NBER WORKING PAPER SERIES

IS SELL-SIDE RESEARCH MORE VALUABLE IN BAD TIMES?

Roger K. Loh
René M. Stulz

Working Paper 19778
http://www.nber.org/papers/w19778

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2014

We thank Marcin Kacperczyk, Oguzhan Karakas, Jeff Kubik, Massimo Massa, Roni Michaely, Jay Ritter, Stijin Van Nieuwerburgh, Paola Sapienza, Siew Hong Teoh, Mitch Warachka, Kent Womack, Frank Yu, Jialin Yu, an anonymous associate editor and two anonymous referees, participants at the AFA 2014 Philadelphia meetings and the 2013 SMU-SUFE Summer Institute of Finance Conference, and at a seminar at the University of Zurich for helpful comments. Brian Baugh, Andrei Gonçalves, and David Hauw provided excellent research assistance. Roger thanks the Sing Lun Fellowship and the Sim Kee Boon Institute for Financial Economics at Singapore Management University for financial support. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Is Sell-Side Research More Valuable in Bad Times?
Roger K. Loh and René M. Stulz
NBER Working Paper No. 19778
January 2014, Revised November 2016
JEL No. F14,F20,F24

ABSTRACT

Because uncertainty is high in bad times, investors find it harder to assess firm prospects and, hence, should value analyst output more. However, higher uncertainty makes analysts' tasks harder so it is unclear if analyst output is more valuable in bad times. We find that, in bad times, analyst revisions have a larger stock-price impact, earnings forecast errors per unit of uncertainty fall, reports are more frequent and longer, and the impact of analyst output increases more for harder-to-value firms. These results are consistent with analysts working harder and investors relying more on analysts in bad times.

Roger K. Loh
Singapore Management University
Lee Kong Chian School of Business
50 Stamford Rd, #04-01
Singapore 178899
Singapore
rogerloh@smu.edu.sg

René M. Stulz
The Ohio State University
Fisher College of Business
806A Fisher Hall
Columbus, OH 43210-1144
and NBER
stulz@cob.osu.edu

1. Introduction

Even though there is a large literature on sell-side analysts' role as information intermediaries, this literature mostly ignores the issue of whether the state of the economy affects the value of analyst output for investors.[1] There are good reasons to believe that the usefulness and performance of sell-side analysts depend on the state of the economy. It is well-known that in bad times such as recessions and crises, there is greater variation in outcomes across firms and across time (see, for instance, Bloom (2009)). To the extent that the role of analysts is to make sense of firms amidst the increased macro uncertainty, their role should be more important in bad times and, consequently, they should work harder in bad times. At the same time, however, the increased uncertainty may make it harder for analysts to perform their job. Further, the drop in trading volume and hence broker profits in bad times may reduce performance rewards, leading to less motivated analysts. Hence, it is not clear whether analyst output is more valuable in bad times than in good times. In this paper, we find that analysts are indeed more valuable in bad times. The stock-price impact of their recommendation and earnings forecast revisions is greater in bad times. We investigate possible explanations for this finding and conclude that the evidence is consistent with analysts working harder and investors relying more on analysts in bad times.

We conduct our investigation using a sample of I/B/E/S Detail earnings forecasts from 1983-2014 and recommendations from 1993-2014. We define bad times in multiple ways. The most obvious approach is to use prominent crises that have occurred in the last two decades, such as the October 1987 crash, the LTCM crisis of 1998, and the credit crisis of 2007-2009. We also define bad times as recession periods marked by the National Bureau of Economic Research (NBER), and as periods of high uncertainty according to the Baker, Bloom, and Davis (2016) policy uncertainty index (from www.policyuncertainty.com). Our measure of the value of analyst

[1] For example, Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), Kecskés, Michaely, and Womack (2016) show that stock prices react to the release of analyst recommendations and a drift follows afterwards. Loh and Stulz (2011) show that some recommendation changes exert a large noticeable change in the firm's stock price and these recommendations can impact the firm's information environment. Bradley, Clarke, Lee, and Ornthanalai (2014) report that recommendations are more likely than earnings announcements or company earnings guidance to cause jumps in intraday stock prices. Others find that analyst coverage reduces information asymmetry, improves visibility (Kelly and Ljungqvist (2012)), disciplines credit rating agencies (Fong, Hong, Kacperczyk, and Kubik (2014)), and affects corporate policies (Derrien and Kecskés (2013)).

output is the price impact, which shows the extent to which analyst signals affect investors' assessment of the value of firms and hence is a measure of how analysts contribute to the information environment of firms.

Using the average two-day abnormal returns to stock recommendation changes, we find that analysts are more impactful during bad times for both downgrades and upgrades. Further, using the definition of influential recommendations in Loh and Stulz (2011), which effectively treats recommendation changes as influential if the stock-price reaction is statistically significant, we find robust evidence that both upgrades and downgrades are more likely to be influential during bad times compared to good times. We also find that the market reacts more strongly to earnings forecast revisions during bad times. Our evidence of greater analyst impact during bad times is robust to controls for firm and analyst characteristics, including analyst fixed effects. We conclude that analyst output is more useful for investors in bad times in that it moves stock prices more.

We perform several robustness tests for our results. Our focus is on macro instead of firm-specific bad times because macro bad times are economically important and because they are more likely to be exogenous to analysts. Prior studies like Frankel, Kothari, and Weber (2006) and Loh and Stulz (2011) show that analyst reports are more informative when firm-level uncertainty is higher. While we already control for firm-level uncertainty in our results, we want to be sure that it is macro (i.e. market-level) uncertainty that drives our results. We decompose a firm's total stock return volatility into market, industry, and firm-specific components. We find that the increased impact of recommendation changes in times of high uncertainty is most robust when the market component is used to define high uncertainty. Second, we investigate whether the market simply reacts more to all types of firm news in bad times (e.g., Schmalz and Zhuk (2015) find that reactions to earnings announcements are larger in recessions). Adapting the methodology in Frankel et al. (2006), we regress a stock's daily absolute returns on a comprehensive set of dummy variables that represent important firm news events, namely, recommendation changes, reiterations, earnings announcements, earnings guidance, dividend announcements, and insider trades. Interacting these news dummies with bad times indicators, we show that not all firm news events are associated with greater bad times impact. Importantly, the market reacts more to recommendation changes (and reiterations) in bad times even after all other news events and their interactions with bad times are controlled for. Hence we believe our finding that analysts have greater impact in bad times is both novel and robust.

We also find that the absolute forecast errors of analysts increase during bad times, which makes it puzzling that their output would have more impact on prices. We show, however, that the traditional metrics of analyst precision are not appropriate to compare precision across good and bad times. The relevant measure of precision for investors is one that takes into account the underlying uncertainty. This is easily seen in a simple Bayesian model. Consider investors who receive a new signal from analysts. The extent to which that signal will change their priors depends on the weight that investors put on the new signal and on the weight they put on their prior (e.g., see Pastor and Veronesi (2009)). As the precision of the signal increases relative to the uncertainty associated with their prior, they put more weight on the signal. Hence, in bad times, investors will put more weight on a signal from an analyst if the ratio of the precision of the signal to the uncertainty of the prior increases. Such an outcome could occur if the precision of the signal is lower in bad times as long as the precision of the signal falls less than the increase in the uncertainty about the prior. A useful way to put this is that the relevant measure of forecast error is a measure of forecast error per unit of uncertainty.

Using prior volatility to normalize absolute forecast errors, we find that this adjusted forecast precision actually *increases* during bad times (scaling by prior volatility is similar to the approach we used to define influential recommendation changes). Importantly however, showing that analyst forecast precision increases when measured against the underlying uncertainty does not mean that analysts automatically become more useful to investors. Specifically, it could be that investors rely less on analysts in bad times if they have better alternative sources of information. For instance, Kacperczyk and Seru (2007) show that how much investors rely on public information depends on the precision of their private information. Hence, in their model, if the analyst signal is public information, investors would rely less on analysts in bad times if investors themselves have better private information.

We examine five possible, non-mutually exclusive, reasons why analysts have more impact in bad times. First, we develop and investigate an analyst reliance hypothesis that builds on Kacperczyk and Seru (2007). Our analyst reliance hypothesis predicts that investors rely more on analysts for their information during bad times.

During bad times, investors have to understand how the macro situation with its attendant uncertainty affects the prospects of firms. Because of the greater macro uncertainty, possible outcomes are more extreme and, consequently, have potentially a greater impact on firms than during good times. Everything else equal, we would expect greater demand for analyst output that helps investors sort out the impact of ongoing macro shocks during bad times compared to good times. If investors already know much about a stock, analysts have less to contribute. Consequently, when analyst output is more valuable, it will be especially more valuable for more opaque stocks. It follows that the cross-sectional implication of the analyst reliance hypothesis is that the extent to which analyst output becomes more valuable in bad times is inversely related to the quality of the information environment for a stock and, therefore, the value of analyst output increases relatively more for stocks of more opaque firms in bad times (namely, stocks with no company guidance, low institutional ownership, high idiosyncratic risk, small size, no options traded, or low coverage). We find supportive evidence that the increased impact of analysts in bad times is higher for stocks with a more opaque information environment.

The analyst reliance hypothesis does not assume that analysts change what they do in bad times. Rather, analysts become more important for investors because investors face challenges that they do not face in good times and analysts help them deal with these challenges. However, it is plausible that analysts also change what they do during bad times. The next three hypotheses are about changes in analyst output in bad times. Our second possible explanation for the increased impact of analysts in bad times is that analysts could be working harder in bad times because of career concerns. Glode (2011) explains the better performance of mutual funds in bad times by the fact that investment managers work harder to produce better payoffs because investors have higher marginal utility in bad times. If the greater uncertainty in bad times causes investors to value analyst signals more, analysts might also work harder to produce better signals in bad times.[2] However, rewards for better performance might be limited in bad times when bonus pools shrink and analysts' employers face financial difficulties due to reduced profits. As a result of these two opposing forces, there is no clear empirical prediction as to whether analysts can be expected to work harder in bad times or not. We find that the stock

[2] This channel is less direct for analysts compared to fund managers. Investors can directly reward good fund managers with more inflows or less outflows. Investors instead can only indirectly reward good analysts through the analyst reputation channel.

volatility-adjusted precision of analysts' earnings forecasts goes up during bad times. This implies that analysts work harder to produce better forecasts in bad times. To investigate for more tangible evidence of whether they work harder, we find that analysts indeed revise their earnings forecasts more frequently and write longer reports in bad times. Further, using regressions that examine analyst attrition, we find evidence that analysts are more likely to leave the I/B/E/S database during bad times. This attrition risk could provide an incentive for analysts to work harder during bad times. Since analysts produce better output in industries with more analyst competition (Merkley, Michaely, and Pacelli (2016)), we would expect analysts to work harder in industries with more analyst competition in bad times and hence that their impact would increase more in such industries. We find strong supportive results for downgrades.

Third, we investigate whether analysts use different skills in bad times. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) find that mutual fund managers display more market-timing skills than stock-picking skills during bad times. It is not clear if analysts also produce more information in bad times that is common across firms when such common (sector/macro) information is more valued by investors. To investigate this, we examine if a recommendation revision on a single firm impacts peer firms. This spillover might occur if part of the information in the revision reflects the analyst's forecast of the common factor. We find some evidence that in bad times the spillover effect of downgrades on peer firms is larger than it is during good times. There is no difference in the spillover effect of upgrades in bad times compared to good times. Hence part of the increased influence of analysts in bad times, particularly for their downgrades, might come from an increased effort to collect and produce negative macro/sector information.

Fourth, there has been much work on potential analyst conflicts of interests (for a review of some of the evidence, see Mehran and Stulz (2007)). If analyst potential conflicts from investment banking are less important in bad times because of lower deal flow, analyst output might become less distorted and hence more valuable. To investigate this, we examine if forecast bias (i.e. the signed forecast error) is different in bad times. If conflicts have less bite in bad times, analysts might be less optimistic in bad times than in good times. We find little support for this hypothesis as the forecast bias is either no different in bad times, or even more optimistic. We also explore whether the increased impact of analysts in bad times is related to the type of broker the analyst works for. In particular, we find that the increased influence of analysts in bad times generally holds for independent brokers as well as for brokers with investment banking business. Overall, we do not find consistent evidence that the conflicts of interest hypothesis is helpful in explaining our results.

Our final and fifth potential explanation for the greater impact of analysts is that it has nothing to do with analyst output per se but is the product of overreaction by investors. Overreaction could be more likely in bad times due to lower liquidity so that trading on analyst revisions causes a temporary price pressure effect when liquidity providers are less able to accommodate the order flow. Alternatively, arbitrageurs might be more constrained in bad times, so that they cannot counteract overreaction by some investors as effectively as they can in good times. We investigate whether stock-price drift after revisions differs in bad times compared to good times and we find very little difference. Importantly, the stock-price drift after revisions does not exhibit reversals in good or bad times. Hence, overreaction is an unlikely explanation for our results.

Our paper is not the first to make the point that economic agents find signals more valuable in bad times. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2015) derive such a result for skilled fund managers, i.e., managers who have access to valuable signals. They show that "[b]ecause asset payoffs are more uncertain, recessions are times when information is more valuable." In their model, fund managers allocate more attention to aggregate shocks in bad times because of the increase in aggregate uncertainty. Since the risk premium is higher in bad times, skilled managers' greater attention to aggregate shocks in bad times leads them to perform better in bad times. In good times, when aggregate uncertainty is lower and the risk premium is lower, fund managers focus more on stock picking and pay more attention to signals about individual stocks. Kacperczyk et al. (2014) find empirical support for their prediction that skilled managers are better at market timing in bad times and better at stock selection in good times.

A few papers have examined aspects of the impact of crises on analyst output. However, none of them tests the hypotheses that we focus on and are as comprehensive in showing that analyst revisions of recommendations and earnings forecasts are more influential in bad times, or showing that it is the macro nature of bad times that matters. Arand and Kerl (2012) examine analysts' earnings forecasts and recommendations around the credit crisis and find that, although forecast accuracy dropped, investors continued to react to revisions in recommendations. Amiram, Landsman, Owens, and Stubben (2014) examine analyst forecast timeliness during periods of high market volatility and find that analysts are less timely and underreact to news in those periods. However, they also find that forecast revisions in these periods actually have more impact in reducing information asymmetry measured by bid-ask spreads. Hope and Kang (2005) also find that forecast errors are higher during bad times. While these papers conclude that investors wrongly pay attention to analysts who appear to be more inaccurate in bad times, we show that, controlling for the underlying uncertainty, analysts are actually more precise during bad times and investors rightly react more strongly to analyst revisions.

The rest of the study is organized as follows. Section 2 summarizes the hypotheses that we test. Section 3 describes our sample and reports our main results which show that analyst output is more influential in bad times. Section 4 reports the results of several robustness tests. In Section 5, we examine how forecast precision differs in good and bad times when we use different measures to scale forecast errors. Section 6 investigates potential explanations for the greater impact of analyst output in bad times, and Section 7 concludes.

2. Hypotheses

Our main goal is to investigate whether analyst revisions in bad times have any differential stock-price impact compared to their impact in good times. We lay out hypotheses that predict a differential impact of analysts in bad times.

2.1. Why analysts might have less impact in bad times

There are several reasons why analysts might have less impact in bad times. First, in bad times the forecasting environment is more difficult and this makes it harder for analysts to make accurate forecasts (difficult environment hypothesis). For example, Jacob (1997), Chopra (1998), and Hope and Kang (2005) find that earnings forecasts are less accurate during bad times. Consequently, this hypothesis predicts that analyst forecasts are more inaccurate and their revisions have a smaller stock-price impact in bad times.

Second, in bad times, there might be limited rewards for analysts who provide better quality output (shirking hypothesis). This is because investment banking deal flow, equity market capitalizations, trading volume, and brokerage business volume shrink in bad times. If brokerages employing analysts have fewer rewards for good performance, analysts might be less motivated to provide quality research in bad times. The greater amount of noise in the information environment also provides a cover for poorer performing analysts, making their lack of effort or skill less noticeable. This is similar to Bertrand and Mullainathan (2001) describing the difficulty that investors have in evaluating manager quality when firm performance is driven by bad macro-economic conditions. This hypothesis also predicts that analyst forecasts are less accurate in bad times and their revisions have less stock-price impact.

Third, investors could be distracted in bad times, paying less attention so that there is less stock-price impact to analyst revisions (inattention hypothesis). Hirshleifer, Lim, and Teoh (2009) show that when a lot of news hits the markets, investors tend to react less to firm news events. In bad times when information uncertainty increases, there is a lot more news that investors have to digest, and hence investors might underreact to a specific type of news such as analyst revisions.

2.2. Why analysts might have more impact in bad times

Kacperczyk et al. (2015) show that information about payoffs with a given precision is more valuable in bad times because of higher uncertainty. An analyst revision is a signal about firm prospects which investors incorporate into stock prices based on their existing priors. In bad times, uncertainty about investors' priors goes up. If the noise in analyst signals does not go up as much as the noise in the prior, analyst signals become more valuable, everything else equal. This assumes that analysts have expertise in incorporating into their forecasts the impact of bad macro conditions on the firms that they cover. Hutton, Lee, and Shu (2012) provide some evidence that analysts can better incorporate the implications of bad macroeconomic news into their forecasts than firm managers. The noise of analyst signals relative to prior uncertainty can decrease either because analysts are able to take steps to make sure that the noise in their signals increases less than the prior uncertainty, or because the prior uncertainty increases more than the noise of analyst signals because sources of information for investors, such as private information, dry up in bad times or become much noisier. We now consider the latter situation for our first hypothesis, and then the former for our second to fourth hypotheses.

Investors have multiple sources of information. They look at public information such as analyst signals, but they may also have access to private information. With opaque firms, public information is limited, but for other firms investors have access to many public information signals that compete with information provided by analysts. It follows that when uncertainty increases due to macro shocks, investor demand for analyst output increases especially for the more opaque firms. However, for analysts to be more valuable to investors in bad times, it is important that the other sources of information of investors do not become more precise or more valuable in bad times compared to analyst information. Such a condition follows from the model of Kacperczyk and Seru (2007). In that model, they evaluate the sensitivity of investors to private and public information when some investors have access to private information. They find that, if private information becomes noisier, investors rely more on public information like analyst signals. Hence, in such a setup, investors will rely more on public information as other sources of information dry up or become noisier. Kacperczyk and Seru (2007) also offer an alternative interpretation of the model, which is that "private" information can also be the ability to process public information more accurately. Bad times can be viewed as a regime change, where the advantage of some investors at processing data may be impaired because they have to adapt to the new regime, or a situation where changes are more extreme so that processing public information is harder because there is little experience with similar situations.

The Kacperczyk and Seru (2007) model motivates our investor reliance on analysts hypothesis to explain the increased impact of analysts in bad times. With this hypothesis, analysts have a greater impact on investors' priors in bad times because investors' private information or information processing ability becomes noisier in bad times. This leads to an increase in uncertainty that makes it harder for investors to assess the consequences of macro shocks. In good times, uncertainty about macro shocks is limited, so that realizations of macro shocks have relatively less impact on firms and hence are not as important in assessing the prospects of firms. In bad times, macro shock realizations are more extreme and have more of an impact on firms. In such a situation, analyst output becomes more valuable because competing sources of information become less valuable in enabling investors to assess the impact of shocks precisely when these shocks are more important. The cross-sectional prediction of the analyst reliance hypothesis is that the increase in uncertainty about the consequence of macro shocks for firms is most important for the firms that investors have less information about, i.e. the more opaque firms. For firms that trade in an environment with much information production, there will be more substitutes for analyst output in bad times than for other firms.

The second hypothesis we investigate is that analysts might work harder in bad times to produce signals that are of better quality and hence signals that have a higher impact (an analyst effort or incentives hypothesis). There is existing evidence in Glode (2011) that fund managers perform better in bad times so as to satisfy investors' higher marginal utility in bad times. While it is easier for investors to reward fund managers (directly through flows) than to reward analysts (indirectly through reputation), this incentive might also be at work in analysts through attrition risk. This hypothesis of greater analyst effort also predicts greater frequency of reports and greater accuracy of earnings forecasts after accounting for the greater uncertainty in bad times. We would expect effort to increase more in industries with more analyst competition since the literature shows that more analyst competition within an industry leads to better analyst output (Merkley, Michaely, and Pacelli (2016)).

