, D., 2010. Is there shareholder expropriation in the United States? An analysis of publicly traded subsidiaries. Journal of Financial and Quantitative Analysis 45 (1), 1–26.

Boni, L., Womack, K. L., 2006. Analysts, industries, and price momentum. Journal of Financial and Quantitative Analysis 41 (01), 85–109.

Bradley, D., Clarke, J., Lee, S., Ornthanalai, C., 2014. Are analysts recommendations informative? Intraday evidence on the impact of time stamp delays. Journal of Finance 69 (2), 645–673.

Campbell, J. Y., Lo, A. W.-C., MacKinlay, A. C., 1997. The Econometrics of Financial Markets. Princeton University press.

Carleton, W. T., Chen, C. R., Steiner, T. L., 1998. Optimism biases among brokerage and non-brokerage firms' equity recommendations: Agency costs in the investment industry. Financial Management 27 (1), 17–30.

Chen, T., Harford, J., Lin, C., 2015. Do analysts matter for governance? Evidence from natural experiments. Journal of Financial Economics 115 (2), 383–410.

Clarke, J., Ferris, S. P., Jayaraman, N., Lee, J., 2006. Are analyst recommendations biased? evidence from corporate bankruptcies. Journal of Financial and Quantitative Analysis 41 (01), 169–196.

Cooper, R. A., Day, T. E., Lewis, C. M., 2001. Following the leader: A study of individual analysts earnings forecasts. Journal of Financial Economics 61 (3), 383–416.

Corrado, C. J., 2011. Event studies: A methodology review. Accounting & Finance 51 (1), 207–234.

Demsetz, R. S., Strahan, P. E., 1997. Diversification, size, and risk at bank holding companies. Journal of Money, Credit, and Banking 29 (3), 300–313.

Fang, L. H., Yasuda, A., 2014. Are stars' opinions worth more? The relation between analyst reputation and recommendation values. Journal of Financial Services Research 46 (3), 235–269.

Flannery, M. J., Kwan, S. H., Nimalendran, M., 2004. Market evidence on the opaqueness of banking firms' assets. Journal of Financial Economics 71 (3), 419–460.

Flannery, M. J., Kwan, S. H., Nimalendran, M., 2013. The 2007-09 Financial Crisis and Bank Opaqueness. Journal of Financial Intermediation 22 (1), 55–84.

Gresse, C., Porteu de la Morandière, L., 2014. Rising and senior stars in European financial analyst rankings: The talented and the famous. Working paper, Université Paris Dauphine.

Guttman, I., 2010. The timing of analysts' earnings forecasts. Accounting Review 85 (2), 513–545.

Hoechle, D., Schaub, N., Schmid, M. M., 2015. Time stamp errors and the stock price reaction to analyst recommendation and forecast revisions. Working Paper 2012/15, University of St. Gallen.

Hong, H., Lim, T., Stein, J. C., 2000. Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. Journal of Finance 55 (1), 265–295.

Hutton, A. P., Marcus, A. J., Tehranian, H., 2009. Opaque financial reports, R^2, and crash risk. Journal of Financial Economics 94 (1), 67–86.

Iannotta, G., 2006. Testing for opaqueness in the European banking industry: Evidence from bond credit ratings. Journal of Financial Services Research 30 (3), 287–309.

Jacob, J., Lys, T. Z., Neale, M. A., 1999. Expertise in forecasting performance of security analysts. Journal of Accounting and Economics 28 (1), 51–82.

Jegadeesh, N., Kim, W., 2006. Value of analyst recommendations: International evidence. Journal of Financial Markets 9 (3), 274–309.

Jegadeesh, N., Kim, W., 2010. Do analysts herd? An analysis of recommendations and market reactions. Review of Financial Studies 23 (2), 901–937.

Jin, L., Myers, S. C., 2006. R^2 around the world: New theory and new tests. Journal of Financial Economics 79 (2), 257–292.

Kerl, A., Ohlert, M., 2015. Star-analysts' forecast accuracy and the role of corporate governance. Journal of Financial Research 38 (1), 93–120.

Lang, M. H., Lins, K. V., Miller, D. P., 2004. Concentrated control, analyst following, and valuation: Do analysts matter most when investors are protected least? Journal of Accounting Research 42 (3), 589–623.