The third hypothesis is an analyst expertise hypothesis. If analysts have expertise to help investors understand the implications of bad times they can employ this expertise only during bad times. For example, in a separate setting, Kacperczyk et al. (2014) show that fund managers have market-timing skills during bad times but stock picking skill in good times. If analysts also have such market-timing skills in bad times, their revisions might contain information for peer firms. This means that the revisions might be more impactful due to them containing more industry information, consistent with some papers finding that analysts have expertise to predict industry returns (e.g., Howe, Unlu, and Yan (2009) and Kadan, Madureira, Wang, and Zach (2012)).

Fourth, the conflicts of interest hypothesis predicts that analysts can be more impactful in bad times when investment banking conflicts decline. To the extent that investment banking conflicts lead analysts to have an optimistic bias in their research (see, e.g., Michaely and Womack (1999)), this bias might be lower in bad times when investment banking revenue drops. Specifically, in bad times, analysts in brokers with investment banking divisions are likely to face less deal-related pressure to bias their research. As a result, their research might be of higher quality and hence have higher impact. We can investigate if analyst optimistic bias goes down in bad times and examine how bad times impact brokers with and without investment banking divisions.

Finally, we investigate an overreaction hypothesis. In bad times, there is evidence that some types of firm news see greater reaction, such as earnings announcements (see, e.g. Schmalz and Zhuk (2015)). This hypothesis predicts that analyst revisions should also see a greater reaction just like all other types of firm news. We also investigate for any evidence that a greater reaction is in fact an overreaction by looking at the future drift of stock prices. Overreaction might be more likely to occur in bad times because arbitrageurs are more constrained in bad times and cannot counteract the inefficient reaction to revisions.

3. Main results

3.1. Bad times definitions

We first define bad times and describe our analyst output sample. We have four proxies for bad times. The first two proxies focus on prominent financial crises. We set the indicator variable *Crisis* equal to one for the periods September-November 1987 (1987 crisis), August-December 1998 (LTCM crisis), and July 2007-March 2009 (credit crisis). Second, we define *Credit Crisis* equal to one for the credit crisis period since this especially sharp and prolonged crisis warrants a separate investigation. The third definition uses NBER-defined recessions, which for our analyst sample are the periods July 1990-March 1991, March-November 2001, and December 2007-June 2009. The fourth measure is the Baker et al. (2016) policy uncertainty index. We define a period of high policy uncertainty (*High Uncertainty*) as one where the historical index is in the top tercile of available values (198308-201402). This measure assigns more months as bad times compared to the earlier three definitions. In our sample, 7.7%, 5.6%, 9.8%, and 33.4% of the months are classified as *Crisis*, *Credit Crisis*, *Recession*, and *High Uncertainty* respectively.

3.2. Earnings forecasts and recommendations data

The analyst data are from Thomson Financial's Institutional Brokers' Estimate System (I/B/E/S) U.S. Detail file.[3] Earnings forecasts are one quarter-ahead forecasts made from 198308-201412 and actual earnings (announced from 198309-201504) are taken from I/B/E/S. We use the unadjusted file to mitigate the rounding problem in I/B/E/S (see, for instance, Diether, Malloy, and Scherbina (2002)). Using the I/B/E/S split-adjustment factors, we adjust the unadjusted forecast so that it is on the same per-share basis as the reported unadjusted actual earnings. As is common practice, financial firms are excluded from our main analysis although we discuss results for this sector in robustness tests (financials are defined as group 29 of the Fama and French (1997) 30-industry definitions).

Individual analyst stock recommendations are from the I/B/E/S Detail file issued from 1993-2014. We define upgrades and downgrades using the analyst's current rating minus the prior rating by the same analyst. A prior rating is assumed to be outstanding if it has not been stopped (checking the I/B/E/S Stopped file) and is less than one year old based on the I/B/E/S review date (following Ljungqvist et al. (2009)). We exclude anonymous analysts, observations with no outstanding prior rating from the same analyst (i.e., analyst initiations or re-initiations are excluded), and recommendation changes where the lagged stock price is less than one dollar. We also remove revisions that occur on firm-news days following Loh and Stulz (2011). This step is important because we do not want recommendations that merely repeat the information contained in firm news releases. Firm-news days are defined as the three trading days centered around a Compustat earnings announcement date or a company earnings guidance date (guidance dates are from First Call Guidelines until it was discontinued on September 29, 2011, and from I/B/E/S Guidance file thereafter), and days with multiple analysts issuing a

[3] Ljungqvist, Malloy, and Marston (2009) report that matched records in the I/B/E/S recommendations data were altered between downloads from 2000 to 2007. Thomson, in response to their paper, fixed the alterations in the recommendation history file as of February 12, 2007. The dataset we use is dated December 17, 2015 and hence reflects these corrections. However, there are still some large brokers missing from the current I/B/E/S forecasts and recommendations files. To reinstate the missing years from these brokers, we use Capital IQ estimates to extract recommendations and earnings forecasts issued by these missing brokers and splice the collected data into our I/B/E/S sample. Spliced observations make up about 1.05% of the total observations in the forecasts sample and 0.45% of the observations in the recommendations sample.

recommendation for the firm.[4] Similar filters are also used when we examine the stock-price impact of earnings forecast revisions. Stock returns are from the Center for Research in Security Prices (CRSP).

3.3. *Evidence of large increases in uncertainty during bad times*

In this section we examine the variance of investors' priors during bad times using an ex ante proxy. We show that there is indeed more uncertainty about the market and about individual stocks in bad times. In Panel A of Table 1, we report daily estimates of the VIX from CBOE as a proxy for ex ante uncertainty. This data starts from 1990 and overlaps most of our 1983-2014 sample. The typical daily VIX (quoted as an annualized standard deviation) in *Crisis* periods is 31.339, while in good times it is 18.865. The VIX in *Crisis* periods is therefore more than 60% greater than in non-*Crisis* times and this difference is statistically significant. The increase in the VIX is similar for the *Credit Crisis* period and *Recession* periods. The increase in the VIX is smaller for the *High Uncertainty* periods but is still sizable. Hence for all our bad times definitions, the ex ante volatility of the market increases sharply in bad times, which is evidence that investors' priors become less precise in bad times.

We turn now to the ex ante volatility for the common stock of individual firms at the time of recommendation changes. Panel B of Table 1 reports the annualized implied volatilities of the stocks five trading days before they are subject to a recommendation change. The implied volatility data is from Option Metrics' Volatility Surface file, using the average of the interpolated implied volatility from puts and calls with 30 days to expiration and a delta of 50. We are able to match 76% of the recommendation changes in our sample with an implied volatility. Starting with the *Crisis* definition of bad times for downgrades, we see that the option-implied volatility is 61.820% in bad times and 47.319% in good times. The difference of 13.501 percentage points is statistically significant. When we turn to upgrades, the differences in implied volatilities are very similar to what they are for downgrades. For all our definitions of bad times, we find similar results. Hence,

[4] One concern with these filters is that if analysts piggyback more on firm news in bad times, a larger fraction of poor quality recommendations might be removed in bad times, hence making the remaining sample of recommendations appear "better" in bad times than in good times. However, we find that it is in good times that analysts piggyback more. For example in non-*Crisis* periods, 37.7% of downgrades (30.3% of upgrades) are removed by the filters compared to 33.8% (27.0% of upgrades) in *Crisis* periods. We also checked if recommendation changes that occur on firm-news days are more impactful in bad times and we find strong evidence for downgrades (all four definitions of bad times) but mixed evidence for upgrades (only two of four definitions). Because it is hard to distinguish whether these effects can be attributed to analysts or to the firm news events themselves, we focus our analysis on the sample that is not contaminated by firm news.

there is clear evidence of higher ex ante volatility at the firm level just before recommendation changes in bad times compared to good times.

3.4. Stock-price impact of recommendation changes

We now address the question of whether analyst output has a greater stock-price impact in bad times. We take the view that if analyst output moves stock prices, it means that investors' priors are changed and hence the analyst output is valuable to investors. We examine first the stock-price impact of recommendation changes.

Because recommendation levels can be biased, recommendation changes are more reliable than levels as a setting to evaluate the impact of analysts (e.g., Boni and Womack (2006) show that rating changes contain more information for returns than rating levels). To estimate the stock-price impact of a recommendation change, we use the cumulative abnormal return (CAR) from the recommendation date to the following trading day, i.e., a day [0,1] event window. If the recommendation is issued on a non-trading day or after trading hours, day 0 is defined as the next trading day. CAR is computed as the cumulative return of the common stock less the cumulative return on an equally weighted characteristics-matched size, book-to-market (B/M), and momentum portfolio (following Daniel, Grinblatt, Titman, and Wermers (1997), thereafter DGTW). Panel A of Table 2, which summarizes our main results, reports the average CAR of recommendation changes, separated into upgrades and downgrades, issued in bad times and in good times with statistical significance based on standard errors clustered by calendar day.

We see that downgrades and upgrades have larger impact during bad times. The differences are stark. Starting with the *Crisis* definition, we see that the average two-day CAR is -2.678% for a recommendation downgrade in *Crisis* periods and is -1.687% in non-*Crisis* periods. Both CARs are significant at the 1% level indicating that analysts have impact in both good and bad times. But the significant difference of -0.991% shows that downgrades have larger impact in bad times. The same is true for upgrades. The CAR for upgrades in *Crisis* periods is 2.658%, while in non-*Crisis* periods it is 2.044%. The difference in these CARs is 0.614% and is again significant at the 1% level. Using other definitions of bad times also shows similar evidence of larger impact of recommendations in bad times.[5]

We now examine whether analysts are more influential in bad times using the influential definition in Loh and Stulz (2011). Loh and Stulz show that it is important to assess whether a recommendation change results in a stock-price reaction that is noticed by investors, meaning that the rating change results in a reaction that is significant at the firm level based on the firm's prior stock-price volatility.[6] Table 2 shows the fraction of recommendation changes that are influential during bad times compared to good times.

The results are striking. For all definitions of bad times, a recommendation downgrade is significantly more likely to be influential during bad times than during good times. The difference is especially large when we use the *Crisis* definition or the *Credit Crisis* definition of bad times. For these definitions, a recommendation downgrade has a probability of being influential that is one third higher during bad times (e.g., 15.278% versus 11.681% for the *Crisis* definition). The differences are smaller for the *Recession* and *High Uncertainty* definitions of bad times. Turning to recommendation upgrades, we find that they are also significantly more likely to be influential in bad times for all definitions of bad times. The results for the fraction of influential recommendations are, therefore, similar to the CAR results.

We plot in Figure 1 the summary of our results in Table 2. We can see that upgrades and downgrades are both associated with stronger stock-price reactions and are more likely to be influential in bad times compared to good times.

Thus far we have only shown univariate results. Because recommendation impact can be affected by other characteristics besides bad times, it is important to examine if our results are robust to controlling for such

---

[5] Using a bad times dummy means that the baseline group is non-bad times, which we term as good times. This approach is consistent with, say, how the NBER only defines recessions and labels other periods as expansions. In unreported tests, we use the monthly market returns to sort non-bad times into two groups, normal times and good times. Using normal times as the baseline group, we continue to find strong evidence of a stronger CAR impact of recommendation changes in bad times. We find little increased impact on CAR in good times compared to normal times, except for upgrades, which have slightly larger impact in good times compared to normal times.

[6] Specifically, we check if the CAR is in the same direction as the recommendation change and the absolute value CAR exceeds $1.96 \times \sqrt{2} \times \sigma_{\varepsilon}$. We multiply by $\sqrt{2}$ since the CAR is a two-day CAR. σ_{ε} is the standard deviation of residuals from a daily time-series regression of past three-month (days −69 to −6) firm returns against the Fama and French (1993) three factors. This measure roughly captures recommendation changes that are associated with noticeable abnormal returns that can be attributed to the recommendation changes.

characteristics. In Table 3, we report estimates of OLS panel regressions where we control for firm, analyst, and recommendation characteristics.

We use the following control variables that are known to be related to the impact of recommendations. *LFR* is the analyst's prior year leader-follower ratio constructed following Cooper, Day, and Lewis (2001), who show that reports from leader analysts exert greater stock-price impact.[7] *Star Analyst* is an indicator variable for analysts elected to the All-American team (whether as first-, second-, third-team, or runner-up statuses) in the latest October *Institutional Investor* annual poll. Fang and Yasuda (2014) show that stars analysts have better performance. Mikhail, Walther, and Willis (1997) show that analyst experience impacts performance. We define *Relative Experience* as the difference between the analyst's experience (number of quarters since appearance on I/B/E/S) and the average experience of all analysts covering the same firm. Next, because forecast accuracy can be a proxy for skill in stock picking (Loh and Mian (2006)), we define *Accuracy Quintile* as the average forecast accuracy quintile (relative to other analysts covering the same firm) of the analyst based on the firms covered in the past year, where the quintile rank is increasing in forecast accuracy. *Broker Size* is the number of analysts employed by the broker as a proxy for analyst ability and availability of resources. We also add the following firm characteristics: *# Analysts* which is one plus the number of analysts covering the firm, *Size* is last June's market cap, *BM* is the book-to-market equity ratio (computed and aligned following Fama and French (2006)), *Momentum* is the buy-and-hold return from month *t*-12 to *t*-2, and *Stock Volatility* is the standard deviation of daily stock returns in the prior month. Adding these controls allows us to determine if our univariate results are robust to controlling for changing firm and analyst characteristics from good to bad times.

The descriptive statistics of these variables are reported in Panel C of Table 1 for the full sample, as well as separately for one of the bad times definitions—*Crisis* and non-*Crisis* periods. These are averages of the characteristics across all the recommendation change observations within the downgrade or upgrade sample. We see that most analyst characteristics look similar between good and bad times, except that there appears to be a

[7] To compute the *LFR*, the gaps between the current recommendation and the previous two recommendations from other brokers are computed and summed. The same is done for the next two recommendations. The leader-follower ratio is the gap sum of the prior two recommendations divided by the gap sum of the next two recommendations. A ratio larger than one indicates a leader analyst, since other brokers issue new ratings quickly in response to the analyst's current recommendation.

smaller fraction of star analysts in bad times. For firm characteristics, we see a decrease in the average *Size*, *Momentum*, *BM*, and *# Analysts* per firm in bad times, while *Stock Volatility* is markedly higher in bad times.

We now turn to the regressions in Table 3 that include these controls. For each definition of bad times, we estimate the CAR regression first using a constant and an indicator variable for bad times. The coefficient on the bad times indicator is the univariate additional impact of downgrades in bad times (equivalent to the CAR difference in Table 2) and the intercept is the good times CAR impact. We then control for firm, analyst, and forecast characteristics, and add industry fixed effects (Fama-French 30 industry groups). Standard errors are clustered by calendar day to account for cross-sectional correlation of returns on the same day.[8] From models 1-8 for downgrades, we see that regardless of whether we have control variables, all the indicator variables for bad times have coefficients that are negative and statistically significant at the 1% level. This shows that analysts' downgrades have more stock-price impact in bad times compared to good times. To gauge the economic magnitude of the effect of bad times after the controls are added, we compare the bad times coefficient to the "Good times $\hat{Y}$", which is the predicted CAR when the control variables are at their means and the bad times indicator is zero. In model 2, the bad times coefficient is -0.998% and the good times predicted CAR is -1.761%, meaning that bad times increase the CAR impact by about 1.57 times, an effect similar to the case without controls.

Looking at the coefficients of the controls, we see that recommendations by analysts with a greater leader-follower ratio have a larger impact. Not surprisingly in light of the earlier literature, we see that recommendation changes by bigger brokers have a greater impact. So do the downgrades of star analysts. Also in line with the literature, recommendation changes have less impact when a firm is followed by more analysts or when the firm is larger. Lastly, the impact of analyst downgrades is greater when the firm's prior stock volatility is higher. Turning to recommendation upgrades, we find that with or without controls, upgrades also have a significantly larger stock-price reaction regardless of the definition of bad times.

[8] We also tried clustering the standard errors by firm or by analyst and the results are typically similar or statistically stronger.

Table 4 repeats the analysis in Table 3 by estimating probit models for whether a recommendation change is influential or not. The marginal effects, which measure the change in probability when changing the variable by one standard deviation centered around its mean (or a 0 to 1 change for a dummy variable), are reported with *z*-statistics in parentheses (based on standard errors clustered by calendar day). We see that recommendation downgrades are more likely to be influential in bad times for all definitions of bad times. Interestingly, the marginal effects of the bad times indicator variables are higher when we control for analyst, firm, and recommendation characteristics and industry fixed effects. For example, in regression 1 of Table 4, the marginal effect on *Crisis* indicates the univariate increase in influential probability of a downgrade in *Crisis* periods is 3.6% (compared to the probit's predicted influential probability of 12.1% in the downgrades sample). When we add control variables, the coefficient on *Crisis* goes up to 6.5% (compared to the predicted probability of 11.7%, labeled "Predicted Prob." in the table). Turning to recommendation upgrades, we find that upgrades are also more likely to be influential during bad times for all definitions and the effect also becomes stronger when we add control variables.

Overall, we find strong evidence that recommendation changes are more impactful during bad times. There is also no asymmetry in our results in that both upgrades and downgrades have increased impact in bad times. Some in the literature suggest that the reaction of the market to good and bad news might be asymmetric depending on whether times are good or bad (e.g. Beber and Brandt (2010) and Veronesi (1999)). We find no evidence of such an asymmetric reaction to the "news" produced by analysts because the increased impact of recommendation changes in bad times applies to both upgrades and downgrades.

Overall, the result that analysts have more impact in bad times is inconsistent with the difficult environment hypothesis, the shirking hypothesis, and the inattention hypothesis, which all predict that analyst research quality should be reduced in bad times. Instead, our result supports hypotheses that predict better-quality analyst output in bad times.

A caveat for our results is that the credit crisis overlaps with a sizable fraction of some bad times definitions. Specifically, 72% and 43% of the *Crisis* and *Recession* months respectively occur in the credit crisis. As a result, when we exclude the credit crisis observations, we find weak and at most mixed evidence that analysts have more impact in *Crisis* or *Recession* periods. However, this issue is mitigated for the *High Uncertainty* definition of bad times as only 12% of *High Uncertainty* months occur in the credit crisis. Using the *High Uncertainty* definition of bad times, excluding credit crisis observations does not affect the evidence of larger analyst impact in bad times.

3.5. Stock-price impact of earnings forecast revisions

Our analysis thus far has looked at stock recommendations, which are essentially the analyst's summary measure of the future prospects of investing in the firm's stock. We now focus on analysts' forecasts of a specific measure of fundamentals—earnings. The use of earnings forecast revisions also allows us to control for the amount of information in the revision by using the forecast revision magnitude. We investigate whether earnings forecasts are more or less useful to investors during bad times by measuring the impact of forecast revisions on the firm's stock price. As before, we use two definitions of impact, the two-day CAR and the influential likelihood. A forecast revision is defined using the analyst's own prior forecast of quarterly earnings, provided that the prior forecast has not been stopped and is still active (less than one year old) using its I/B/E/S review date. The revision is then scaled by the lagged CRSP stock price and we call this the *Forecast Revision*. We remove forecast revisions on dates that coincide with corporate events (namely, the three trading days around earnings announcements and guidance dates, and multiple-forecast dates) so that we do not falsely give credit to the analyst for company announcement-driven stock-price changes.

Figure 2 (left two charts) plots the univariate average forecast revision CARs. We see clear evidence that forecast revisions have more stock-price impact in bad times. Table 5 then estimates regressions with control variables. An important added control is *Forecast Revision* itself because one naturally expects larger-magnitude revisions to be associated with larger stock-price changes. Table 5 reports the regressions of forecast revision CARs where the standard errors are clustered by calendar day. In regression (1) which has no control variables, we see that the downward forecast revision CAR is much more negative in *Crisis* times. The intercept of the regression is -0.294% while the coefficient on the indicator variable is -0.398% (t=6.50), meaning that the stock-price reaction to a downward revision during bad times is more than double the reaction during good times.

Adding the control variables to the regression does not meaningfully change the statistical or economic effect of bad times (in model 2, the bad times coefficient is -0.384 compared to the good times predicted CAR of -0.230). The coefficient on *Forecast Revision* itself is positive and significant meaning that it is not the case that larger-magnitude revisions explain the greater CAR impact.[9] Similar results hold for the other definitions of bad times. When we turn to upward revisions, the CAR is significantly higher for the *Crisis* and *Credit Crisis* definitions of bad times, but not for other definitions. Further, the impact of bad times on the CAR is smaller. For the *Crisis* definition, the intercept is 0.439% and the estimate of the coefficient on the indicator variable is 0.198%, i.e. about one-third higher than in bad times, which contrasts with an impact that is more than double in bad times for downward revisions.

Figure 2 (right two charts) and Table 6 examine whether an earnings forecast revision is more likely to be influential in bad times. Table 6 estimates probits where the dependent variable is an indicator variable that equals one when the forecast is deemed to be influential. The results are stronger than in the earlier table with all the marginal effects being statistically significant, indicating that analysts make more influential earnings forecast revisions in bad times compared to good times. The economic effect is also large. For example, the marginal effect for *Crisis* in model 2 is 0.036, which means that in *Crisis* times the influential probability of a downward revision goes up by 3.6%, a big increase from the 4.5% predicted influential probability in the probit model.

From these results, we conclude that analyst output is indeed more valuable in bad times. Whether we consider their recommendation changes, which represent their overall assessment of a firm's prospects, or a specific change in their forecasts of a firm's upcoming short-term fundamentals (quarterly earnings), we find that analysts have a more influential impact on stock prices.

[9] When we estimate the bad times regression with only *Forecast Revision* as a single control in unreported results, the coefficient on *Forecast Revision* is much stronger for both the downward and upward revision sample. In the presence of other control variables, we see from Table 5 that the effect of *Forecast Revision* is much weaker. If we add an interaction of *Forecast Revision* with bad times, the coefficients on such interactions are never significant.

4. Robustness tests

We conduct several robustness tests to examine if our results of greater analyst impact in bad times are new to the literature and whether they are robust.

4.1. Does market-wide or firm-specific uncertainty drive our results?

Our definition of bad times is based on changes in aggregate economic activity. We use a market-wide definition instead of a firm-specific definition because market-wide bad times are more likely to be exogenous to the analyst and to the industry. Some previous studies have examined how firm-level uncertainty affects analysts' output. For example, Frankel et al. (2006) find that analyst reports are more informative when trading volume and stock return volatility are higher, and Loh and Stulz (2011) find that analyst recommendations are more influential when firms have higher forecast dispersion. Although our earlier results already control for firm-specific uncertainty, we explore a different method to see how controlling for the role of firm-specific uncertainty affects our results.

We first decompose a firm's prior month total variance of daily stock returns into macro, industry (Fama-French 30 groups), and residual (firm-specific) components by regressing a firm's daily returns on market (CRSP value-weighted) returns and a market-purged industry return. We define high uncertainty as the highest tercile of the relevant variance component over the firm's history and show in Panel A of Table 7 the recommendation change CAR regressed on these three high uncertainty dummies. We see that all three are related to significantly larger CAR impact in the univariate setting. When we put all three uncertainty dummies together and add control variables, we see that only the coefficient on the market-wide uncertainty dummy remains robust and statistically significant across all specifications. Hence, we believe our results are new in that it is market-wide uncertainty rather than firm-specific uncertainty that drives the higher impact of analysts during periods of high uncertainty.

4.2. Do reports that reiterate recommendations have more impact?

Although we find that analyst reports containing revisions are more impactful in bad times, it might not mean that all analyst reports have more impact in bad times if reports that reiterate recommendations are less informative in bad times. For example, if analysts have less information in bad times, they might choose to just reiterate old ratings instead of revising them. And if these reiterations have mostly no impact in bad times, we might overstate the impact of analyst reports in bad times when we exclude reiterations from our sample.

We first examine, in unreported results, the frequency of recommendation changes and reiterations in bad times. It is well known that I/B/E/S does not record all reiterations (see for example, Brav and Lehavy (2003)). Besides the recorded reiterations on I/B/E/S, we infer other reiterations by assuming that the most recent outstanding I/B/E/S rating is reiterated whenever there is a quarterly forecast in the I/B/E/S detail file or a price target forecast in the I/B/E/S price target file but no corresponding new rating in the recommendation file. As before, we remove observations that occur together with firm news. We show that in non-*Crisis* periods, the average total number of recommendation changes per month for a firm (across all analysts covering it) is 0.183. In *Crisis* times, this goes up to 0.238 (a 30% increase). We find across all other bad times definitions that the number of recommendation changes also goes up in bad times. Hence, there is no evidence that analysts are more reluctant to revise recommendations in bad times. For reiterations, we find 0.771 reiterations per month in non-*Crisis* times and 0.903 in *Crisis* times (a 17% increase). Across all bad times definitions, we also find evidence that the number of reiterations goes up. There is also no evidence that the number of reiterations goes up at the expense of the number of revisions.

We now investigate in Panel B of Table 7 whether these more numerous reiterations in bad times have any differential impact compared to good times. We show that the impact of unfavorable reiterations (reiterated sell or hold) is indeed higher in bad times across all specifications, similar to our findings on revisions. Hence analysts are also more impactful when issuing reiterations in bad times. We find less evidence of this for favorable reiterations (reiterated buy), with mostly lower impact in bad times. Overall, we conclude that there is no evidence analysts reiterate more in bad times at the expense of revising less. Their bad times reiterations, especially of unfavorable ratings, are also more informative compared to those in good times.

4.3. Does the market react more to all types of firm news in bad times?

We now examine if all firm news have a greater impact in bad times. If this were the case, it would suggest that there is something systematic about how the market reacts to news in bad times and the heightened reaction to analyst output in bad times can be explained by the fact that the market reacts more to every piece of news rather than that the market reacts more to analyst output only. This investigation makes sense in light of Schmalz and Zhuk (2015) who find that the market reacts more to earnings announcements in bad times. We adapt the methodology in Frankel et al. (2006) by estimating a big panel regression of daily absolute individual stock returns on a comprehensive set of dummy variables that represent important firm news events, namely, recommendation changes, reiterations, earnings announcements, earnings guidance, dividend announcements, insider trade events, and the announcement of insider trades. Following Frankel et al., these dummies are set to one in day 0 of the event, or day 1 of the event if the announcement occurs after trading hours (when the event time is available for us to check this). Dividend announcements are taken from the CRSP event file and insider trades are from the Thomson Insider Form 4 files. The insider trade date is the date when the insider trade occurs and the filing date is when it is reported to the SEC and hence publicly known.

We expect the coefficient on these firm news dummies to be positive and the recommendation-related dummies to remain positive in the presence of the other firm news dummies. As controls, we include several firm characteristics such as size, B/M, momentum, idiosyncratic volatility, etc., and also industry fixed effects. We add bad times indicators whose coefficients are expected to be positive if the market is in general more volatile in bad times. We then interact these firm news dummies with bad times indicators and expect such interactions to be positive if the market reacts more to any news in bad times. Of important interest is whether the recommendation-related interactions with bad times remain significantly positive in the presence of the other firm news dummies and their interactions. If so, it will show that the finding of greater reaction to recommendations in bad times is robust to controlling for the market's differential reaction to news in general in bad times. The standard errors are clustered by calendar day.

We show in Panel C of Table 7 that the recommendation change and reiteration dummies are always statistically significant alone and in the presence of other firm news dummies. This shows that both recommendation changes and reiterations are more informative in bad times, confirming the earlier results. When including all the interactions with bad times, the coefficient on the recommendation change dummy interacted with bad times remains positive and significant and often has the largest magnitude (that recommendations elicit the largest reaction when compared to other firm events is in general also consistent with Bradley et al. (2014)). This confirms the robustness of our main findings to controlling for the differential impact of firm news in bad times. We also see that the market does *not* react more to all types of firm news in bad times. Earnings announcements do indeed elicit a greater reaction in bad times but guidance announcements elicit lower reaction. There is also mixed evidence on a greater reaction to dividend announcements and insider trades and announcements in bad times.

4.4. Alternative specifications and samples

Differences in analyst characteristics could spuriously explain our results. This could be the case if somehow analysts are better on average in bad times than in good times. Controlling for analyst characteristics addresses the concern that the overall quality of the pool of analysts is different in bad times. While it seems unlikely that the change in the analyst pool can be large enough to explain our findings which already control for analyst characteristics, we conduct two further tests. First, we identify a set of seasoned analysts who are present before and after the longest bad times period, i.e. the credit crisis. These are analysts who appear in I/B/E/S before 2007 and continue to issue reports after March 2009. These seasoned analysts are responsible for almost half of the recommendations in our sample. We repeat our tests on this subsample to ascertain the performance differential between good and bad times for this set of analysts. Second, we add analyst fixed effects when analyzing this subsample. With this approach, the increased impact of analyst recommendations and forecasts during the credit crisis cannot be explained by a selection effect or unobserved analyst characteristics. In unreported results we show that the impact of recommendation changes continues to be higher in bad times compared to good times when analyst fixed effects are added. In many cases the results are stronger. For example, in the model with control variables, the marginal effect of a *Crisis* period on the influential probability of a downgrade is 0.059. Adding analyst fixed effects, the marginal effect becomes 0.067. For upgrades, the increased probability of being influential in Crisis period is 0.043 and this is unchanged when analyst fixed effects are added.

In a separate and unreported analysis, we control for whether an analyst's career starts during bad times. Presumably, analysts who begin careers during bad times have more experience with bad times and might do better in such periods. Or it could be that brokers hire analysts with special expertise when bad times strike. To test if this effect drives our results, we define a dummy variable that equals one for an analyst who joined the profession in any bad times period. We also define another dummy variable for analysts who begin their career in the credit crisis. Adding these dummy variables to our main regressions, we find that these two coefficients are mostly statistically insignificant and all our results are unaffected. We conclude that analysts who join brokers during bad times are unlikely to be the main contributors to our results that analysts produce better research in bad times.

Finally, we also repeat our analysis on financial firms. We exclude financial firms from our baseline analysis because many of the macro bad times periods started in the financial sector, e.g. the credit crisis and most of the recessions. As such, for the financial sector, the periods which we define as macro bad times are mostly also industry bad times. Industry bad times might also not be as exogenous to analysts as macro bad times are. Nevertheless, we repeat our analysis on financial firms (group 29 of the Fama-French 30-industry definitions). We find that recommendation changes made by analysts on financial firms also have significantly greater CAR impact in bad times. For example, the mean recommendation downgrade CAR in non-*Crisis* periods is -1.087% but the downgrade in bad times elicits an additional -2.118% abnormal return. For upgrades, the non-*Crisis* CAR is 1.315% but the *Crisis* CAR is larger by 1.473%. All results are similarly strong for other bad times definitions and after the addition of controls. For the CAR impact of earnings forecast revisions, the coefficients on the bad times dummies are mostly insignificant. Hence, while our recommendation change results are robust to firms in the financial industry, the results for forecast revisions are weaker for these firms. Importantly, it is hard to distinguish for this set of firms whether the results are triggered by industry or macro bad times

5. Are analyst signals more precise in bad times?

Having established that our results of analyst output being more influential in bad times is strong and robust, we now investigate why it is so. We might expect that analysts are more influential because their signals are more precise in bad times. If analysts have more precise signals in bad times, their forecast errors should be lower. The literature typically measures forecast errors by the absolute difference between the actual and forecasted earnings per share, scaled by the absolute value of actual earnings or price to account for firm heterogeneity. With such a measure of forecast error, it would be surprising if forecast errors were lower in bad times because in bad times earnings naturally become harder to forecast. Indeed, we find that this traditional measure of absolute forecast errors shows that analysts are less precise in bad times, consistent with Jacob (1997), Chopra (1998), and Hope and Kang (2005).

We argue that this traditional measure of forecast errors is not the appropriate measure to understand why analysts are more influential in bad times. The usefulness of analyst signals of a given precision depends on the uncertainty that investors face. To wit, if investors face no underlying uncertainty about the prospects of a firm, analyst signals that have a small amount of noise are useless. Hence, to compare the usefulness of analyst forecasts over time, the precision of their signals has to be evaluated relative to the uncertainty about the prospects of the firm. This is similar in spirit to the way which we define influential recommendations by scaling by the prior volatility of returns. When we use this new approach, we find that analysts are actually *more* precise in bad times.

5.1. Using a traditional measure of forecast error

We first report results using a traditional measure of forecast error. For each analyst, the forecast error is actual earnings minus the final unrevised one-quarter-ahead forecast. We focus on forecasts that are revisions of prior forecasts since those are the ones which we found earlier to be associated with higher stock-price reactions. We scale forecast errors by the absolute value of actual earnings instead of stock prices because bad times periods are by definition associated with lower stock prices, so that forecast errors get magnified when scaled by stock prices. When scaling forecast errors by the absolute value of actual earnings, denominator values smaller than $0.25 are set to $0.25 to limit the impact of small denominators. Scaled forecast errors are then winsorized at the extreme 1% before we take absolute values.[10]

Models 1-8 in Table 8 formally test whether the traditional measure of absolute forecast error of analysts in bad times is larger. Standard errors are clustered by industry-quarter where the industry definition is the Fama and French (1997) 30-industry groupings. We also tried clustering by analyst-quarter or firm-quarter and the results are usually similar or stronger. We use similar control variables as those in the earlier tables but also add control variables that are relevant for predicting the accuracy of analyst forecasts from the literature. Lim (2001) shows that analysts trade off optimism and accuracy because optimism facilitates access to private information from the covered firm's management. We add optimism as a control where *Optimistic* is a dummy variable that equals one when the forecast is in the top half among all final unrevised forecasts in that quarter. Clement (1999) stresses the importance of controlling for forecast recency because forecasts closer to the actual earnings announcement date will obviously be more accurate. Log *Days to Annc* is the number of days that the forecast date is before the announcement date of actual earnings and serves as a control for forecast recency. As Bradley, Jordan, and Ritter (2008) suggest, days with activity from multiple analysts most likely are caused by a corporate news release. Forecast accuracy may be different when the forecast is made in response to a corporate news release. *Multiple Forecast Day* is an indicator variable representing days where the forecast falls on a day on which more than one analyst issues a forecast on the firm. To control for differences of opinion among analysts, we include the *Dispersion* of forecasts measured as the standard deviation of quarterly forecasts making up the final consensus scaled by the absolute value of the mean estimate.

[10] One concern related to using the absolute value of actual earnings as the deflator is that lower earnings in bad times could artificially inflate forecast errors (although negative earnings might mitigate this concern). In robustness tests, when estimating the multivariate regressions for the traditional measure of forecast errors, we use unscaled forecast errors while controlling for the stock price of the firm in addition to all the other control variables. We find that our results are similar.

We see in Table 8 that traditional absolute forecast errors are significantly larger in bad times. Model 1 shows that in non-*Crisis* times the absolute forecast error is 14.835 percent of actual earnings. In *Crisis* times, the absolute forecast error is 2.775 percent higher. This increase in the absolute forecast error is also robust after taking into account analyst, firm, and forecast characteristics. The same results hold for all the other definitions of bad times, which appear to tell us that analysts are more imprecise during bad times.

5.2. Absolute forecast errors scaled by stock volatility

We now examine whether analyst forecast errors are larger in bad times after we account for the greater uncertainty that investors face in bad times. To do this, we normalize the absolute forecast errors by the stock's prior month daily stock return volatility (annualized). This new scaling allows us to examine whether the increase in absolute forecast error can be explained by the increase in the underlying uncertainty surrounding the firm in bad times. This approach is similar in spirit to our earlier approach of using prior volatility to scale the return impact of recommendation changes to identify influential revisions. To our knowledge, the literature has not considered such a measure of forecast precision, which is akin to measuring the forecast error per unit of uncertainty. Models 9 to 16 in Table 8 show the results of this new measure of adjusted forecast precision. We see that the intercept of model 9 is 26.852, which can be interpreted as the percentage absolute forecast error per unit (100%) of stock volatility. Hence, the coefficient on the *Crisis* variable of -6.667 describes the difference in the uncertainty-adjusted forecast precision during bad times compared to good times. This number tells us that the analysts' precision improves by 25% ($\frac{-6.667}{26.852}$) during bad times. Model 2 shows that this percentage improvement is almost unchanged with the addition of control variables. Across all the bad times definitions, we see that after the addition of control variables, the finding that the precision of analyst earnings forecasts is higher in bad times is statistically significant. We also tried using the implied volatility (when available) five trading days before forecast as a proxy for the uncertainty facing the firm and we find similar results.

These results of improved analyst forecast precision during bad times supports our main finding that analyst revisions have larger stock-price impact in bad times. This larger impact is justified by the higher earnings forecast precision per unit uncertainty in bad times compared to good times.

6. Why is analyst output more impactful in bad times?

So far, we have shown that analyst output is more impactful in bad times and that analysts offer more precise signals during bad times after taking into account the uncertainty facing investors. In this section, we explore five possible, non-mutually exclusive explanations for these results. We presented these potential explanations in Section 2. There is clearly no support for the hypotheses in Section 2 which predict that analysts will be less impactful in bad times. We investigate instead potential explanations for why analysts might be more impactful in bad times, namely the reliance on analysts hypothesis, the hypothesis that analysts work harder in bad times, the hypothesis that analyst output reflects different skills in bad times, the hypothesis that conflicts of interest affect analyst output less in bad times, and the overreaction hypothesis.

6.1. Reliance on analysts hypothesis

The analyst reliance hypothesis predicts that analyst output becomes more valuable in bad times especially for more opaque stocks. We use several characteristics to proxy for stocks which are more opaque and might have more reliance on analysts, namely, stocks with no company guidance, low institutional ownership, high idiosyncratic volatility to total volatility ratio, small size, no traded options (a proxy for less informed trading), and low analyst coverage.[11]

We examine the impact of these characteristics on our main results in a cross-sectional analysis by interacting the bad times dummies with dummy variables representing these characteristics. *NoGuidance* equals

[11] In the uncertainty literature, an increase in idiosyncratic volatility is a proxy for an increase in uncertainty (Bloom (2009)). It has also been viewed as evidence of informed trading, e.g. in Roll (1988), as a proxy for skewness (Bali, Cakici, and Whitelaw (2011)), and as a proxy for illiquidity (Han and Lesmond (2011)). Ultimately, it is an empirical question whether analysts have more or less impact on high idiosyncratic volatility stocks during bad times. With our discussion in Section 2 of the analyst reliance hypothesis, if idiosyncratic volatility is a proxy for uncertainty, everything else equal we would expect analyst output to be more valuable for stocks with higher idiosyncratic volatility provided that the precision of analyst output decreases less than proportionately when uncertainty increases. Whether this is true or not is an empirical issue.

one when the firm has had no earnings guidance in the last month. For institutional ownership, *LowIO* equals one for the lowest quintile of firms sorted by the most recent Thomson 13F-reported fraction of shares owned by institutions. For idiosyncratic volatility, *HighIVOLfrac* equals one for the highest quintile of stocks sorted on the prior quarter fraction of firm-specific daily return volatility over the total volatility (total variance is decomposed into its market, industry, and residual components as described in the robustness tests earlier). *SmallSize* equals one for the lowest quintile rank (NYSE breakpoints) of the prior June market cap. *NoOptions* equals one when the firm has no traded options (checking for availability of data in Option Metrics). Finally, *LowCoverage* equals one for the lowest analyst coverage quintile based on number of analysts issuing recommendations in the prior quarter. We use dummy variables for these cross-sectional tests for ease of interpreting the coefficients but we find similar results if we use the rank (when possible) of the firm characteristic instead.

In Table 9, we report the coefficient of the bad times dummies, firm characteristics dummies, and their interactions (for brevity, the coefficients of the control variables are unreported). We see that for most of the proxies for opacity, greater opacity is associated with a greater impact of recommendation changes in good times. When the opacity proxies are interacted with bad times, this relation become stronger, which shows a stronger increase in the impact of analysts in bad times compared to good times for such firms. The strongest results are for the *NoGuidance*, *SmallSize*, and *LowCoverage* interactions. This evidence is consistent with the hypothesis that investors rely more on analysts in bad times for stocks that are more opaque.

We also examine in unreported results interactions of analyst characteristics, whether some analysts are more likely to do better than other analysts in becoming more impactful in bad times. We look at large brokers (top quintile based on analysts issuing ratings in the prior quarter), current star analyst status, and high experienced analysts (top quintile based on number of quarters in I/B/E/S as of the current quarter), and highly influential analysts (top quintile of fraction of influential recommendations in the previous year). There is some evidence that the last characteristics is associated with greater impact in bad times, but not for the other characteristics. The highly influential analysts have more impact for downgrades in bad times for the credit crisis and recession definitions of bad times.