Leone, A. J., Wu, J. S., 2007. What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts. Working Paper FR02–12, Simon School of Business.

Loh, R. K., Stulz, R. M., 2011. When are analyst recommendation changes influential? Review of Financial Studies 24 (2), 593–627.

Loh, R. K., Stulz, R. M., 2016. Is sell-side research more valuable in bad times? Working Paper WP 2013-19, Ohio State University, Fisher College of Business.

Morgan, D. P., 2002. Rating Banks: Risk and Uncertainty in an Opaque Industry. American Economic Review 92 (4), 874–888.

Moyer, R. C., Chatfield, R. E., Sisneros, P. M., 1989. Security Analyst Monitoring Activity: Agency Costs and Information Demands. Journal of Financial and Quantitative Analysis 24 (04), 503–512.

Petrella, G., Resti, A., 2013. Supervisors as information producers: Do stress tests reduce bank opaqueness? Journal of Banking & Finance 37 (12), 5406–5420.

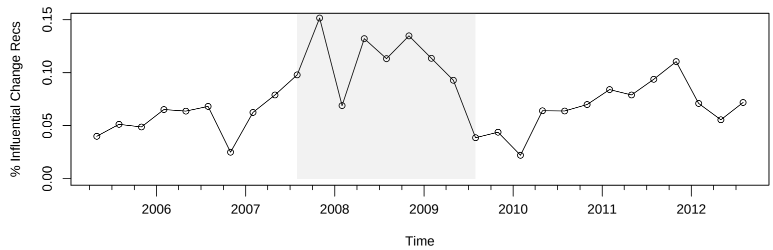
Stickel, S. E., 1992. Reputation and performance among security analysts. Journal of Finance 47 (5), 1811–1836.

Stickel, S. E., 1995. The anatomy of the performance of buy and sell recommendations. Financial Analysts Journal 51 (5), 25–39.

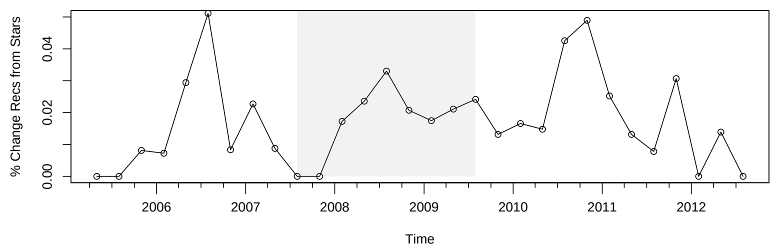
Womack, K. L., 1996. Do brokerage analysts' recommendations have investment value? Journal of Finance 51 (1), 137–167.

Zitzewitz, E., 2012. Forensic economics. Journal of Economic Literature 50 (3), 731–769.

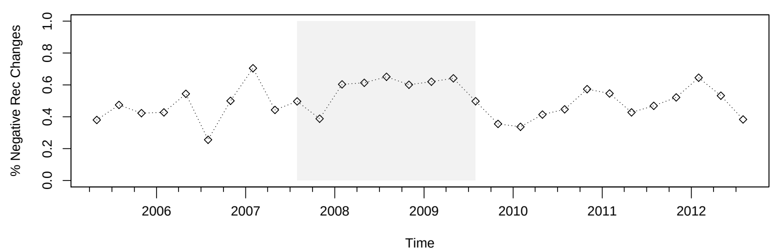
Zwiebel, J., 1995. Block investment and partial benefits of corporate control. Review of Economic Studies 62 (2), 161–185.



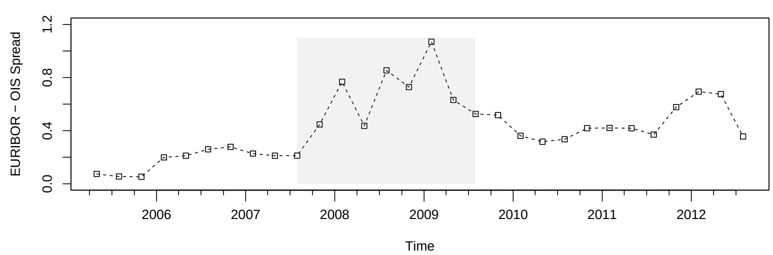
(a) Proportion of recommendation changes that are influential



(b) Proportion of recommendation changes that are made by star analysts



(c) Proportion of negative recommendation changes



(d) EURIBOR - OIS spread

Figure 1. Evolution of the proportion of influential recommendation changes, of recommendation changes made by star analysts, of negative recommendations and evolution of the mean quarterly EURIBOR - OIS spread from the quarter ending on 31st March 2005 to that ending on 30th June 2012. In all the plots, the shaded area highlights the financial crisis period (1st July 2007 to 30 June 2009).