6.2. Analyst effort and incentives

We examine the role of analyst incentives as an explanation for why analysts are more impactful during bad times. Studies have argued that the higher marginal utility of investors during bad times motivates fund managers to perform better (e.g. Glode (2011)). If analysts also face such motivations, their effort to produce better research might go up in bad times. For fund managers, investors can immediately reward the manager with fund flows. For analysts, this channel is more indirect in that good analysts build their reputation but do not receive direct rewards from investors. Further, bad times are also periods where analysts might face pressures about their careers due to attrition risk and shrinking compensation. The higher likelihood of losing their jobs conditional on effort might motivate them to work harder.

In Table 10, we examine whether analysts are more likely to disappear during bad times using probits of analyst attrition. For the recommendations sample, *Disappear* is a dummy variable which equals one for the analyst-year combination where the analyst makes no recommendation in I/B/E/S across all firms in the next year. This proxies for the analyst losing her job. Looking over a period of one year minimizes the possibility that the analyst's recommendation frequency was temporarily reduced. The bad times indicator equals one if the next year contains a relevant bad times period. Control variables are averaged for each analyst-year combination. Standard errors in this table are clustered by analyst.

We see that across the different bad times periods, analysts are 1-4% more likely to disappear from I/B/E/S. This is a sizable change given that the predicted probability of attrition is about 11-13% in these models. One important independent variable in the regressions is the probability that an analyst is influential that year computed as the fraction of the analyst's recommendation changes that are influential. We see that this influential likelihood is typically negatively related to analyst attrition—issuing high impact recommendation changes reduces the chances that the analyst disappears. When we interact this influential probability with bad times, we see the reduced likelihood of attrition. Together, these results provide the motivation for the analyst to work harder to avoid attrition in bad times since attrition is more likely in bad times and research impact reduces attrition likelihood.

In unreported results, we estimate the attrition probits on the quarterly earnings forecasts sample. *Disappear* now equals one when the analyst made no one quarter-ahead forecast for quarterly earnings on any firm in I/B/E/S for the next two quarters. The bad times dummy variables are set to one if the next two quarters contain a relevant bad times period. We find evidence that both the crisis and credit crisis definitions of bad times have higher attrition likelihood, about 2-3% higher probabilities. We also define the *Forecast Accuracy Quintile* variable as the average accuracy quintile (higher quintile number denotes greater accuracy among all analysts covering the same firm) of the analyst for all the firms covered that quarter. We show that greater accuracy does indeed reduce attrition likelihood. We then interact accuracy with bad times and find significant coefficients only for the credit crisis. We conclude that career concerns is a plausible explanation for why analysts would work harder in bad times and being influential in their recommendation changes seems to be more important than earnings forecast accuracy in reducing attrition risk.[12]

Having established that attrition likelihood is related to performance, we examine two additional measures of analyst output quantity to examine if there is evidence that the increased impact and precision is accompanied by more effort in bad times. We already saw evidence that the number of recommendation changes and reiterations increases. We look now at analyst activity defined as the number of forecasts made by the analyst for a firm-quarter combination. For each firm, we assume that the period of a particular analyst's coverage starts with the first quarter and stops with the last quarter that the analyst features in I/B/E/S for that firm. We then count the number of forecasts that the analyst makes in each of the coverage quarters. Quarters within the coverage period with no forecast from the analyst are assigned a forecast activity of zero.

We estimate regressions explaining forecast activity in Table 11 where the dependent variable is the log of one plus the number of analyst forecasts. The regressions are at the firm-quarter-analyst level. The control variables are now averages of the characteristic within the analyst-firm-quarter combination. The relevant bad times indicator variables are set equal to one when any part of a calendar quarter is defined as bad times for that particular definition. We see from the coefficients on the bad times indicators that there is indeed more analyst

[12] In unreported tests, we examine if analysts who leave I/B/E/S are replaced by checking if any of the firms they covered are now covered by another analyst in the same broker. We find about half of analysts are replaced. Using a replaced dummy as the dependent variable in the probits, we get weaker results.

activity in bad times even after controlling for all other variables. Given the dependent variable is the log of one plus the analyst activity, a *Crisis* coefficient of 0.063 with a non-*Crisis* coefficient of 0.642 in model 1 represents about a 14% increase in analyst activity. This evidence of increased activity holds true regardless of the definition of bad times or the presence of control variables.[13]

The second measure of output quantity is the number of pages in the analyst report. We use the number of pages in the report as a proxy for the amount of information or effort that that analyst spends on the report. Unfortunately, this information is not recorded by I/B/E/S. From 1994-2014, we therefore hand collect this data from analyst reports downloadable from Thomson ONE up to September 2011, and from Thomson Eikon from October 2011 to December 2014 (Thomson recently migrated users of T1.com to Eikon, but both databases draw from the same source database formerly known as Investext). Without downloading the actual reports, one can download a spreadsheet of headlines (but restricted to 50 observations at a time) which contains information on the broker name, covered firm name, report title, date, and the number of pages in the report. To keep the data collection effort manageable, we download all the headlines for one large broker and hand match the firm names in the titles of the reports to CRSP. We end up with a large sample of 85,525 reports and we regress the number of pages in these reports on a bad times dummy and firm-level control variables.[14] We add the firm characteristics market *Beta*, *Size* quintile (based on NYSE breakpoints), B/M quintile, *Momentum* quintile, and *Stock Volatility* (standard deviation of last month's daily returns) as controls. We also add dummy variables indicating when the report is issued within a trading day of an earnings announcement and an earnings guidance event. These reports might be of a different length because they contain additional information about the announcement in addition to the analyst's own analysis.

[13] The increased activity of analysts means that analysts have less time between the earnings forecasts that they issue. If becoming busier affects the accuracy of their forecasts, it may be important to control for analyst busyness in our forecast error regressions. In unreported results, we add a new control variable, the log of the number of firms covered by the analyst. Not only are our results unaffected, this control variable is never statistically significant.

[14] This number of reports from just one broker seems large in relation to our full sample because the Thomson research report databases contain all analyst reports including reiterations while databases such as I/B/E/S and First Call typically excludes reiterations (see e.g., Brav and Lehavy (2003)). We do not observe in the downloaded spreadsheets whether a report is a reiteration. However, because reiterations often occur on firm news days, we tried excluding all reports that occur on earnings announcement dates and earnings guidance dates (about two-thirds of the sample is left) and we get similar results that reports in bad times are longer.

Table 12 reports these results. Looking at model 1, we see that the average report length is 10.237 pages. In *Crisis* times however, the report length increases by 1.336 pages, a 13% increase. This shows that a typical report issued in bad times contains more information. After we add control variables in model 2, the results remain robust and the report is longer by 1.552 pages (an increase from the good times predicted number of pages, 10.220). Note that one of the controls is the firm's recent volatility of daily stock returns, which shows that the larger number of pages is not due to larger firm-specific volatility but due to the macroeconomic bad times. For all the other definitions of bad times, except for the *Recession* definition, we see similar evidence of longer reports in bad times. The overall evidence of longer reports is consistent with the analyst exerting more effort in incorporating more information in the report and provides an explanation for why reports have more impact in bad times.[15]

In unreported tests, we also looked at the competition faced by analysts. The literature shows that the quality of analyst output is higher where analysts face more competition (e.g., Hong and Kacperczyk (2010) and Merkley et al. (2016)). If analysts have incentives to work harder in bad times, this means that competition will be more intense. This suggests that in bad times analysts will have stronger incentives to improve their output in industries with more competition. We find strong evidence supporting that hypothesis for downgrades but not upgrades. For downgrades, competition is associated with a significantly greater impact of downgrades across all definitions of bad times and irrespective of whether we use controls (including industry fixed effects) or not.

Overall, results in this section show that analysts are more likely to lose their jobs in bad times and analysts partly react to the increased possibility of losing their job by working harder. Evidence of increased effort comes from their more frequent forecast revisions, their longer reports, and from the fact that the increased impact is higher in industries where analysts compete more.

[15] Li (2008) finds that managers also provide longer reports in bad times. Longer reports might not always mean better quality and quantity of information as Loughran and McDonald (2014) show that length might reduce readability of financial reports. De Franco, Hope, Vyas, and Zhou (2015) also suggest that long analyst reports are less readable although they do not find that report length is negatively related to price impact. However, our evidence of greater length in the analyst reports is accompanied by evidence of the increased impact of the reports, which is consistent with better and more information in the reports.

6.3. Do analysts have different skills in bad times?

Recent work in the mutual fund literature finds that managers use different skills in bad times compared to good times (see Kacperczyk et al. (2015)). Specifically, in bad times, market-timing skills are more valuable than stock-picking skills because common factors that affect stock returns are more important for generating alpha in bad times. If the analysts also follow this change of skill emphasis, they might produce more of the type of information that is valuable across firms in bad times. There is some evidence that analysts have ability to predict industry returns (e.g., Howe et al. (2009) and Kadan et al. (2012)) and that analyst coverage at the industry level has spillover effects to the firm level (Merkley et al. (2016)). A simple way to detect the presence of common information is to examine whether their recommendation revisions on a firm spills over more to the other covered firms in bad times compared to good times.

We form for each recommendation change a portfolio of peer firms consisting of firms that the analyst has issued a recommendation on in the last one year. We then measure the CAR of these peer firms (equally weighting the CAR for all peers) around the recommendation change, excluding peers that also receive a recommendation from the same analyst on the same date. A typical recommendation change is associated with about ten peer firms in our sample. Table 13 reports regressions using this average peer CAR as the dependent variable. Looking at model 1's intercept coefficient, we find that downgrades in non-*Crisis* times are associated with a CAR of -0.054% (t=3.37) for the peer firms. This shows that revisions do spill over to other firms covered by the same analyst. We are interested to know whether this spillover effect increases in bad times. Indeed, we see that the coefficient on *Crisis* is -0.104% (t=1.78)—evidence of a larger spillover for downgrades in bad times, albeit significant only at the 10% level. When we estimate a regression with all the relevant controls and industry fixed effects, the difference remains significant at -0.105% (t=1.71). We get stronger and more significant results with the *Credit Crisis* and *Recession* definitions, which show that there is some evidence of greater spillover of downgrades to peer firms during bad times. Next we examine upgrades in models 9-16. We see that although upgrades spill over positively to peer firms in good times (e.g. 0.110% for the non-*Crisis* definition of good times), there is no evidence that bad times increase this spillover effect.

We find some evidence showing that negative information produced by analysts during bad times contains a common component. This offers some support for the hypothesis that analysts display different skills in bad times.

6.4. Potential analyst conflicts of interests

A possible explanation for the greater impact of analysts is that in bad times potential conflicts of interest are less important. To investigate this hypothesis, we examine the impact of bad times on an analyst's optimistic bias. If bad times reduce investment banking conflicts and if the optimistic bias can be attributed to conflicts of interest, we should find that analyst forecast optimism goes down in bad times. We estimate a regression with the dependent variable being the signed forecast error, which is the signed version of our absolute forecast error regressions in Table 8. We find in unreported results that the forecast error when scaled by the absolute value of actual earnings, is mostly insignificantly different in bad times compared to good times. When we scale the forecast error by prior volatility, analysts are actually more optimistic in bad times than in good times. Hence there is little evidence for the conflicts of interest hypothesis that analysts are less optimistic in bad times.

We also identify the subset of brokers that have no investment banking business and compare the bad times impact of their analysts to impact of analysts of brokers with underwriting business. Using the I/B/E/S broker translation file to obtain the broker name, we search for information about the broker online to define a dummy variable, *Underwriter*, which equals zero if we find unequivocal information that the broker is an independent broker with no investment banking business, and one otherwise. We find that independent brokers are responsible for about only 10% of the recommendation changes in our sample. If the reduction of conflicts of interests is responsible for the increased impact of analysts in bad times, independent brokers might not experience an increased impact given that they are not affected by the reduction of conflicts. We interact the bad times dummies with *Underwriter* and re-estimate the downgrade and upgrade CAR impact regressions. In unreported results, we find that in almost all cases, the coefficients on the bad times dummies are still strong and significant, showing that independent brokers also have more impact during bad times. This is inconsistent with the conflicts hypothesis. For the interaction terms between the underwriter indicator and bad times, there is some evidence that brokers with underwriting business have a greater bad times impact than independent brokers in about half of the specifications. While this seems to be supportive of the conflicts story, underwriter brokers also have more impact in good times than independent brokers. Together, these results imply that brokers with underwriting business are in general better than independent brokers, perhaps due to their larger size and resources. Consequently, there seems to be little support for the conflicts of interest hypothesis in explaining why analysts are more impactful during bad times.

6.5. Does the market overreact to analysts in bad times?

Another explanation for the seemingly greater impact of analysts in bad times is that analysts are not really more impactful but investors simply overreact to analysts. Such overreaction might stem from the reduction in liquidity provision during bad times so that there is a greater price impact when investors trade in response to recommendations. Or it could stem from arbitrageurs being more constrained in bad times so that they cannot effectively trade against the overreaction by some investors.

To investigate this, we form daily-rebalanced calendar-time portfolios that buy stocks from trading day 2 following the revision to day 21, i.e. a one-month drift. We follow the standard approach in Barber, Lehavy, and Trueman (2007) when computing average daily returns, in which one dollar is placed in each revision and the weight of the revised stock varies from day 2 to day 21 according to its cumulative return since entering the portfolio. The portfolio’s daily returns are compounded to monthly returns and regressed on the Carhart (1997) four factors plus a dummy variable for bad times. The bad times dummy is also interacted with each of the four factors to allow factor exposures to vary according to bad times. Consequently, the intercept measures the revision drift in good times, and the bad times dummy identifies whether the drift in bad times is statistically different from the good times drift. For each bad times definition we have four portfolios—recommendation downgrades, recommendation upgrades, downward forecast revisions, and upward forecast revisions—a total of 16 portfolios.

In unreported results, we find that the intercepts of the regressions are all significantly negative for negative revisions and significantly positive for positive revisions indicating that there is a stock-price drift to analyst revisions in good times. Of interest is the coefficient on the bad times dummies and we find that this coefficient is statistically insignificant for almost all portfolios. This is evidence that the drift in bad times is statistically indistinguishable from the drift in good times. We also add up the intercept and the coefficient on bad times to measure the stock-price drift of revisions during bad times. In all cases, we do not find any significant drift that is in the opposite of the direction of the revision. Overall, we do not find evidence that the larger stock-price impact of analysts in bad times is due to investor overreaction.

7. Conclusion

We assemble a large sample of analysts' earnings forecasts and recommendations from 1983-2014 and examine the value of sell-side equity research in bad times. Using various definitions of bad times, we find that analysts' stock recommendation changes and earnings forecast revisions have more impact during bad times compared to good times. We investigate the precision of analysts' earnings forecasts and find that while they are more imprecise using a traditional measure of forecast accuracy, a new measure of forecast accuracy which adjusts for the increase in uncertainty shows that analysts are actually more precise during bad times. We investigate various potential hypotheses to explain the increased impact of analysts in bad times and find that analyst incentives leading to increased effort and a greater reliance of investors on analysts in bad times likely explain these results. We also show that downgrades by analysts in bad times have an increased negative impact on peer firms, indicating that analyst downgrades have a larger common sector component in bad times. Alternative possible explanations hypothesizing reduced conflicts or interests or overreaction of investors to analysts in bad times cannot account for our results. In sum, we show that analysts' role in financial markets increases in importance during bad times because they work harder to have more impact and investors rely more on them.

References

Amiram, Dan, Wayne R. Landsman, Edward Owens, and Stephen R. Stubben, 2014, Analysts' forecasts during periods of high market uncertainty, Working paper, Columbia University.

Arand, Daniel and Alexander G. Kerl, 2012, Analyst research and investor reactions: Evidence from the 2008 financial crisis, Working paper, University of Giessen.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, 2016, Measuring economic policy uncertainty, *Quarterly Journal of Economics*, forthcoming.

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427-446.

Barber, Brad M., Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001, Can investors profit from the prophets? Security analysts' recommendations and stock returns, *Journal of Finance* 56, 531-563.

Barber, Brad M., Reuven Lehavy, and Brett Trueman, 2007, Comparing the stock recommendation performance of investment banks and independent research firms, *Journal of Financial Economics* 85, 490-517.

Beber, Alessandro and Michael W. Brandt, 2010, When it cannot get better or worse: The asymmetric impact of good and bad news on bond returns in expansions and recessions, *Review of Finance* 14, 119-155.

Bertrand, Marianne and Sendhil Mullainathan, 2001, Are CEOs rewarded for luck? The ones without principals are, *Quarterly Journal of Economics* 116, 901-932.

Bloom, Nicholas, 2009, The impact of uncertainty shocks, *Econometrica* 77, 623-685.

Boni, Leslie and Kent L. Womack, 2006, Analysts, industries, and price momentum, *Journal of Financial and Quantitative Analysis* 41, 85-109.

Bradley, Daniel, Jonathan Clarke, Suzanne Lee, and Chayawat Ornthanalai, 2014, Are analysts' recommendations informative? Intraday evidence on the impact of time stamp delays, *Journal of Finance* 69, 645-673.

Bradley, Daniel J., Bradford D. Jordan, and Jay R. Ritter, 2008, Analyst behavior following IPOs: The 'bubble period' evidence, *Review of Financial Studies* 21, 101-133.

Brav, Alon and Reuven Lehavy, 2003, An Empirical Analysis of Analysts' Target Prices: Short-term Informativeness and Long-term Dynamics, *The Journal of Finance* 58, 1933-1968.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chen, Shuping, Dawn Matsumoto, and Shiva Rajgopal, 2011, Is silence golden? An empirical analysis of firms that stop giving quarterly earnings guidance, *Journal of Accounting and Economics* 51, 134-150.

Chopra, Vijay Kumar, 1998, Why so much error in analysts' earnings forecasts?, *Financial Analysts Journal* 54, 35-42.

Clement, Michael B., 1999, Analyst forecast accuracy: Do ability, resources and portfolio complexity matter?, *Journal of Accounting and Economics* 27, 285-303.

Cooper, Rick A., Theodore E. Day, and Craig M. Lewis, 2001, Following the leader: A study of individual analysts' earnings forecasts, *Journal of Financial Economics* 61, 383-416.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035-1058.

De Franco, Gus, Ole-Kristian Hope, Dushyantkumar Vyas, and Yibin Zhou, 2015, Analyst report readability, *Contemporary Accounting Research* 32, 76-104.

Derrien, François and Ambrus Kecskés, 2013, The real effects of financial shocks: Evidence from exogenous changes in analyst coverage, *Journal of Finance* 68, 1407–1440.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross-section of stock returns, *Journal of Finance* 57, 2113-2141.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F. and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153-193.

Fama, Eugene F. and Kenneth R. French, 2006, The value premium and the CAPM, *Journal of Finance* 61, 2163-2185.

Fang, Lily H. and Ayako Yasuda, 2014, Are stars' opinions worth more? The relation between analyst reputation and recommendation values, *Journal of Financial Services Research* 46, 235-269.

Fong, Kingsley Y. L., Harrison G. Hong, Marcin T. Kacperczyk, and Jeffrey D. Kubik, 2014, Do security analysts discipline credit rating agencies?, Working paper, Princeton University.

Frankel, Richard, S.P. Kothari, and Joseph Weber, 2006, Determinants of the informativeness of analyst research, *Journal of Accounting and Economics* 41, 29-54.

Glode, Vincent, 2011, Why mutual funds “underperform”, *Journal of Financial Economics* 99, 546-559.

Han, Yufeng and David Lesmond, 2011, Liquidity biases and the pricing of cross-sectional idiosyncratic volatility, *Review of Financial Studies* 24, 1590-1629.

Hirshleifer, David, Sonya Lim, and Siew Hong Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *Journal of Finance* 64, 2289-2325.

Hong, Harrison and Marcin Kacperczyk, 2010, Competition and bias, *Quarterly Journal of Economics* 125, 1683-1725.

Hope, Ole-Kristian and Tony Kang, 2005, The association between macroeconomic uncertainty and analysts' forecast accuracy, *Journal of International Accounting Research* 4, 23-38.