Table 1. Definition of variables used in regressions. Recommendation changes made on date d are related to the accounting variables that appear in financial statements disclosed prior to d. Sources: analyst recommendations from the Thomson-Reuters Institutional Brokers Estimate System (I/B/E/S) International Historical Detail File, accounting variables, market prices and dividend history from Bloomberg, foreign exchange rates from the European Central Bank (http://www.ecb.int/stats/exchange/eurofxref/html/index.en.html), inflation rates from the Organisation for Economic Co-operation and Development (https://data.oecd.org/price/inflation-cpi.htm).

Variable	Description
Underlying variables	
CAR	Cumulative Abnormal Return measured over the period [0, 1], where 0 is the trading day during which a recommendation change is made. If recommendation changes are issued outside of trading hours, 0 is the next trading day
Dependent variables	
INFLUENTIAL	Binary variable that takes the value 1 if the CAR associated with a recommendation change is statistically significant and has the same sign as the recommendation change, and 0 otherwise
Standardized CAR	CAR divided by the standard deviation of the market model with which CAR is measured (period [-69, -6])
Accounting variables	
MINORITIES_TO_EQUITY	Last reported minority interests divided by total shareholders' equity
EQUITY_TO_ASSETS	Last reported total shareholders' equity divided by total assets
LOANS_TO_ASSETS	Last reported total loans divided by total assets
Analysts	
BROKER_COVERAGE	Natural logarithm of the number of firms that were at least once part of the STOXX Europe 600 index between 2005 and 2012 over which a broker made recommendations in the preceding 365 calendar days
INFLUENTIAL_BEFORE_ANY	Binary variable that is set to 1 if an analyst has previously made influential recommendation changes for any bank, and to 0 otherwise
INFLUENTIAL_BEFORE_SAME	Binary variable that is set to 1 if an analyst has previously made influential recommendation changes for the same bank, and to 0 otherwise
LEADER	Binary variable that takes the value 1 if a recommendation change is made by a lead analyst, and 0 otherwise. Lead analysts are identified as those whose perfect foresight Leader-Follower Ratio over the sample period is in the top decile of the distribution. Following Cooper *et al.* (2001), the Leader-Follower Ratio is calculated as the ratio of the sum of the time differences between a recommendation and each of the previous two recommendations made by other analysts, to the sum of the time differences between the recommendation and each of the next two recommendations made by other analysts
STAR	Binary variable that takes the value 1 if a recommendation change is made by an analyst that is ranked in the latest All-Europe rankings of *Institutional Investor Europe*, and 0 otherwise
Information environment	
LOG_ASSETS	Natural logarithm of last reported total assets, inflation-adjusted to 31st December 2012 and converted to EUR as necessary
NUM_ANALYSTS	Number of analysts having issued at least one recommendation on a bank over the preceding 365 calendar days

Table 1. Definition of variables used in regressions (continued).

Recommendations	
AWAY	Binary variable that takes the value 1 if a recommendation goes away from the consensus and 0 otherwise. Following Jegadeesh and Kim (2010), recommendations that diverge from the consensus are those where the absolute deviation of the new recommendation from the consensus is larger than the absolute deviation of the prior recommendation from the consensus. Recommendations are standardised on a scale from 1 ("buy") to 3 ("sell")
CHANGE_REC	Magnitude of recommendation change, taking values between -3 and 3, excluding 0 (no recommendation change)
CONCURRENT_FORECAST	Binary variable that takes the value 1 if earnings forecasts are made within a 3-day period around recommendation changes, and 0 otherwise
REC_LEVEL	Recommendation level after a recommendation change (coded on a scale between 1, "strong sell", and 5, "strong buy")
REC_SD	Standard Deviation of analyst recommendations, taken as an indicator of uncertainty
Other controls	
EUR_OIS_SPREAD	Spread between the EUR Overnight Indexed Swap (OIS) and 3-month EURIBOR, used as a gauge of the intensity of the global financial crisis, and later, of the Eurozone debt crisis
PRIOR_PERFORMANCE	Absolute return on the recommended stock over the period [-69, -6]
VOLATILITY	Standard Deviation of the residuals of the market model with which CAR is measured (period [-69, -6])

Table 2. Statistics on recommendation changes in the sample. The sample of recommendation changes are from the I/B/E/S International Historical Detail File between early 2005 and mid 2012 and relate to 80 European banks. Recommendation changes are calculated as the difference between a broker's latest recommendation minus its previous recommendation. Recommendations are coded on a scale between 1 (Strong Sell) and 5 (Strong Buy). Recommendations lapse after 365 days unless they are confirmed or stopped by the broker. Recommendation changes greater or equal (resp. smaller or equal) than 3 (resp. -3) are grouped together because of their small number. Cumulative Abnormal Returns (CAR) are calculated over 2 days starting on the day of the recommendation change (or following that day if outside of market hours). Influential recommendation changes are those that are followed by CAR that are statistically significant and have the same sign as the recommendation change. LS Percentage is the comparable percentage of recommendation changes reported by Loh and Stulz (2011).

					Standardized Returns		
Rec Change	Frequency	Percentage	% Influential	% Star	Mean	Median	LS Percentage
-3	100	1.9%	13.0%	1.0%	-0.494	-0.295	0.8%
-2	702	13.6%	8.4%	2.4%	-0.557	-0.526	15.0%
-1	1,791	34.8%	7.0%	1.9%	-0.366	-0.319	38.9%
1	1,728	33.6%	8.0%	1.6%	0.388	0.288	33.5%
2	740	14.4%	8.1%	2.0%	0.372	0.316	11.3%
3	89	1.7%	3.4%	0.0%	0.535	0.659	0.5%
All	5,150	100.0%	7.7%	1.8%	-0.0196	-0.051	100.0%

Table 3. Number of analysts that have been ranked among the All-Europe analysts by *Institutional Investor Europe* between 2005 and 2012. Source: *Institutional Investor Europe*.

Broker	Gross Number of Analysts	Repeated Awards	Net Number of Analysts
All	37	22	15
Minus (removed from the academic version of I/B/E/S)			
Merrill Lynch	7	5	2
Lehman Brothers	2	1	1
Plus (transfers)			
Autonomous Research	0	0	1
Nomura	0	0	1
Equals			
Remaining	28	15	14

Table 4. Summary statistics: Means (and standard deviations) of dependent and control variables, for the overall sample (column 1), clustered by the type of influence of each recommendation. The influential (resp. non-influential) column clusters recommendation changes that are influential (resp. are not influential). The star (resp. non-star) column clusters recommendation changes that are made by All-Europe star analysts and non-star analysts. The superscripts ***, **, and * denote statistical significance levels of 1%, 5%, and 10% for a t-test between the mean of the influential and non-influential subsamples, and the star and non-star subsamples. Variable definitions are provided in Table 1.