Howe, John S., Emre Unlu, and Xuemin (Sterling) Yan, 2009, The predictive content of aggregate analyst recommendations, *Journal of Accounting Research* 47, 799-822.

Hutton, Amy P., Lian Fen Lee, and Susan Z. Shu, 2012, Do managers always know better? The relative accuracy of management and analyst forecasts, *Journal of Accounting Research* 50, 1217-1244

Jacob, John, 1997, Discussion of do security analysts improve their performance with experience?, *Journal of Accounting Research* 35, 159-166.

Kacperczyk, Marcin and Amit Seru, 2007, Fund manager use of public information: New evidence on managerial skills, *Journal of Finance* 62, 485-528.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, Time-varying fund manager skill, *Journal of Finance* 69, 1455-1484.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2015, A rational theory of mutual funds' attention allocation, *Econometrica*, forthcoming.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach, 2012, Analysts' industry expertise, *Journal of Accounting and Economics* 54, 95-120.

Kecskés, Ambrus, Roni Michaely, and Kent L. Womack, 2016, Do earnings estimates add value to sell-side analysts' investment recommendations?, *Management Science*, forthcoming.

Kelly, Bryan and Alexander Ljungqvist, 2012, Testing asymmetric-information asset pricing models, *Review of Financial Studies* 25 1366-1413.

Li, Feng, 2008, Annual report readability, current earnings, and earnings persistence, *Journal of Accounting and Economics* 45, 221-247.

Lim, Terrence, 2001, Rationality and analysts' forecast bias, *Journal of Finance* 56, 369-385.

Ljungqvist, Alexander, Christopher J. Malloy, and Felicia C. Marston, 2009, Rewriting history, *Journal of Finance* 64, 1935-1960.

Loh, Roger K. and G. Mujtaba Mian, 2006, Do accurate earnings forecasts facilitate superior investment recommendations?, *Journal of Financial Economics* 80, 455-483.

Loh, Roger K. and René M. Stulz, 2011, When are analyst recommendation changes influential?, *Review of Financial Studies* 24, 593-627.

Loughran, Tim and Bill McDonald, 2014, Measuring readability in financial disclosures, *Journal of Finance* 69, 1540-6261.

Mehran, Hamid and René M. Stulz, 2007, The economics of conflicts of interest in financial institutions, *Journal of Financial Economics* 85, 267-296.

Merkley, Kenneth, Roni Michaely, and Joseph Pacelli, 2016, Does the scope of the sell-side analyst industry matter? An examination of bias, accuracy, and information content of analyst reports, *Journal of Finance*, forthcoming.

Michaely, Roni and Kent L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653-686.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1997, Do security analysts improve their performance with experience?, *Journal of Accounting Research* 35, 131-157.

Pastor, Lubos and Pietro Veronesi, 2009, Learning in financial markets, *Annual Review of Financial Economics* 1, 361-381.

Roll, Richard, 1988, R^2, *Journal of Finance* 43, 1540-6261.

Schmalz, Martin C. and Sergey Zhuk, 2015, Revealing downturns, Working paper, University of Michigan.

Veronesi, Pietro, 1999, Stock market overreactions to bad news in good times: A rational expectations equilibrium model, *Review of Financial Studies* 12, 975-1007.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* 51, 137-167.

Table 1: Change in uncertainty during bad times and descriptive statistics of recommendation change sample

Panel A reports the average daily VIX over bad times from 1990-2014. Panel B reports the average annualized implied volatility (*Implvol*, from 1996-2014) for the recommendation change sample measured five trading days before the recommendation event. Implied volatility is from the Option Metrics Volatility Surface file using the average of the interpolated implied volatility from puts and calls with 30 days to expiration and a delta of 50. A recommendation change is defined as an analyst's current rating minus her prior outstanding rating (initiations and reiterations are excluded) and changes made around earnings announcement and guidance days, and on multiple-recommendation days are excluded. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. In parentheses are *t*-statistics (based on standard errors clustered by calendar day), where *, **, and *** denote statistical significance of the differences in VIX/implied volatility at 10%, 5%, and 1% respectively. Panel C reports the descriptive statistics of the recommendation change sample by downgrades and upgrades for *Crisis* and non-*Crisis* periods. CAR (in percent) is the average day [0,1] cumulative abnormal return, where the benchmark is the return from a characteristics-matched DGTW portfolio. *LFR* is the analyst's prior-year leader-follower ratio (computed from recommendations), *Star Analyst* is a dummy indicating the analyst is a star in the most recent *Institutional Investor* poll, *Experience* is the analyst's experience (in quarters), *Accuracy Quintile* is the average forecast accuracy quintile of the analyst's past-year's covered firms (quintile 5=most accurate), *Broker Size* is the number of analysts employed, *# Analysts* is the number of analysts covering the firm, *Size* is last June's market cap, *BM* is the book-to-market ratio, and *Momentum* is the month *t*-12 to *t*-2 buy-and-hold return, and *Stock Volatility* is the month *t*-1 volatility of daily stock returns.

Panel A: VIX

Bad times definition	Variable	Average daily VIX (%)		
		Bad times	Good times	Difference
Crisis	VIX	31.339	18.865	12.474***(21.56)
	#obs	547	5752	
Credit Crisis	VIX	31.261	19.096	12.165***(17.39)
	#obs	441	5858	
Recession	VIX	29.899	18.558	11.341***(26.50)
	#obs	772	5527	
High Uncertainty	VIX	24.172	17.870	6.302***(27.01)
	#obs	2205	3882	

Panel B: Implied volatility before recommendation changes

Bad times definition	Rec-change	Variable	Option-implied volatility in annualized %			
			Bad times	Good times	Difference	
Crisis	Downgrade	Implvol	61.024	48.896	12.128***	(12.08)
		#obs	8522	38218		
	Upgrade	Implvol	57.961	47.311	10.650***	(11.24)
		#obs	7828	37990		
Credit Crisis	Downgrade	Implvol	61.523	49.251	12.272***	(10.46)
		#obs	7070	39670		
	Upgrade	Implvol	58.308	47.567	10.741***	(9.93)
		#obs	6668	39150		
Recession	Downgrade	Implvol	67.361	47.425	19.936***	(22.86)
		#obs	8634	38106		
	Upgrade	Implvol	63.812	46.305	17.506***	(21.80)
		#obs	7393	38425		
High Uncertainty	Downgrade	Implvol	55.164	47.889	7.275***	(11.35)
		#obs	20678	26062		
	Upgrade	Implvol	52.432	46.723	5.709***	(10.17)
		#obs	19319	26499		

Table 1 (Cont'd)

Panel C: Descriptive statistics of the recommendations change sample

Variables	Full sample			Bad times: Crisis periods			Good times: Non-Crisis periods		
	Mean	Stdev	#Obs	Mean	Stdev	#Obs	Mean	Stdev	#Obs
				Downgrades sample					
CAR(%)	-1.822	6.852	71,070	-2.678	9.216	9,648	-1.687	6.392	61,422
LFR	2.377	2.880	66,386	2.307	2.930	9,052	2.388	2.872	57,334
Star Analyst	0.130	0.336	71,070	0.109	0.312	9,648	0.133	0.340	61,422
Experience (#qtrs)	27.33	20.53	71,070	28.17	20.16	9,648	27.20	20.58	61,422
Accuracy Quintile	2.980	0.429	63,974	2.986	0.401	8,661	2.979	0.433	55,313
Broker Size (# analysts)	50.82	49.33	71,070	50.93	54.27	9,648	50.80	48.51	61,422
# Analysts per firm	9.642	6.397	71,070	9.288	5.819	9,648	9.697	6.481	61,422
Size ($m)	7,940	25,124	71,070	9,372	27,443	9,648	7,716	24,733	61,422
BM	0.512	0.636	71,070	0.454	0.436	9,648	0.521	0.661	61,422
Momentum	0.132	0.671	71,070	-0.048	0.530	9,648	0.160	0.686	61,422
Stock Volatility	0.031	0.022	71,069	0.041	0.026	9,648	0.029	0.020	61,421
				Upgrades sample					
CAR(%)	2.123	6.095	67,425	2.658	6.768	8,688	2.044	5.985	58,737
LFR	2.379	2.771	63,493	2.310	2.859	8,203	2.389	2.757	55,290
Star Analyst	0.139	0.346	67,425	0.116	0.320	8,688	0.143	0.350	58,737
Experience (#qtrs)	27.89	20.78	67,425	28.57	20.17	8,688	27.79	20.87	58,737
Accuracy Quintile	2.981	0.417	60,759	2.989	0.390	7,838	2.980	0.420	52,921
Broker Size (# analysts)	51.86	48.96	67,425	50.57	53.28	8,688	52.05	48.29	58,737
# Analysts per firm	10.083	6.344	67,425	9.640	5.736	8,688	10.149	6.426	58,737
Size ($m)	8,591	25,266	67,425	10,306	28,733	8,688	8,337	24,703	58,737
BM	0.536	0.730	67,425	0.459	0.387	8,688	0.547	0.767	58,737
Momentum	0.201	0.714	67,425	0.047	0.584	8,688	0.224	0.729	58,737
Stock Volatility	0.029	0.020	67,424	0.036	0.024	8,688	0.027	0.019	58,736

Table 2: Recommendation impact and influential likelihood in bad times

Two-day CAR (in percent) is the average day [0,1] cumulative abnormal return and Influential Probability is the percentage of influential recommendation changes. Influential changes are those whose two-day CARs are in the same direction as the recommendation change and is 1.96 times larger than expected based on the prior three-month idiosyncratic volatility of the stock (following Loh and Stulz (2011)). The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1993-2014. A recommendation change is defined as an analyst's current rating minus her prior outstanding rating (initiations and reiterations are excluded) and changes made around earnings announcement and guidance days, and on multiple-recommendation days are excluded. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Bad times definition	Rec-changes	Variable	Two-day CAR (%)			Influential Probability (%)		
			Bad times	Good times	Difference	Bad times	Good times	Difference
Crisis	Downgrades	Percent	-2.678***	-1.687***	-0.991***	15.278***	11.681***	3.596***
		t-stat	(-25.72)	(-55.18)	(-9.14)	(31.72)	(71.51)	(7.08)
		#obs	9648	61422		9648	61422	
	Upgrades	Percent	2.658***	2.044***	0.614***	16.494***	13.564***	2.930***
		t-stat	(27.86)	(68.19)	(6.15)	(24.48)	(77.86)	(4.21)
		#obs	8688	58737		8688	58737	
Credit Crisis	Downgrades	Percent	-2.925***	-1.686***	-1.239***	16.273***	11.664***	4.609***
		t-stat	(-27.79)	(-54.70)	(-11.31)	(30.48)	(72.27)	(8.27)
		#obs	7792	63278		7792	63278	
	Upgrades	Percent	2.804***	2.041***	0.764***	17.378***	13.527***	3.852***
		t-stat	(26.15)	(68.76)	(6.87)	(22.16)	(78.70)	(4.80)
		#obs	7262	60163		7262	60163	
Recession	Downgrades	Percent	-2.813***	-1.665***	-1.148***	13.589***	11.945***	1.644***
		t-stat	(-28.39)	(-54.31)	(-11.08)	(29.72)	(71.91)	(3.38)
		#obs	9714	61356		9714	61356	
	Upgrades	Percent	2.992***	2.003***	0.989***	14.877***	13.813***	1.064*
		t-stat	(23.61)	(72.06)	(7.63)	(24.89)	(76.32)	(1.70)
		#obs	8147	59278		8147	59278	
High Uncertainty	Downgrades	Percent	-2.134***	-1.638***	-0.495***	13.761***	11.073***	2.688***
		t-stat	(-38.84)	(-45.55)	(-7.55)	(51.39)	(57.77)	(8.16)
		#obs	26292	43059		26292	43059	
	Upgrades	Percent	2.290***	2.029***	0.261***	14.989***	13.115***	1.873***
		t-stat	(50.47)	(52.86)	(4.40)	(49.25)	(61.10)	(5.03)
		#obs	24038	41478		24038	41478	

Table 3: Panel regression of recommendation CAR in bad times

The panel regressions estimate the effect of bad times on recommendation downgrade and upgrade two-day CARs (in percent) controlling for recommendation, firm, and analyst characteristics. The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1993-2014. A recommendation change is defined as an analyst's current rating minus her prior outstanding rating (initiations and reiterations are excluded) and changes made around earnings announcement and guidance days, and on multiple-recommendation days are excluded. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. *LFR* is the analyst's prior-year leader-follower ratio (computed from recommendations), *Star Analyst* is from the *Institutional Investor* poll, *Relative Experience* is the difference between the analyst's experience (in quarters) against the average of peers covering the same firm, *Accuracy Quintile* is the average forecast accuracy quintile of the analyst's past-year's covered firms (quintile 5=most accurate), *Broker Size* is the number of analysts employed, *# Analysts* is 1+ the number of analysts covering the firm, *Size* is last June's market cap, *BM* is the book-to-market ratio, and *Momentum* is the month *t*-12 to *t*-2 buy-and-hold return, and *Stock Volatility* is the month *t*-1 volatility of daily stock returns. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E) rely on the Fama-French 30-industry groupings.

Variables	Dependent variable: CAR of downgrades								Dependent variable: CAR of upgrades							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Crisis	-0.991***	-0.998***							0.614***	0.639***						
	(9.14)	(8.01)							(6.15)	(5.19)						
Credit Crisis			-1.239***	-1.383***							0.764***	0.878***				
			(11.31)	(11.78)							(6.87)	(6.23)				
Recession					-1.148***	-1.018***							0.989***	0.838***		
					(11.08)	(8.61)							(7.63)	(5.96)		
High Uncertainty							-0.495***	-0.557***							0.261***	0.383***
							(7.55)	(7.68)							(4.40)	(5.86)
LFR		-0.036***		-0.036***		-0.035***		-0.033**		0.026***		0.026***		0.026***		0.025***
		(2.81)		(2.82)		(2.75)		(2.54)		(3.19)		(3.18)		(3.15)		(2.99)
Star Analyst		-0.173**		-0.174**		-0.168**		-0.209**		0.048		0.048		0.046		0.082
		(2.15)		(2.16)		(2.08)		(2.56)		(0.37)		(0.37)		(0.35)		(0.63)
Relative Experience		-0.007***		-0.007***		-0.007***		-0.007***		0.010***		0.010***		0.010***		0.009***
		(4.01)		(3.94)		(3.95)		(3.84)		(6.15)		(6.11)		(6.15)		(5.74)
Accuracy Quintile		-0.234***		-0.234***		-0.239***		-0.222***		0.299***		0.293***		0.298***		0.301***
		(3.54)		(3.53)		(3.61)		(3.32)		(4.30)		(4.21)		(4.29)		(4.23)
Log Broker Size		-0.488***		-0.498***		-0.477***		-0.479***		0.523***		0.529***		0.517***		0.520***
		(15.18)		(15.73)		(15.05)		(14.80)		(14.97)		(15.00)		(15.19)		(14.88)
Log # Analysts		0.214***		0.201***		0.233***		0.292***		-0.499***		-0.490***		-0.500***		-0.523***
		(2.83)		(2.65)		(3.07)		(3.77)		(8.18)		(8.05)		(8.20)		(8.46)
Log Size		0.222***		0.236***		0.226***		0.206***		-0.365***		-0.372***		-0.376***		-0.357***
		(8.58)		(9.35)		(8.95)		(8.02)		(15.18)		(15.54)		(14.79)		(14.70)
Log BM		0.135***		0.146***		0.132***		0.162***		0.045		0.041		0.043		0.031
		(3.05)		(3.28)		(2.96)		(3.61)		(1.18)		(1.08)		(1.14)		(0.79)
Momentum		-0.126*		-0.131**		-0.155**		-0.094		-0.159***		-0.155***		-0.131**		-0.171***
		(1.90)		(1.96)		(2.32)		(1.41)		(2.95)		(2.87)		(2.53)		(3.13)
Stock Volatility		-20.864***		-20.447***		-19.364***		-22.774***		27.134***		26.806***		24.983***		28.953***
		(7.92)		(7.87)		(7.23)		(8.70)		(7.75)		(7.70)		(7.59)		(8.13)
Intercept	-1.687***	-2.095***	-1.686***	-2.219***	-1.665***	-2.257***	-1.638***	-1.953***	2.044***	5.007***	2.041***	5.087***	2.003***	5.234***	2.029***	4.829***
	(55.18)	(5.33)	(54.70)	(5.71)	(54.31)	(5.79)	(45.55)	(5.00)	(68.19)	(13.37)	(68.76)	(13.60)	(72.06)	(13.48)	(52.86)	(12.67)
Good times $\hat{Y}$	-1.687	-1.761	-1.686	-1.745	-1.665	-1.754	-1.638	-1.693	2.044	2.140	2.041	2.127	2.003	2.118	2.029	2.088
#Obs	71070	59511	71070	59511	71070	59511	69351	58163	67425	56901	67425	56901	67425	56901	65516	55395
Adj R-Sq	0.0024	0.0199	0.0032	0.0213	0.0033	0.0199	0.0012	0.0194	0.0011	0.0432	0.0015	0.0439	0.0028	0.0438	0.0004	0.0427
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 4: Probit of recommendation influential probability in bad times

The probit regressions estimate the marginal effect (in percent) of bad times on the influential probability of the CAR for recommendation changes controlling for recommendation, firm, and analyst characteristics. Influential changes are those whose two-day CARs are in the same direction as the recommendation change and is 1.96 times larger than expected based on the prior three-month idiosyncratic volatility of the stock (following Loh and Stulz (2011)). The sample is from 1993-2014. A recommendation change is defined as an analyst's current rating minus her prior outstanding rating (initiations and reiterations are excluded) and changes made around earnings announcement days and on earnings guidance days, and on multiple-recommendation days are excluded. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. *LFR* is the analyst's prior-year leader-follower ratio (computed from recommendations), *Star Analyst* is from the *Institutional Investor* poll, *Relative Experience* is the difference between the analyst's experience (in quarters) against the average of peers covering the same firm, *Accuracy Quintile* is the average forecast accuracy quintile of the analyst's past-year's covered firms (quintile 5=most accurate), *Broker Size* is the number of analysts employed, *# Analysts* is 1+ the number of analysts covering the firm, *Size* is last June's market cap, *BM* is the book-to-market ratio, and *Momentum* is the month *t*-12 to *t*-2 buy-and-hold return, and *Stock Volatility* is the month *t*-1 volatility of daily stock returns. In parentheses are *z*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects rely on the Fama-French 30-industry groupings.