Variable	Overall	Non-Influential	Influential	No Star	Star
CAR	-0.020	-0.031	0.120	-0.013	-0.371*
	(1.872)	(1.445)	(4.518)	(1.872)	(1.859)
MINORITIES_TO_EQUITY	0.062	0.061	0.068	0.062	0.062
	(0.073)	(0.071)	(0.087)	(0.072)	(0.082)
EQUITY_TO_ASSETS	0.052	0.052	0.050	0.052	0.055
	(0.021)	(0.021)	(0.022)	(0.021)	(0.029)
LOANS_TO_ASSETS	0.536	0.536	0.546	0.538	0.467***
	(0.184)	(0.185)	(0.178)	(0.184)	(0.194)
BROKER_COVERAGE	4.708	4.695	4.863***	4.699	5.207***
	(1.220)	(1.222)	(1.179)	(1.218)	(1.194)
INFLUENTIAL_BEFORE_ANY	0.422	0.422	0.431	0.422	0.426
	(0.494)	(0.494)	(0.496)	(0.494)	(0.497)
INFLUENTIAL_BEFORE_SAME	0.109	0.109	0.105	0.108	0.170
	(0.312)	(0.312)	(0.307)	(0.310)	(0.378)
STAR	0.018	0.018	0.025	0.000	1.000
	(0.134)	(0.132)	(0.157)	(0.000)	(0.000)
LOG_ASSETS	12.605	12.615	12.485*	12.598	13.004*
	(1.299)	(1.297)	(1.308)	(1.294)	(1.465)
NUM_ANALYSTS	25.780	25.897	24.388***	25.772	26.245
	(8.629)	(8.636)	(8.431)	(8.595)	(10.309)
AWAY	0.450	0.446	0.501**	0.449	0.532
	(0.498)	(0.497)	(0.501)	(0.497)	(0.502)
CHANGE_REC	-0.004	-0.001	-0.040	-0.001	-0.149***
	(1.461)	(1.458)	(1.490)	(1.461)	(1.451)
CONCURRENT_FORECAST	0.944	0.943	0.957	0.943	1.000***
	(0.230)	(0.232)	(0.202)	(0.232)	(0.000)
REC_LEVEL	3.255	3.258	3.213	3.252	3.415
	(1.084)	(1.082)	(1.106)	(1.084)	(1.082)
REC_SD	0.966	0.964	0.984*	0.965	1.032
	(0.185)	(0.184)	(0.200)	(0.186)	(0.171)
EUR_OIS_SPREAD	0.454	0.449	0.514***	0.453	0.513
	(0.292)	(0.288)	(0.326)	(0.292)	(0.291)
PRIOR_PERFORMANCE	-0.036	-0.031	-0.092***	-0.036	-0.021*
	(0.266)	(0.269)	(0.226)	(0.266)	(0.270)
VOLATILITY	0.019	0.019	0.018**	0.019	0.020
	(0.013)	(0.013)	(0.010)	(0.013)	(0.012)
N	5,150	4,751	399	5,056	94

Table 5. Pooled probit regressions to assess when recommendation changes made by sell-side analysts influence stock prices, estimated using the whole sample and using subsamples of recommendation changes associated with positive and with negative CARs. The binary dependent variable takes the value one if the 2-day Cumulative Abnormal Return (CAR) starting on the day of the recommendation change is statistically significant and has the same sign as the recommendation change level, and zero otherwise. If a recommendation change is made outside of trading hours, the 2-day CAR starts on the following trading day. The sample includes 5,150 recommendation changes relating to 80 listed European bank stocks made by 646 distinct analysts between January 2005 and September 2012. The independent variables are described in Table 2. The superscripts ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively, and z statistics are reported in parentheses below the parameter estimates. Standard errors are clustered by calendar days.

	INFLUENTIAL		
	ALL	POSITIVE	NEGATIVE
MINORITIES_TO_EQUITY	0.9428**	1.0425*	1.1676*
	(0.3992)	(0.5699)	(0.6320)
EQUITY_TO_ASSETS	−4.3555***	−6.2175***	−2.7917
	(1.6196)	(2.3049)	(2.5012)
LOANS_TO_ASSETS	0.2018	0.4835	−0.0092
	(0.2101)	(0.3430)	(0.2934)
BROKER_COVERAGE	0.0636***	0.1112***	0.0295
	(0.0245)	(0.0378)	(0.0374)
INFLUENTIAL_BEFORE_ANY	0.0364	0.0830	0.0883
	(0.0612)	(0.0979)	(0.0942)
INFLUENTIAL_BEFORE_SAME	−0.0511	−0.2997**	0.0620
	(0.0918)	(0.1481)	(0.1358)
STAR	0.1639	0.0857	0.2733
	(0.1791)	(0.2637)	(0.2517)
LOG_ASSETS	−0.0590	−0.0914	−0.0333
	(0.0383)	(0.0623)	(0.0572)
NUM_ANALYSTS	−0.0115**	−0.0103	−0.0134*
	(0.0047)	(0.0076)	(0.0073)
AWAY	0.0894	0.1078	−0.0183
	(0.0545)	(0.0857)	(0.0907)
CHANGE_REC	−0.0086	0.4085***	−0.4362***
	(0.0286)	(0.0405)	(0.0390)
CONCURRENT_FORECAST	0.0434	0.0263	−0.1534
	(0.1271)	(0.2004)	(0.1830)
REC_LEVEL	0.0132	0.0317	−0.0221
	(0.0381)	(0.0597)	(0.0565)
REC_SD	0.2652*	0.0613	0.1880
	(0.1520)	(0.2335)	(0.2493)
EUR_OIS_SPREAD	0.4304***	0.5371***	0.3300**
	(0.1038)	(0.1703)	(0.1473)
PRIOR_PERFORMANCE	−0.5724***	−0.6814***	−0.6209***
	(0.1312)	(0.2275)	(0.1959)
VOLATILITY	−15.5799***	−20.0210***	−13.9915***
	(3.1905)	(6.1679)	(4.4950)
Intercept	−0.9941*	−1.0744	−1.0801
	(0.5195)	(0.9173)	(0.6805)
Observations	5,150	2,490	2,660
Pseudo R^2	0.037	0.158	0.153
Chi^2 test	107.3***	394.23***	359.97***