Variables	Dependent variable: Influential dummy for downgrades								Dependent variable: Influential dummy for upgrades							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Crisis	0.036***	0.065***							0.029***	0.055***						
	(7.56)	(12.02)							(4.45)	(8.03)						
Credit Crisis			0.046***	0.079***							0.039***	0.067***				
			(9.00)	(13.30)							(5.15)	(8.60)				
Recession					0.016***	0.048***							0.011*	0.042***		
					(3.49)	(8.65)							(1.74)	(6.29)		
High Uncertainty							0.027***	0.040***							0.019***	0.032***
							(8.30)	(11.50)							(5.09)	(8.31)
LFR		0.001***		0.001***		0.001***		0.001***		0.001**		0.001**		0.001**		0.001**
		(3.42)		(3.42)		(3.35)		(3.02)		(2.50)		(2.47)		(2.46)		(2.27)
Star Analyst		-0.002		-0.002		-0.003		0.000		-0.014***		-0.014***		-0.014***		-0.012***
		(0.52)		(0.51)		(0.67)		(0.06)		(3.04)		(3.03)		(3.14)		(2.63)
Relative Experience		0.000***		0.000***		0.000***		0.000***		0.001***		0.001***		0.001***		0.001***
		(4.46)		(4.41)		(4.44)		(3.77)		(6.86)		(6.86)		(6.90)		(5.71)
Accuracy Quintile		0.018***		0.018***		0.019***		0.017***		0.015***		0.015***		0.015***		0.016***
		(5.56)		(5.58)		(5.65)		(5.19)		(4.20)		(4.12)		(4.25)		(4.49)
Log Broker Size		0.030***		0.030***		0.030***		0.029***		0.034***		0.035***		0.034***		0.034***
		(19.61)		(19.85)		(19.14)		(18.76)		(19.73)		(19.82)		(19.48)		(19.71)
Log # Analysts		-0.006***		-0.007***		-0.006***		-0.006***		-0.051***		-0.050***		-0.052***		-0.051***
		(5.12)		(5.41)		(4.77)		(4.76)		(15.12)		(15.05)		(15.32)		(15.02)
Log Size		-0.006***		-0.007***		-0.006***		-0.006***		-0.012***		-0.012***		-0.012***		-0.012***
		(5.12)		(5.41)		(4.77)		(4.76)		(8.84)		(9.09)		(8.46)		(8.31)
Log BM		-0.005***		-0.005***		-0.005***		-0.007***		0.002		0.002		0.002		0.001
		(2.70)		(2.95)		(2.72)		(3.64)		(1.13)		(1.01)		(0.98)		(0.26)
Momentum		0.008***		0.008***		0.008***		0.007***		-0.007**		-0.006**		-0.006**		-0.007***
		(3.77)		(3.77)		(3.93)		(3.17)		(2.49)		(2.45)		(2.37)		(2.82)
Stock Volatility		-1.288***		-1.273***		-1.296***		-1.182***		-1.704***		-1.700***		-1.729***		-1.550***
		(13.25)		(13.22)		(12.98)		(12.23)		(13.47)		(13.48)		(13.85)		(12.28)
Predicted Prob.	0.121	0.117	0.121	0.117	0.122	0.118	0.120	0.117	0.139	0.134	0.139	0.134	0.139	0.135	0.138	0.134
#Obs	71070	59511	71070	59511	71070	59511	69351	58163	67425	56901	67425	56901	67425	56901	65516	55395
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 5: Panel regression of forecast revision CAR in bad times

The panel regressions estimate the effect of bad times on earnings forecast revisions two-day CARs (in percent) controlling for forecast, firm, and analyst characteristics. The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1983-2014. *Forecast Revision* is the analyst's current one-quarter-ahead earnings forecast minus her prior outstanding forecast (i.e., initiations are excluded) scaled by price and revisions made around earnings announcement and guidance days, and on multiple-forecast days are excluded. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. Other controls are as defined in Table 3. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E.) rely on the Fama-French 30-industry groupings.

Variables	Dependent variable: CAR of downward revisions								Dependent variable: CAR of upward revisions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Crisis	-0.398***	-0.384***							0.198***	0.170**						
	(6.50)	(5.49)							(2.79)	(2.13)						
Credit Crisis			-0.525***	-0.533***							0.211***	0.169*				
			(7.91)	(7.14)							(2.68)	(1.96)				
Recession					-0.323***	-0.238***							0.108	0.019		
					(5.87)	(3.50)							(1.55)	(0.23)		
High Uncertainty							-0.070**	-0.095***							0.021	0.013
							(2.31)	(2.79)							(0.70)	(0.39)
Forecast Revision		6.865*		6.785*		6.855*		6.547*		9.306		9.214		9.548		8.969
		(1.81)		(1.79)		(1.81)		(1.72)		(1.18)		(1.17)		(1.21)		(1.12)
LFR		-0.025***		-0.024***		-0.026***		-0.027***		0.040***		0.040***		0.041***		0.042***
		(4.31)		(4.17)		(4.56)		(4.61)		(6.05)		(6.03)		(6.12)		(6.18)
Star Analyst		0.025		0.021		0.034		0.035		-0.093***		-0.094***		-0.097***		-0.098***
		(0.76)		(0.65)		(1.03)		(1.04)		(2.67)		(2.68)		(2.78)		(2.69)
Relative Experience		-0.001		-0.001		-0.001		-0.001		0.001		0.001		0.001		0.001
		(0.87)		(0.88)		(0.88)		(1.04)		(0.72)		(0.72)		(0.75)		(0.61)
Accuracy Quintile		-0.015		-0.015		-0.014		-0.004		0.040		0.040		0.039		0.037
		(0.55)		(0.58)		(0.54)		(0.17)		(1.45)		(1.45)		(1.42)		(1.29)
Log Broker Size		-0.057***		-0.057***		-0.058***		-0.067***		0.052***		0.052***		0.053***		0.050***
		(3.30)		(3.32)		(3.38)		(3.75)		(2.86)		(2.86)		(2.92)		(2.68)
Log # Analysts		0.096**		0.092**		0.108***		0.134***		-0.076*		-0.079*		-0.087**		-0.093**
		(2.31)		(2.22)		(2.59)		(3.10)		(1.78)		(1.85)		(2.06)		(2.09)
Log Size		0.033**		0.039***		0.028**		0.019		-0.075***		-0.075***		-0.070***		-0.070***
		(2.34)		(2.75)		(1.98)		(1.28)		(5.18)		(5.15)		(4.84)		(4.69)
Log BM		-0.019		-0.016		-0.018		-0.019		0.012		0.011		0.010		0.015
		(0.85)		(0.73)		(0.81)		(0.83)		(0.53)		(0.51)		(0.43)		(0.63)
Momentum		0.040		0.034		0.043		0.069		0.073**		0.072**		0.067*		0.063*
		(0.94)		(0.80)		(0.98)		(1.56)		(2.04)		(2.03)		(1.86)		(1.75)
Stock Volatility		-1.036		-0.438		-1.506		-3.383		4.416*		4.537*		5.057**		5.295**
		(0.46)		(0.20)		(0.64)		(1.51)		(1.88)		(1.94)		(2.09)		(2.23)
Intercept	-0.294***	-0.646***	-0.288***	-0.717***	-0.296***	-0.598***	-0.323***	-0.465**	0.439***	1.234***	0.441***	1.231***	0.447***	1.184***	0.453***	1.205***
	(20.46)	(3.00)	(20.06)	(3.36)	(20.35)	(2.76)	(19.78)	(2.14)	(31.41)	(5.34)	(31.68)	(5.33)	(32.34)	(5.12)	(24.25)	(5.10)
Good times $\hat{Y}$	-0.294	-0.230	-0.288	-0.220	-0.296	-0.243	-0.323	-0.244	0.439	0.413	0.441	0.415	0.447	0.427	0.453	0.426
#Obs	172482	105097	172482	105097	172482	105097	164257	99663	112149	69773	112149	69773	112149	69773	107047	66470
Adj R-Sq	0.0009	0.0030	0.0013	0.0036	0.0007	0.0024	0.0001	0.0022	0.0002	0.0053	0.0002	0.0052	0.0001	0.0051	-0.0000	0.0051
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 6: Probit of forecast revision influential probability in bad times

The probit regressions estimate the marginal effect (in percent) of bad times on the influential probability of the CAR for earnings forecast revisions controlling for forecast, firm, and analyst characteristics. Influential revisions are those whose two-day CARs are in the same direction as the revision and is 1.96 times larger than expected based on the prior three-month idiosyncratic volatility of the stock (following Loh and Stulz (2011)). The sample is from 1983-2014. *Forecast Revision* is the analyst's current one-quarter-ahead earnings forecast minus her prior outstanding forecast (i.e., initiations are excluded) scaled by price and revisions made around earnings announcement and guidance days, and on multiple-forecast days are excluded. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. *Forecast Revision* is analyst's current forecast minus her prior forecast, scaled by the stock price. Other controls are as defined in Table 3. In parentheses are *z*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E.) rely on the Fama-French 30-industry groupings.

Variables	Dependent variable: Influential dummy for downward revisions								Dependent variable: Influential dummy for upward revisions							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Crisis	0.025***	0.036***							0.017***	0.024***						
	(8.89)	(10.96)							(5.85)	(6.57)						
Credit Crisis			0.029***	0.042***							0.020***	0.025***				
			(9.25)	(11.51)							(6.28)	(6.43)				
Recession					0.016***	0.028***							0.005*	0.010***		
					(6.16)	(8.82)							(1.77)	(2.63)		
High Uncertainty							0.011***	0.016***							0.004**	0.006***
							(7.00)	(9.28)							(2.57)	(2.77)
Forecast Revision		-0.340***		-0.334***		-0.338***		-0.321***		0.740***		0.725***		0.746***		0.676**
		(4.48)		(4.43)		(4.43)		(4.17)		(2.70)		(2.65)		(2.72)		(2.41)
LFR		0.001***		0.001***		0.001***		0.001***		0.001***		0.001***		0.001***		0.001***
		(4.83)		(4.71)		(5.42)		(5.96)		(4.92)		(4.86)		(5.11)		(5.27)
Star Analyst		-0.000		-0.000		-0.001		-0.000		-0.001		-0.001		-0.002		-0.002
		(0.17)		(0.13)		(0.61)		(0.05)		(0.61)		(0.60)		(0.83)		(0.67)
Relative Experience		0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000
		(0.60)		(0.64)		(0.58)		(0.69)		(1.19)		(1.20)		(1.25)		(1.33)
Accuracy Quintile		0.002		0.002		0.002		0.001		0.003*		0.003*		0.003*		0.003*
		(1.36)		(1.40)		(1.43)		(0.71)		(1.92)		(1.93)		(1.91)		(1.76)
Log Broker Size		0.003***		0.003***		0.003***		0.004***		0.004***		0.004***		0.004***		0.004***
		(3.92)		(4.00)		(4.04)		(4.64)		(4.07)		(4.06)		(4.16)		(3.93)
Log # Analysts		-0.001*		-0.001**		-0.001		-0.001		-0.015***		-0.015***		-0.016***		-0.018***
		(1.90)		(2.05)		(1.54)		(0.73)		(5.77)		(5.87)		(6.19)		(6.43)
Log Size		-0.001*		-0.001**		-0.001		-0.001		-0.003***		-0.003***		-0.003***		-0.002**
		(1.90)		(2.05)		(1.54)		(0.73)		(3.57)		(3.51)		(3.02)		(2.48)
Log BM		-0.001		-0.002*		-0.002		-0.002**		-0.003**		-0.003**		-0.003**		-0.003**
		(1.45)		(1.67)		(1.59)		(2.34)		(2.25)		(2.28)		(2.47)		(2.54)
Momentum		0.005***		0.005***		0.005***		0.002		0.001		0.001		0.001		0.000
		(3.54)		(3.52)		(3.75)		(1.41)		(0.68)		(0.66)		(0.41)		(0.08)
Stock Volatility		-0.501***		-0.504***		-0.501***		-0.326***		-0.601***		-0.588***		-0.557***		-0.480***
		(7.44)		(7.61)		(7.16)		(4.77)		(7.24)		(7.15)		(6.62)		(5.83)
Predicted Prob.	0.049	0.045	0.049	0.045	0.049	0.045	0.048	0.044	0.053	0.050	0.053	0.050	0.053	0.050	0.053	0.051
#Obs	172481	105097	172481	105097	172481	105097	164256	99663	112147	69773	112147	69773	112147	69773	107045	66470
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 7: Robustness tests

Panel A estimates the effect of high firm, industry, and market uncertainty on the two-day CAR (in percent) of recommendation changes. Control variables are estimated for even specifications but not reported (see Table 3 for definitions of controls). A firm's total variance of daily stock returns in the prior month is decomposed into a market, industry, and firm part by regressing daily returns on market returns and a market-purged industry return (Fama-French 30 industry groups). High uncertainty equals one when the relevant component is in the top tercile within the firm's time-series of monthly variance components. Panel B estimates the effect of bad times on the two-day CARs (in percent) of recommendation reiterations. The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1993-2014. A recommendation reiteration is either an explicit reiteration from the I/B/E/S recommendation file, or an assumed reiteration that the analyst's outstanding rating is reiterated when there is a quarterly earnings or target price forecast with no new rating issued. Control variables (in even specifications but unreported) are the same as those in Table 3 plus forecast revision over price and target price over current price when available or zero otherwise. Reiterations made around earnings announcement and guidance days and on multiple-reiteration days are excluded. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. Panel C regresses the daily absolute returns of firms in the CRSP file from 1993-2014 on firm news event dummies and bad times dummies, excluding observations where the lagged price is less than one dollar. Event dummies equals one for day 0 of the announcement, or day 1 if the announcement occurs after trading hours (checking when we have the time stamps). Earnings announcement dates are from Compustat and times from I/B/E/S, guidance events are from First Call Guidelines (I/B/E/S Guidance from 2011 onwards), dividend events are from the CRSP event file, and insider trade events are from the Thomson Insider Form 4 file. *Size*, *BM*, and *Momentum* are as defined in Table 3. Other control variables *Lag Return*, *Idio. Volatility*, *Turnover*, and *Inst. Ownership* are measured in the prior month. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E.) rely on the Fama-French 30-industry groupings.

Panel A: Panel regression of recommendation change CAR on different measures of high uncertainty

Variables	Dependent variable: CAR of downgrades								Dependent variable: CAR of upgrades							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
High Firm Uncertainty	-1.091***	0.149					-0.932***	0.061	1.707***	0.266*					1.618***	0.347**
	(11.64)	(1.08)					(9.93)	(0.44)	(16.32)	(1.86)					(15.28)	(2.44)
High Ind. Uncertainty			-0.297***	-0.004			0.001	0.012			0.143***	0.020			-0.199***	0.012
			(5.29)	(0.07)			(0.02)	(0.18)			(2.69)	(0.30)			(3.90)	(0.19)
High Mkt Uncertainty					-0.783***	-0.501***	-0.622***	-0.497***					0.757***	0.379***	0.555***	0.404***
					(13.77)	(6.81)	(10.71)	(6.63)					(14.60)	(5.01)	(9.90)	(5.20)
Good times $\hat{Y}$	-1.590	-1.928	-1.703	-1.895	-1.471	-1.670	-1.345	-1.689	1.820	2.176	2.067	2.214	1.786	2.051	1.667	1.975
Observations	71067	59510	71067	59510	71067	59510	71067	59510	67424	56901	67424	56901	67424	56901	67424	56901
Adj R-Sq	0.0042	0.0177	0.0004	0.0176	0.0032	0.0187	0.0061	0.0186	0.0114	0.0422	0.0001	0.0421	0.0038	0.0428	0.0134	0.0430
Controls, Ind F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Panel B: Panel regression of reiteration CAR in bad times

Variables	Dependent variable: CAR of unfavorable recommendation reiterations								Dependent variable: CAR of favorable recommendation reiterations							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Crisis	-0.262***	-0.173***							-0.163***	-0.105**						
	(5.72)	(3.78)							(3.52)	(2.39)						
Credit Crisis			-0.293***	-0.215***							-0.163***	-0.110**				
			(6.02)	(4.45)							(3.12)	(2.21)				
Recession					-0.252***	-0.164***							-0.167***	-0.131***		
					(5.36)	(3.42)							(3.83)	(3.06)		
High Uncertainty							-0.090***	-0.100***							-0.021	-0.029
							(3.79)	(4.23)							(0.91)	(1.29)
Non-bad times $\hat{Y}$	-0.064	-0.076	-0.064	-0.073	-0.065	-0.077	-0.060	-0.056	0.175	0.166	0.171	0.164	0.178	0.171	0.164	0.164
Observations	248676	243190	248676	243190	248676	243190	237063	231964	347922	339883	347922	339883	347922	339883	334452	326827
Adj R-Sq	0.0004	0.0024	0.0005	0.0024	0.0004	0.0023	0.0001	0.0023	0.0001	0.0023	0.0001	0.0023	0.0001	0.0023	0.0000	0.0023
Controls, Ind. F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 7 (Cont'd)

Panel C: Regression of firm-day absolute returns on firm news events and bad times

Variables	Dependent variable: Firm-day absolute returns											
	Bad times definition used											
	Crisis			Credit Crisis			Recession			High Uncertainty		
BadTimes	0.471***	0.432***	0.411***	0.185***	0.380***	0.353***	0.517***	0.416***	0.395***	-0.179***	0.098***	0.090***
	(11.75)	(15.96)	(15.19)	(4.31)	(11.83)	(10.98)	(16.24)	(15.83)	(15.10)	(7.78)	(7.30)	(6.67)
Recchg Dum	1.656***	2.020***	2.028***	1.652***	2.022***	2.030***	1.630***	2.002***	2.012***	1.506***	1.936***	1.947***
	(67.10)	(97.96)	(98.84)	(67.90)	(99.15)	(99.91)	(66.95)	(98.71)	(99.69)	(50.09)	(75.37)	(76.95)
Reiteration Dum		0.704***	0.672***		0.702***	0.660***		0.701***	0.662***		0.693***	0.606***
		(91.30)	(86.11)		(90.86)	(85.75)		(91.18)	(84.57)		(87.24)	(62.70)
Earn Annc Dum		1.221***	1.191***		1.220***	1.197***		1.220***	1.195***		1.227***	1.190***
		(80.29)	(76.37)		(79.28)	(75.44)		(79.80)	(75.77)		(78.59)	(66.90)
Guidance Dum		1.730***	1.753***		1.729***	1.808***		1.726***	1.746***		1.780***	2.069***
		(44.26)	(41.90)		(44.18)	(42.41)		(44.31)	(40.76)		(44.15)	(35.78)
Dividend Dum		-0.138***	-0.149***		-0.138***	-0.155***		-0.136***	-0.140***		-0.135***	-0.142***
		(17.09)	(18.09)		(17.17)	(19.05)		(16.85)	(16.96)		(16.11)	(14.16)
Insider Trade Dum		-0.099***	-0.101***		-0.101***	-0.104***		-0.094***	-0.099***		-0.100***	-0.106***
		(13.88)	(13.61)		(14.03)	(13.88)		(13.03)	(13.20)		(13.59)	(11.50)
Insider File Dum		0.261***	0.253***		0.262***	0.262***		0.259***	0.256***		0.262***	0.267***
		(43.27)	(44.46)		(43.12)	(41.88)		(42.74)	(41.01)		(41.91)	(35.55)
BadTimes×Recchg Dum	0.503***	0.439***	0.370***	0.726***	0.516***	0.430***	0.712***	0.592***	0.509***	0.575***	0.353***	0.320***
	(6.79)	(6.70)	(5.96)	(9.11)	(7.20)	(6.38)	(9.49)	(8.69)	(7.82)	(12.11)	(8.48)	(8.06)
BadTimes×Reiteration Dum			0.259***			0.407***			0.296***			0.219***
			(8.46)			(13.40)			(10.69)			(12.58)
BadTimes×Earn Annc Dum			0.319***			0.367***			0.249***			0.131***
			(5.43)			(5.87)			(4.32)			(3.66)
BadTimes×Guidance Dum			-0.254**			-0.888***			-0.187*			-0.703***
			(2.20)			(10.48)			(1.92)			(8.87)
BadTimes×Dividend Dum			0.113***			0.203***			0.043			0.020
			(3.27)			(5.28)			(1.25)			(1.07)
BadTimes×Insider Trade Dum			0.005			0.036			0.044			0.015
			(0.18)			(1.46)			(1.51)			(0.95)
BadTimes×Insider File Dum			0.081***			-0.003			0.030			-0.016
			(2.61)			(0.12)			(1.36)			(1.23)
Log Size		-0.194***	-0.194***		-0.193***	-0.192***		-0.196***	-0.196***		-0.193***	-0.193***
		(117.79)	(117.83)		(118.10)	(118.12)		(117.40)	(117.41)		(115.07)	(115.12)
Log BM		-0.123***	-0.123***		-0.125***	-0.125***		-0.128***	-0.128***		-0.132***	-0.132***
		(54.57)	(54.61)		(55.34)	(55.38)		(58.79)	(58.74)		(60.08)	(60.06)
Momentum		-0.014***	-0.014***		-0.018***	-0.018***		-0.010**	-0.010**		-0.025***	-0.025***
		(2.73)	(2.72)		(3.57)	(3.56)		(2.04)	(2.03)		(4.82)	(4.81)
Lag Return		-1.157***	-1.156***		-1.177***	-1.176***		-1.172***	-1.171***		-1.210***	-1.209***
		(41.93)	(41.94)		(41.86)	(41.87)		(41.87)	(41.90)		(42.45)	(42.46)
Idio. Volatility		35.031***	35.030***		35.324***	35.317***		34.846***	34.842***		35.788***	35.787***
		(110.75)	(110.76)		(110.89)	(110.90)		(107.69)	(107.74)		(109.44)	(109.47)
Turnover		-4.391***	-4.412***		-4.548***	-4.573***		-4.248***	-4.277***		-4.473***	-4.507***
		(19.16)	(19.27)		(19.96)	(20.08)		(18.59)	(18.76)		(18.66)	(18.81)
Inst. Ownership		-0.530***	-0.530***		-0.533***	-0.533***		-0.520***	-0.520***		-0.497***	-0.497***
		(64.62)	(64.55)		(68.99)	(68.85)		(59.34)	(59.31)		(54.26)	(54.14)
Intercept	2.381***	3.865***	3.865***	2.413***	3.857***	3.858***	2.375***	3.892***	3.893***	2.512***	3.827***	3.829***
	(237.99)	(139.36)	(139.41)	(235.87)	(138.54)	(138.60)	(228.36)	(137.57)	(137.62)	(224.73)	(133.76)	(133.92)
# Observations	2.11e+07	2.01e+07	2.01e+07	2.11e+07	2.01e+07	2.01e+07	2.11e+07	2.01e+07	2.01e+07	2.05e+07	1.95e+07	1.95e+07
Ind. F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-Sq	0.0158	0.1344	0.1344	0.0144	0.1338	0.1339	0.0163	0.1343	0.1344	0.0148	0.1326	0.1327

Table 8: Absolute forecast error in bad times

The panel regressions estimate the effect of bad times on an analyst's absolute forecast error (in percent). Absolute forecast error is actual minus forecasted earnings, divided by the absolute value of actual earnings (models 1-8) (denominators less than $0.25 are set to $0.25), or divided by the daily stock return volatility (annualized) in the month before the forecast (models 9-16). Forecast errors are winsorized at the extreme 1% before taking absolute values. Bad times are as defined in Table 1. *Optimistic Forecast* is an indicator variable equal to one if the forecast is above the final consensus, *LFR* is the analyst's prior-year leader-follower ratio (computed from forecasts), *Star Analyst* is from the *Institutional Investor* poll, *Relative Experience* is the difference between the analyst's experience (in quarters) against the average of peers covering the same firm, *Accuracy Quintile* is the average forecast accuracy quintile of the analyst's past-year's covered firms (quintile 5=most accurate), *Days to Annc* is the number of days from the forecast to the earnings announcement date, *Multiple Forecast Day* is a dummy indicating that more than one analyst issued a forecast on that day, *Broker Size* is the number of analysts employed, *# Analysts* is 1+ the number of analysts covering the firm, *Size* is last June's market cap, *BM* is the book-to-market ratio, *Momentum* is the month *t*-12 to *t*-2 buy-and-hold return, and *Dispersion* is the dispersion of forecasts making up the final consensus. In parentheses are *t*-statistics based on standard errors clustered by industry-quarter (Fama-French 30 industries), where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E.) rely on the Fama-French 30-industry groupings.

Variables	Dependent variable: Absolute forecast error scaled by absolute value of actual earnings								Dependent variable: Absolute forecast error scaled by stock volatility							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Crisis	2.775***	2.952***							-6.667***	-6.705***						
	(5.11)	(6.96)							(6.87)	(9.21)						
Credit Crisis			3.341***	3.626***							-5.417***	-5.590***				
			(5.49)	(7.81)							(5.05)	(7.15)				
Recession					2.807***	2.985***							-7.933***	-7.234***		
					(5.11)	(7.14)							(8.44)	(10.02)		
High Uncertainty							1.128***	0.996***							0.828	-1.015*
							(4.01)	(4.41)							(1.08)	(1.82)
Optimistic Forecast		-0.090		-0.104		-0.075		-0.064		-1.325***		-1.309***		-1.359***		-1.196***
		(0.80)		(0.93)		(0.66)		(0.55)		(5.68)		(5.61)		(5.87)		(5.16)
LFR		-0.209***		-0.212***		-0.203***		-0.196***		-0.492***		-0.494***		-0.504***		-0.498***
		(14.17)		(14.39)		(13.75)		(13.03)		(14.63)		(14.67)		(14.98)		(14.44)
Star Analyst		0.793***		0.808***		0.764***		0.868***		2.620***		2.651***		2.679***		2.953***
		(6.72)		(6.85)		(6.47)		(7.20)		(9.52)		(9.62)		(9.75)		(10.92)
Relative Experience		-0.008***		-0.008***		-0.008***		-0.008***		-0.026***		-0.026***		-0.026***		-0.023***
		(4.29)		(4.31)		(4.27)		(4.10)		(5.09)		(5.10)		(5.12)		(4.51)
Accuracy Quintile		-0.801***		-0.798***		-0.794***		-0.787***		-0.973***		-0.970***		-0.990***		-0.827***
		(11.19)		(11.17)		(11.11)		(10.68)		(6.40)		(6.36)		(6.52)		(5.44)
Log Days to Annc		1.219***		1.232***		1.220***		1.207***		1.052***		1.024***		1.052***		1.095***
		(19.01)		(19.07)		(19.05)		(18.47)		(7.58)		(7.37)		(7.63)		(7.78)
Mutiple Forecast Day		-1.561***		-1.551***		-1.596***		-1.569***		-2.629***		-2.637***		-2.546***		-2.549***
		(14.33)		(14.25)		(14.49)		(13.93)		(10.49)		(10.52)		(10.23)		(10.24)
Log Broker Size		-0.305***		-0.300***		-0.316***		-0.335***		-0.506***		-0.522***		-0.476***		-0.640***
		(5.12)		(5.07)		(5.20)		(5.29)		(3.96)		(4.07)		(3.78)		(5.00)
Log # Analysts		0.756***		0.752***		0.765***		0.415		-2.876***		-2.712***		-2.931***		-1.985***
		(2.95)		(2.94)		(3.00)		(1.50)		(4.71)		(4.44)		(4.85)		(3.33)
Log Size		-1.969***		-1.979***		-1.966***		-1.886***		4.107***		4.081***		4.110***		3.630***
		(27.10)		(27.43)		(27.13)		(24.72)		(16.79)		(16.68)		(16.99)		(15.46)
Log BM		2.579***		2.568***		2.608***		2.530***		7.164***		7.216***		7.086***		7.527***
		(20.09)		(20.04)		(20.37)		(18.64)		(24.50)		(24.57)		(24.03)		(24.76)
Momentum		-2.259***		-2.233***		-2.104***		-2.540***		0.775**		0.917**		0.360		1.175***
		(10.91)		(10.85)		(10.62)		(11.27)		(1.99)		(2.33)		(0.99)		(2.93)
Dispersion		0.000		0.000		0.000		0.000		-0.000		-0.000		-0.000		-0.000
		(1.46)		(1.46)		(1.47)		(1.48)		(0.35)		(0.32)		(0.36)		(0.30)
Intercept	14.835***	45.065***	14.829***	45.148***	14.759***	44.948***	14.700***	44.618***	26.852***	-16.951***	26.616***	-17.075***	27.199***	-16.669***	25.123***	-13.060***
	(104.43)	(49.53)	(105.20)	(49.77)	(106.84)	(49.73)	(90.89)	(48.64)	(63.64)	(6.13)	(63.71)	(6.17)	(65.12)	(6.06)	(53.27)	(4.78)
Good times $\hat{Y}$	14.835	13.905	14.829	13.884	14.759	13.826	14.700	13.838	26.852	26.728	26.616	26.509	27.199	26.971	25.123	25.720
Observations	406644	334974	406644	334974	406644	334974	388570	318887	406642	334973	406642	334973	406642	334973	388568	318886
Adj R-Sq	0.0017	0.0786	0.0022	0.0793	0.0021	0.0789	0.0007	0.0763	0.0025	0.0824	0.0014	0.0814	0.0042	0.0833	0.0001	0.0807
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 9: Cross-sectional tests of CAR impact of recommendation changes in bad times

The panel regressions add firm characteristics interactions in estimating the effect of bad times on recommendation downgrade (models 1-8) and upgrade (models 9-16) two-day CARs (in percent) controlling for recommendation, firm, and analyst characteristics. The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1993-2014. A recommendation change is defined as an analyst's current rating minus her prior outstanding rating (initiations and reiterations are excluded) and changes made around earnings announcement and guidance days, and on multiple-recommendation days are excluded. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. The firm characteristics dummies are as follows. *NoGuidance* (Panel A) equals one for firms with no earnings guidance in the prior month. *LowIO* (Panel B) equals one for the lowest quintile 13F-reported fraction of shares owned by institutions. *HighIVOLfrac* (Panel C) equals one for the highest quintile of the stocks sorted on the prior month fraction of firm-specific daily return volatility over the total volatility (estimated by regressing daily returns on market returns and market-purged industry returns). *LowSize* (Panel D) equals one for the lowest NYSE-breakpoint quintile rank of the prior June market cap. *NoOptions* (Panel E, 1996-2014) equals one when the firm has no data in Option Metrics. *LowCoverage* (Panel F) equals one for the lowest analyst coverage quintile based on number of analysts issuing recommendations in the prior quarter. Control variables, unreported, are the same as those in Table 3, except that the relevant control is dropped when it is related to the firm characteristic dummy (e.g. *Logsize* is dropped in the *SmallSize* panel). In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E.) rely on the Fama-French 30-industry groupings.

	Dependent variable: CAR of downgrades								Dependent variable: CAR of upgrades							
Variables	Crisis		Credit Crisis		Recession		High Uncertainty		Crisis		Credit Crisis		Recession		High Uncertainty	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Low guidance firms interacted with bad times																
Bad times	-0.794***	-0.806***	-0.881***	-0.977***	-0.919***	-0.723***	-0.486***	-0.507***	0.485***	0.386***	0.554***	0.497***	0.763***	0.388***	0.191***	0.198***
	(8.98)	(8.41)	(9.32)	(9.65)	(9.65)	(6.64)	(8.31)	(8.25)	(5.54)	(3.57)	(5.77)	(4.06)	(8.29)	(3.54)	(3.72)	(3.59)
NoGuidance	-0.914***	-0.669***	-0.843***	-0.547***	-0.888***	-0.605***	-0.974***	-0.746***	2.030***	1.440***	1.990***	1.374***	1.923***	1.286***	1.861***	1.269***
	(9.05)	(5.32)	(8.04)	(4.20)	(8.56)	(4.71)	(8.99)	(5.61)	(18.06)	(11.11)	(17.96)	(10.71)	(21.83)	(11.76)	(13.78)	(8.09)
Bad times×NoGuidance	-0.812**	-0.394	-1.624***	-1.344***	-1.520***	-1.262***	-0.249	0.000	0.506*	0.465	0.920***	0.996***	1.900***	2.213***	0.732***	0.699***
	(2.07)	(0.87)	(4.15)	(3.11)	(3.76)	(2.82)	(1.00)	(0.00)	(1.69)	(1.34)	(2.84)	(2.64)	(2.92)	(2.81)	(3.39)	(2.74)
Good times $\hat{Y}$	-1.714	-1.787	-1.725	-1.790	-1.696	-1.796	-1.642	-1.712	2.060	2.172	2.063	2.168	2.031	2.174	2.054	2.155
#Obs	71087	59524	71087	59524	71087	59524	69368	58176	67436	56908	67436	56908	67436	56908	65527	55402
Adj R-Sq	0.0061	0.0197	0.0075	0.0214	0.0078	0.0203	0.0048	0.0194	0.0174	0.0441	0.0180	0.0449	0.0207	0.0462	0.0170	0.0441
Panel B: Low institutional ownership firms interacted with bad times																
Bad times	-0.965***	-0.980***	-1.204***	-1.356***	-1.129***	-1.006***	-0.486***	-0.544***	0.617***	0.649***	0.757***	0.879***	0.987***	0.840***	0.264***	0.384***
	(8.92)	(7.86)	(11.01)	(11.52)	(10.89)	(8.48)	(7.36)	(7.47)	(6.15)	(5.23)	(6.77)	(6.20)	(7.56)	(5.93)	(4.42)	(5.84)
LowIO	-0.241	0.067	-0.232	0.099	-0.375	-0.061	0.060	0.611	0.183	0.529	0.007	0.248	0.077	0.222	0.089	0.001
	(0.63)	(0.12)	(0.62)	(0.19)	(0.97)	(0.11)	(0.17)	(1.15)	(0.32)	(0.51)	(0.01)	(0.25)	(0.14)	(0.21)	(0.11)	(0.00)
Bad times×LowIO	-3.829*	-5.202*	-5.472**	-7.141*	-3.524	-5.814	-1.652	-3.516**	-0.489	-2.660	1.174	-0.301	0.489	-0.042	0.027	0.551
	(1.89)	(1.65)	(2.12)	(1.80)	(1.59)	(1.51)	(1.61)	(2.09)	(0.37)	(1.34)	(0.84)	(0.14)	(0.36)	(0.02)	(0.03)	(0.30)
Good times $\hat{Y}$	-1.688	-1.761	-1.688	-1.745	-1.665	-1.753	-1.642	-1.697	2.045	2.140	2.043	2.129	2.006	2.120	2.030	2.089
#Obs	70688	59224	70688	59224	70688	59224	69083	57959	67092	56657	67092	56657	67092	56657	65265	55213
Adj R-Sq	0.0028	0.0202	0.0037	0.0218	0.0036	0.0203	0.0013	0.0196	0.0011	0.0433	0.0015	0.0439	0.0028	0.0438	0.0004	0.0427
Panel C: High IVOL fraction firms interacted with bad times																
Bad times	-0.942***	-1.197***	-1.157***	-1.531***	-1.128***	-1.314***	-0.506***	-0.698***	0.562***	0.861***	0.703***	1.073***	0.997***	1.202***	0.253***	0.493***
	(8.72)	(9.71)	(10.84)	(13.19)	(11.29)	(11.87)	(7.68)	(9.46)	(5.76)	(7.50)	(6.52)	(8.19)	(7.60)	(7.91)	(4.27)	(7.75)
HighIVOLfrac	-0.293***	0.036	-0.279**	0.059	-0.352***	-0.020	-0.375***	-0.102	0.512***	-0.303***	0.519***	-0.305***	0.621***	-0.238**	0.510***	-0.278**
	(2.62)	(0.28)	(2.52)	(0.46)	(3.21)	(0.16)	(2.98)	(0.73)	(5.03)	(2.69)	(5.17)	(2.73)	(6.19)	(2.18)	(4.37)	(2.09)
Bad times×HighIVOLfrac	-1.022*	-0.987	-1.790***	-1.814**	-0.694	-0.645	-0.043	0.113	1.004**	0.970*	1.282**	1.359**	0.170	0.611	0.336	0.219
	(1.86)	(1.57)	(2.60)	(2.33)	(1.08)	(0.87)	(0.16)	(0.35)	(2.28)	(1.88)	(2.41)	(2.15)	(0.34)	(1.04)	(1.37)	(0.86)
Good times $\hat{Y}$	-1.694	-1.734	-1.695	-1.729	-1.667	-1.713	-1.634	-1.640	2.051	2.111	2.047	2.106	2.002	2.073	2.031	2.048
#Obs	71084	59523	71084	59523	71084	59523	69365	58175	67435	56908	67435	56908	67435	56908	65526	55402
Adj R-Sq	0.0028	0.0166	0.0038	0.0182	0.0036	0.0171	0.0014	0.0152	0.0020	0.0376	0.0025	0.0385	0.0036	0.0393	0.0011	0.0360
Controls, Ind. F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 9 (Cont'd)

Variables	Dependent variable: CAR of downgrades								Dependent variable: CAR of upgrades							
	Crisis		Credit Crisis		Recession		High Uncertainty		Crisis		Credit Crisis		Recession		High Uncertainty	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel D: Small size firms interacted with bad times																
Bad times	-0.781***	-0.782***	-0.882***	-0.979***	-0.946***	-0.746***	-0.469***	-0.483***	0.430***	0.318***	0.513***	0.440***	0.746***	0.355***	0.200***	0.191***
	(8.75)	(8.10)	(9.28)	(9.58)	(10.42)	(7.07)	(8.07)	(7.93)	(4.97)	(2.97)	(5.44)	(3.64)	(8.15)	(3.23)	(3.89)	(3.48)
SmallSize	-0.897***	-0.656***	-0.826***	-0.538***	-0.893***	-0.609***	-0.932***	-0.711***	1.978***	1.376***	1.944***	1.316***	1.891***	1.245***	1.865***	1.266***
	(8.95)	(5.27)	(7.91)	(4.14)	(8.67)	(4.75)	(8.55)	(5.31)	(17.45)	(10.35)	(17.40)	(10.00)	(21.49)	(11.34)	(13.71)	(7.89)
Bad times×SmallSize	-0.790**	-0.367	-1.551***	-1.215***	-1.353***	-1.086**	-0.294	-0.068	0.685**	0.673**	1.066***	1.167***	1.916***	2.203***	0.665***	0.660***
	(2.02)	(0.82)	(4.02)	(2.87)	(3.31)	(2.41)	(1.18)	(0.23)	(2.34)	(1.98)	(3.39)	(3.19)	(2.97)	(2.83)	(3.08)	(2.59)
Good times $\hat{Y}$	-1.705	-1.780	-1.714	-1.778	-1.681	-1.782	-1.635	-1.708	2.063	2.176	2.063	2.169	2.028	2.173	2.047	2.154
#Obs	70312	58885	70312	58885	70312	58885	68610	57550	66865	56433	66865	56433	66865	56433	64972	54943
Adj R-Sq	0.0059	0.0193	0.0073	0.0209	0.0075	0.0198	0.0046	0.0189	0.0170	0.0441	0.0176	0.0449	0.0202	0.0461	0.0165	0.0440
Panel E: No options firms interacted with bad times																
Bad times	-0.734***	-0.754***	-0.915***	-1.044***	-0.897***	-0.790***	-0.290***	-0.375***	0.395***	0.406***	0.498***	0.571***	0.677***	0.498***	0.030	0.111*
	(7.57)	(7.10)	(8.83)	(9.44)	(9.00)	(6.90)	(4.52)	(5.46)	(4.12)	(3.45)	(4.74)	(4.30)	(6.66)	(4.13)	(0.54)	(1.81)
NoOptions	-0.386***	0.420***	-0.366***	0.476***	-0.396***	0.435***	-0.369***	0.367**	1.091***	-0.160	1.050***	-0.229	1.006***	-0.309**	1.022***	-0.228
	(3.63)	(3.15)	(3.29)	(3.44)	(3.55)	(3.11)	(3.22)	(2.53)	(8.15)	(0.97)	(8.05)	(1.43)	(9.96)	(2.49)	(6.61)	(1.18)
Bad times×NoOptions	-0.944*	-0.742	-2.028***	-2.120***	-0.987**	-0.716	-0.414	-0.108	0.609*	0.508	1.516***	1.699***	1.738**	1.994*	0.410	0.442
	(1.82)	(1.15)	(3.72)	(3.28)	(2.20)	(1.41)	(1.44)	(0.32)	(1.70)	(1.21)	(3.56)	(3.36)	(1.96)	(1.75)	(1.60)	(1.44)
Good times $\hat{Y}$	-1.861	-1.957	-1.860	-1.945	-1.836	-1.949	-1.862	-1.931	2.245	2.363	2.241	2.353	2.210	2.353	2.297	2.387
#Obs	63540	52969	63540	52969	63540	52969	61821	51621	60619	50964	60619	50964	60619	50964	58710	49458
Adj R-Sq	0.0027	0.0201	0.0041	0.0221	0.0035	0.0202	0.0012	0.0193	0.0046	0.0465	0.0054	0.0476	0.0068	0.0480	0.0039	0.0457
Panel F: Low coverage firms interacted with bad times																
Bad times	-0.894***	-0.926***	-1.047***	-1.176***	-0.961***	-0.848***	-0.478***	-0.547***	0.645***	0.718***	0.764***	0.909***	0.823***	0.708***	0.245***	0.357***
	(8.86)	(8.36)	(9.61)	(9.96)	(9.34)	(7.33)	(7.55)	(8.16)	(6.65)	(6.28)	(7.24)	(7.05)	(8.02)	(6.09)	(4.36)	(5.97)
LowCoverage	-0.579***	-0.081	-0.581***	-0.031	-0.452**	0.070	-0.483**	-0.208	1.089***	0.235	1.077***	0.230	1.058***	0.296	0.879***	0.063
	(2.69)	(0.32)	(2.74)	(0.12)	(2.12)	(0.27)	(1.99)	(0.74)	(5.84)	(1.00)	(5.84)	(0.99)	(5.83)	(1.27)	(4.20)	(0.24)
Bad times×LowCoverage	-0.925	-1.310	-1.195	-2.050**	-1.929**	-2.285***	-0.687	-0.366	0.446	1.282**	0.637	1.531***	0.877	1.074*	0.826**	1.138**
	(1.23)	(1.45)	(1.38)	(1.98)	(2.56)	(2.61)	(1.43)	(0.60)	(0.89)	(2.26)	(1.20)	(2.64)	(1.52)	(1.84)	(2.15)	(2.45)
Good times $\hat{Y}$	-1.621	-1.697	-1.626	-1.694	-1.609	-1.704	-1.563	-1.622	1.903	1.984	1.902	1.979	1.884	1.989	1.899	1.952
#Obs	61280	51950	61280	51950	61280	51950	59869	50831	59384	50527	59384	50527	59384	50527	57814	49264
Adj R-Sq	0.0032	0.0220	0.0037	0.0232	0.0042	0.0220	0.0020	0.0213	0.0034	0.0460	0.0038	0.0469	0.0045	0.0456	0.0024	0.0446
Controls, Ind. F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 10: Analyst attrition in bad times

Probits of analyst attrition are estimated for the recommendations sample (1993-2014). In the recommendations sample, variables are averaged within each analyst-year combination and *Disappear* equals one when the analyst makes no recommendation in I/B/E/S in the next year. The bad times indicator=1 if any month in the next year contains the relevant bad times period. *Crisis* is defined as the periods Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. *Rec Influ Prob* is the fraction of influential recommendation changes made by the analyst that year. Other control variables are as defined in relevant earlier tables. In parentheses are *z*-statistics where *, **, and *** denote statistical significance (standard errors clustered by analyst) at 10%, 5%, and 1% respectively.