Table 6. Pooled OLS regressions to assess the magnitude of the influence on stock prices of recommendation changes made by sell-side analysts, estimated using the whole sample and using subsamples of recommendation changes associated with positive and with negative CARs. The binary dependent variable is the standardized 2-day Cumulative Abnormal Return (CAR) starting on the day of the recommendation change, that is, the CAR divided by the standard deviation of residuals of the market model with which the CAR was established. If a recommendation change is made outside of trading hours, the 2-day CAR starts on the following trading day. The sample includes 5,150 recommendation changes relating to 80 listed European bank stocks made by 646 distinct analysts between January 2005 and September 2012. The independent variables are described in Table 2. The superscripts ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively, and z statistics are reported in parentheses below the parameter estimates. Standard errors are clustered by calendar days.

	STANDARDIZED_RETURN		
	ALL	POSITIVE	NEGATIVE
MINORITIES_TO_EQUITY	0.1211	0.3201	−0.7359*
	(0.4059)	(0.4023)	(0.3793)
EQUITY_TO_ASSETS	0.2279	−2.8776*	3.4180*
	(1.7378)	(1.4975)	(1.9600)
LOANS_TO_ASSETS	0.0649	0.3338*	−0.2992
	(0.2111)	(0.2013)	(0.2323)
BROKER_COVERAGE	0.0450**	0.0583**	−0.0068
	(0.0229)	(0.0247)	(0.0196)
INFLUENTIAL_BEFORE_ANY	−0.0337	0.0906	−0.0927
	(0.0651)	(0.0640)	(0.0646)
INFLUENTIAL_BEFORE_SAME	−0.1168	−0.1638*	−0.0881
	(0.0953)	(0.0925)	(0.0998)
STAR	−0.3468*	−0.0973	−0.2757*
	(0.1928)	(0.2037)	(0.1485)
LOG_ASSETS	−0.0186	−0.0553	0.0244
	(0.0375)	(0.0378)	(0.0331)
NUM_ANALYSTS	−0.0033	−0.0050	0.0022
	(0.0047)	(0.0048)	(0.0042)
AWAY	0.0665	−0.0168	0.0472
	(0.0528)	(0.0519)	(0.0493)
CHANGE_REC	0.2343***	0.0884***	0.0931***
	(0.0295)	(0.0295)	(0.0295)
CONCURRENT_FORECAST	0.0501	−0.0577	0.1902
	(0.1451)	(0.1115)	(0.1475)
REC_LEVEL	0.0810**	0.0507	0.0028
	(0.0403)	(0.0390)	(0.0449)
REC_SD	0.0706	0.2258	−0.1085
	(0.1573)	(0.1556)	(0.1540)
EUR_OIS_SPREAD	0.0307	0.3493***	−0.3000***
	(0.1393)	(0.1333)	(0.1158)
PRIOR_PERFORMANCE	−0.4525***	−0.6483***	0.3903***
	(0.1180)	(0.1086)	(0.1131)
VOLATILITY	0.0609	−12.5042***	9.0951***
	(2.3853)	(2.0198)	(2.5372)
Intercept	−0.3724	1.5394***	−1.6713***
	(0.5174)	(0.5683)	(0.4395)
Observations	5,150	2,490	2,660
R^2	0.0518	0.0521	0.0340
Adjusted R^2	0.0487	0.0456	0.0277
F Statistic	16.4939***	7.9905***	5.4638***

Table 7. Pooled probit regression to analyse how recommendation changes made by All-Europe star sell-side analysts differ from those made by non-stars. The binary dependent variable takes the value one for recommendation changes made by star analysts and zero otherwise. The sample includes 5,150 recommendation changes relating to 80 listed European bank stocks made by 646 distinct analysts between January 2005 and September 2012. The independent variables are described in Table 2. The marginal effects for continuous dependent variables are the decreases in probability when the variables decrease from their mean value by one standard deviation. The marginal effects for binary variables are the decreases in probability when the variables decrease from 1 to 0. The superscripts ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively, and z statistics are reported in parentheses below the parameter estimates. Standard errors are clustered by calendar days.

	STAR	Marginal Effects
MINORITIES_TO_EQUITY	−1.5106*	-0.0068
	(0.8965)	
EQUITY_TO_ASSETS	9.6721***	0.0090
	(2.8228)	
LOANS_TO_ASSETS	−0.8661**	-0.0098
	(0.3607)	
BROKER_COVERAGE	0.1717***	0.0089
	(0.0506)	
INFLUENTIAL_BEFORE_ANY	−0.1944*	-0.0123
	(0.1102)	
INFLUENTIAL_BEFORE_SAME	0.3455**	0.0128
	(0.1404)	
LOG_ASSETS	0.1449**	0.0084
	(0.0567)	
NUM_ANALYSTS	−0.0102	-0.0050
	(0.0081)	
AWAY	0.1391	0.0063
	(0.0936)	
CHANGE_REC	−0.1755***	-0.017
	(0.0449)	
CONCURRENT_FORECAST	3.8994***	0.022
	(0.0786)	
REC_LEVEL	0.2651***	0.0113
	(0.0708)	
REC_SD	0.8631***	0.0071
	(0.2590)	
EUR_OIS_SPREAD	0.2196	0.0031
	(0.1678)	
PRIOR_PERFORMANCE	0.2946*	0.0038
	(0.1567)	
VOLATILITY	2.7919	0.0018
	(3.8785)	
Intercept	−10.3232***	
	(0.9006)	
Observations	5,150	
Pseudo R^2	0.105	
Chi^2 test	4,329.3***	

Table 8. Pooled probit regression to analyse how recommendation changes made by analysts who are timeliness leaders (following Cooper *et al.* (2001)) differ from those made by followers. The binary dependent variable takes the value one for recommendation changes made by lead analysts and zero when it is made by followers. The sample includes 4,895 recommendation changes relating to 80 listed European bank stocks made by 492 distinct analysts between January 2005 and September 2012. The independent variables are described in Table 2. The marginal effects for continuous dependent variables are the decreases in probability when the variables decrease from their mean value by one standard deviation. The marginal effects for binary variables are the decreases in probability when the variables decrease from 1 to 0. The superscripts ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively, and z statistics are reported in parentheses below the parameter estimates. Standard errors are clustered by calendar days.

	LEADER	Marginal Effects
MINORITIES_TO_EQUITY	−0.0027	-0.000
	(0.4623)	
EQUITY_TO_ASSETS	−6.1093***	-0.016
	(1.6249)	
LOANS_TO_ASSETS	0.1257	0.002
	(0.2398)	
BROKER_COVERAGE	−0.0070	-0.001
	(0.0302)	
INFLUENTIAL_BEFORE_ANY	−0.3169***	-0.045
	(0.0855)	
INFLUENTIAL_BEFORE_SAME	0.2439**	0.022
	(0.1064)	
LOG_ASSETS	−0.0838*	-0.014
	(0.0447)	
NUM_ANALYSTS	0.0063	0.006
	(0.0057)	
AWAY	0.0478	0.005
	(0.0723)	
CHANGE_REC	0.0352	0.005
	(0.0374)	
CONCURRENT_FORECAST	−0.0337	-0.004
	(0.1777)	
REC_LEVEL	−0.0641	-0.008
	(0.0541)	
REC_SD	−0.0437	-0.001
	(0.1997)	
EUR_OIS_SPREAD	0.2513*	0.008
	(0.1348)	
PRIOR_PERFORMANCE	0.0551	0.002
	(0.1331)	
VOLATILITY	−1.3950	-0.002
	(2.6829)	
Intercept	−0.2212	
	(0.5930)	
Observations	4,895	
Pseudo R^2	0.023	
Chi^2 test	43.146***	