Variables	Dependent variable: Recommendations sample, Disappear from I/B/E/S next year							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crisis	0.008*	0.010**						
	(1.81)	(2.18)						
Credit Crisis			0.034***	0.037***				
			(6.11)	(6.38)				
Recession					0.042***	0.034***		
					(8.67)	(6.78)		
High Uncertainty							0.026***	0.028***
							(5.20)	(5.65)
Rec Influ Prob	-0.030***	-0.020**	-0.030***	-0.020**	-0.032***	-0.023***	0.009	0.019
	(3.34)	(2.18)	(3.52)	(2.27)	(3.61)	(2.62)	(0.47)	(1.05)
Crisis×Rec Influ Prob	-0.034**	-0.034**						
	(2.01)	(1.97)						
Credit Crisis×Rec Influ Prob			-0.055***	-0.056***				
			(2.93)	(2.91)				
Recession×Rec Influ Prob					-0.037**	-0.029		
					(2.14)	(1.62)		
High Uncertainty×Rec Influ Prob							-0.058***	-0.058***
							(2.88)	(2.90)
LFR		-0.000		-0.000		-0.001		-0.000
		(0.67)		(0.73)		(0.92)		(0.75)
Relative Experience		-0.000**		-0.000**		-0.000**		-0.000**
		(2.14)		(2.27)		(2.24)		(2.43)
Log Broker Size		-0.012***		-0.012***		-0.013***		-0.012***
		(6.80)		(6.78)		(7.09)		(6.95)
Log Size		-0.003**		-0.003**		-0.004***		-0.004***
		(2.40)		(2.56)		(2.97)		(3.03)
Log BM		-0.008***		-0.007**		-0.006**		-0.009***
		(2.71)		(2.35)		(2.13)		(3.25)
Momentum		-0.024***		-0.023***		-0.025***		-0.024***
		(5.58)		(5.40)		(5.93)		(5.66)
Stock Volatility		0.895***		0.973***		0.782***		0.819***
		(7.65)		(8.20)		(6.83)		(7.14)
Predicted Prob.	0.128	0.114	0.128	0.114	0.127	0.114	0.128	0.114
#Obs	38546	35508	38546	35508	38546	35508	38546	35508

Table 11: Panel regression of analyst activity in bad times

The panel regressions estimate the effect of bad times on analyst forecast activity (1+an analyst's # of forecasts per firm-quarter) controlling for forecast, analyst, and firm characteristics. We define the starting and ending quarter of coverage using the first and last one-quarter-ahead forecast of the analyst-firm-broker combination. We then count the number of quarterly earnings forecasts per quarter for each calendar quarter. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. Analyst and forecast characteristics are the averages within the analyst-firm quarter. *Optimistic Forecast* is an indicator variable equal to one if the forecast is above the final consensus, *LFR* is the analyst's prior-year leader-follower ratio (computed from forecasts), *Star Analyst* is from the *Institutional Investor* poll, *Relative Experience* is the difference between the analyst's experience (in quarters) against the average of peers covering the same firm, *Accuracy Quintile* is the average forecast accuracy quintile of the analyst's past-year's covered firms (quintile 5=most accurate), *Days to Annc* is the number of days from the forecast to the earnings announcement date, *Multiple Forecast Day* is a dummy indicating that more than one analyst issued a forecast on that day, *Broker Size* is the number of analysts employed, *# Analysts* is 1+ the number of analysts covering the firm, *Size* is last June's market cap, *BM* is the book-to-market ratio, *Momentum* is the month *t*-12 to *t*-2 buy-and-hold return, and *Dispersion* is the dispersion of forecasts making up the final consensus. In parentheses are *t*-statistics based on standard errors clustered by industry-quarter, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E.) rely on the Fama-French 30-industry groupings.

Variables	Dependent variable: Log (1 + # forecasts per firm-quarter)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crisis	0.063***	0.067***						
	(6.34)	(10.27)						
Credit Crisis			0.094***	0.082***				
			(8.11)	(10.75)				
Recession					0.069***	0.069***		
					(8.21)	(11.74)		
High Uncertainty							0.048***	0.030***
							(7.92)	(7.16)
Optimistic Forecast		0.011***		0.011***		0.011***		0.011***
		(8.82)		(8.78)		(8.91)		(8.74)
LFR		0.002***		0.002***		0.002***		0.003***
		(11.27)		(11.01)		(11.11)		(12.41)
Star Analyst		-0.028***		-0.027***		-0.029***		-0.028***
		(13.72)		(13.47)		(13.98)		(13.25)
Relative Experience		0.000***		0.000***		0.000***		0.000***
		(5.08)		(5.01)		(5.15)		(5.78)
Accuracy Quintile		0.028***		0.028***		0.029***		0.028***
		(25.97)		(25.95)		(26.23)		(25.69)
Log Days to Annc		-0.019***		-0.020***		-0.019***		-0.020***
		(9.45)		(9.63)		(9.12)		(9.70)
Mutiple Forecast Day		-0.038***		-0.038***		-0.038***		-0.038***
		(21.02)		(21.35)		(21.25)		(20.30)
Log Broker Size		0.037***		0.037***		0.037***		0.037***
		(39.39)		(39.31)		(39.23)		(38.39)
Log # Analysts		0.261***		0.260***		0.259***		0.258***
		(61.69)		(61.77)		(62.16)		(58.63)
Log Size		-0.039***		-0.038***		-0.038***		-0.039***
		(32.33)		(32.31)		(32.44)		(31.81)
Log BM		0.008***		0.008***		0.009***		0.005***
		(5.45)		(5.23)		(6.68)		(3.15)
Momentum		-0.004*		-0.003		-0.001		-0.007***
		(1.81)		(1.57)		(0.53)		(3.08)
Dispersion		0.018***		0.018***		0.017***		0.019***
		(12.72)		(12.72)		(12.75)		(12.49)
Intercept	0.642***	0.497***	0.641***	0.500***	0.639***	0.492***	0.619***	0.501***
	(194.02)	(28.80)	(198.10)	(29.08)	(189.89)	(28.46)	(157.11)	(28.86)
Good times $\hat{Y}$	0.642	0.680	0.641	0.680	0.639	0.678	0.619	0.667
Observations	1916213	1250891	1916213	1250891	1916213	1250891	1850104	1201285
Adj R-Sq	0.0021	0.1001	0.0037	0.1006	0.0031	0.1007	0.0035	0.0981
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes

Table 12: Analyst report length in bad times

The list of all U.S. analyst reports issued by one large U.S. broker from 1994-2014 is downloaded from Thomson ONE (up to Sep 2011) and Thomson Eikon (from Oct 2011 onwards) and the number of pages in each report is regressed against a bad times dummy and control variables. Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. Beta is the stock's market beta based on three years of past monthly returns. *Size Quintile* is based on the stock's prior June's market cap using NYSE breakpoints. *Momentum Quintile* is based on the month *t*-12 to *t*-2 buy-and-hold stock return sorted as at month *t*-1. *BM Quintile* is based on the firm's book-to-market ratio. *Stock Volatility* is the month *t*-1 volatility of daily stock returns. *Earnings Annc Dummy* (*Guidance Dummy*) indicates that the analyst report is issued within three trading days of an earnings announcement (earnings guidance). Earnings announcement dates are from Compustat and guidance dates are from First Call Guidelines and I/B/E/S Guidance. In parentheses are *t*-statistics based on standard errors clustered by the date of the analyst report, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E.) rely on the Fama-French 30-industry groupings.

Variables	Dependent variable: Number of pages in an analyst report							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crisis	1.336***	1.552***						
	(8.84)	(9.99)						
Credit Crisis			1.916***	1.991***				
			(13.21)	(12.34)				
Recession					-0.928***	-0.098		
					(5.80)	(0.62)		
High Uncertainty							1.429***	1.356***
							(13.61)	(14.35)
Beta		0.386***		0.379***		0.389***		0.396***
		(10.41)		(10.24)		(10.37)		(10.35)
Size Quintile		0.091***		0.094***		0.086***		0.100***
		(3.68)		(3.79)		(3.43)		(3.94)
Momentum Quintile		-0.172***		-0.171***		-0.150***		-0.152***
		(7.92)		(7.89)		(6.81)		(6.86)
BM Quintile		0.072***		0.071***		0.077***		0.093***
		(3.14)		(3.08)		(3.34)		(3.94)
Stock Volatility		-68.509***		-68.194***		-66.087***		-66.818***
		(26.86)		(26.96)		(24.67)		(26.31)
Earnings Annc Dummy		-0.068		-0.101		-0.023		0.026
		(0.77)		(1.13)		(0.26)		(0.29)
Guidance Dummy		0.644***		0.636***		0.644***		0.501***
		(8.97)		(8.89)		(8.87)		(6.93)
Intercept	10.237***	11.305***	10.215***	11.296***	10.433***	11.292***	9.678***	10.626***
	(178.98)	(66.07)	(179.86)	(66.18)	(182.87)	(65.83)	(122.69)	(58.01)
Good times $\hat{Y}$	10.237	10.220	10.215	10.208	10.433	10.345	9.678	9.706
#Obs	85525	84707	85525	84707	85525	84707	81583	80806
Adj R-Sq	0.0024	0.0552	0.0043	0.0566	0.0015	0.0520	0.0097	0.0624
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes

Table 13: Response of peer firms to recommendation changes in bad times

The panel regressions estimate the effect of recommendation changes on peer firms' two-day CARs (in percent) during bad times, controlling for recommendation, firm, and analyst characteristics. Peer firms are firms in the same industry which did not experience a recommendation by the same analyst that day but for which the analyst has issued a recommendation on in the last one year. The CAR benchmark is a characteristics-matched DGTW portfolio for the peer firm. The sample is from 1993-2014. Recommendation changes are the current rating minus the individual analyst's prior outstanding rating (initiations and reiterations are excluded). Recommendation changes made around earnings announcement and guidance days, and on multiple-recommendation days are excluded following Loh and Stulz (2011). Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index. Control variables are as defined in Table 3. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects (F.E) rely on the Fama-French 30-industry groupings.

Variables	Dependent variable: CAR of peer firms of downgrades								Dependent variable: CAR of peer firms of upgrades							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Crisis	-0.104*	-0.105*							-0.021	-0.042						
	(1.78)	(1.71)							(0.36)	(0.73)						
Credit Crisis			-0.131**	-0.153**							-0.046	-0.077				
			(2.09)	(2.32)							(0.67)	(1.20)				
Recession					-0.163**	-0.196**							0.020	-0.052		
					(2.44)	(2.54)							(0.31)	(0.84)		
High Uncertainty							-0.035	-0.019							-0.034	-0.028
							(0.96)	(0.47)							(1.10)	(0.92)
LFR		0.001		0.001		0.001		0.000		0.007*		0.007*		0.007*		0.006
		(0.19)		(0.19)		(0.21)		(0.07)		(1.69)		(1.69)		(1.70)		(1.57)
Star Analyst		-0.040		-0.040		-0.040		-0.040		0.079**		0.078**		0.079**		0.076**
		(0.86)		(0.86)		(0.87)		(0.84)		(2.09)		(2.09)		(2.10)		(1.97)
Relative Experience		-0.001		-0.001		-0.001		-0.001		-0.000		-0.000		-0.000		0.000
		(0.78)		(0.76)		(0.72)		(1.08)		(0.08)		(0.07)		(0.08)		(0.15)
Accuracy Quintile		0.005		0.005		0.005		0.001		-0.014		-0.013		-0.014		-0.014
		(0.13)		(0.13)		(0.12)		(0.02)		(0.38)		(0.36)		(0.38)		(0.39)
Log Broker Size		-0.041***		-0.042***		-0.040**		-0.041**		0.024*		0.024*		0.025*		0.029**
		(2.61)		(2.69)		(2.56)		(2.56)		(1.80)		(1.74)		(1.83)		(2.08)
Log # Analysts		-0.040		-0.042		-0.042		-0.030		0.063**		0.062**		0.064**		0.065**
		(1.46)		(1.52)		(1.53)		(1.10)		(2.50)		(2.42)		(2.51)		(2.53)
Log Size		0.000		0.002		0.005		-0.004		-0.000		0.001		0.000		-0.002
		(0.04)		(0.19)		(0.41)		(0.37)		(0.04)		(0.08)		(0.02)		(0.19)
Log BM		-0.006		-0.005		-0.006		-0.009		0.017		0.017		0.017		0.017
		(0.34)		(0.28)		(0.35)		(0.48)		(1.04)		(1.06)		(1.05)		(1.05)
Momentum		-0.040*		-0.041*		-0.049**		-0.036*		-0.042**		-0.043**		-0.044**		-0.041**
		(1.84)		(1.88)		(2.25)		(1.68)		(2.10)		(2.14)		(2.18)		(2.01)
Stock Volatility		-1.190		-1.124		-0.590		-1.634		3.681***		3.761***		3.808***		3.488***
		(1.02)		(0.96)		(0.47)		(1.41)		(3.53)		(3.61)		(3.68)		(3.18)
Intercept	-0.054***	0.185	-0.053***	0.169	-0.045***	0.122	-0.059***	0.247	0.110***	-0.171	0.112***	-0.183	0.105***	-0.185	0.122***	-0.155
	(3.37)	(0.91)	(3.34)	(0.84)	(3.04)	(0.60)	(3.68)	(1.19)	(8.74)	(1.08)	(8.92)	(1.15)	(8.50)	(1.17)	(8.20)	(0.96)
Good times $\hat{Y}$	-0.054	-0.066	-0.053	-0.063	-0.045	-0.053	-0.059	-0.077	0.110	0.120	0.112	0.123	0.105	0.121	0.122	0.127
#Obs	68725	58670	68725	58670	68725	58670	67111	57357	65482	56238	65482	56238	65482	56238	63670	54765
Adj R-Sq	0.0002	0.0017	0.0002	0.0019	0.0005	0.0022	0.0000	0.0017	-0.0000	0.0020	0.0000	0.0021	-0.0000	0.0020	0.0000	0.0020
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Figure 1: Impact of recommendation changes in bad times

The figure plots the mean two-day CAR and the influential probability of recommendation changes (in percent). The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1993-2014. A recommendation change is defined as an analyst's current rating minus her prior outstanding rating (initiations and reiterations are excluded). Changes made around earnings announcement and guidance days, and on multiple-recommendation days are excluded. Influential changes are those whose two-day CARs are in the same direction as the recommendation change and is 1.96 times larger than expected based on the prior three-month idiosyncratic volatility of the stock (following Loh and Stulz (2011)). Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period 1983-2014) of the Baker et al. (2016) uncertainty index.

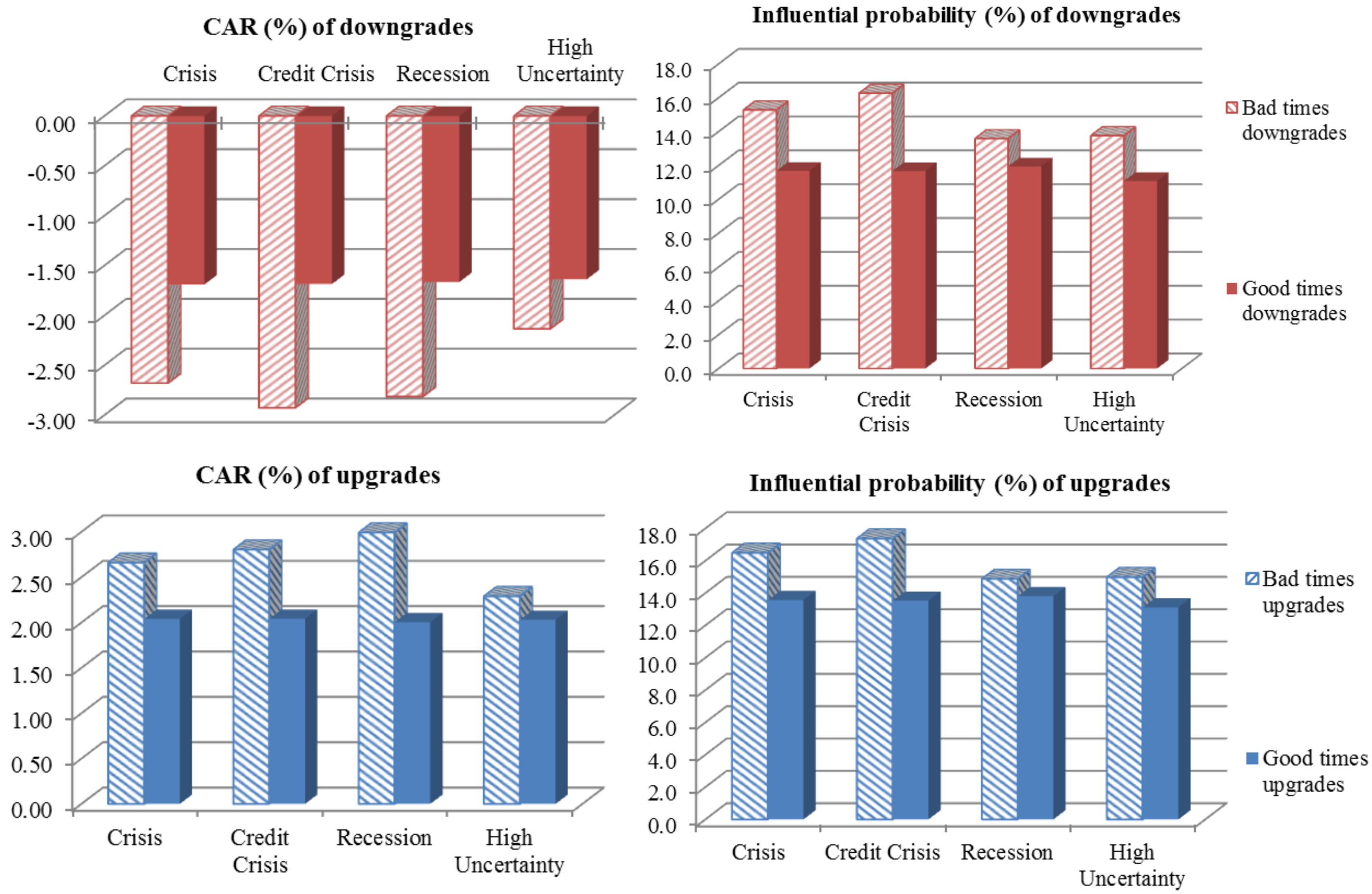

Figure 2: Impact of earnings forecast revisions in bad times

The figure plots the mean two-day CAR and the influential probability of earnings forecast revisions (in percent). The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1983-2014. A forecast revision is the analyst's current one-quarter-ahead earnings forecast minus her prior outstanding forecast (i.e., initiations are excluded) scaled by price. Revisions made around earnings announcement and guidance days, and on multiple-forecast days are excluded. Influential revisions are those whose two-day CARs are in the same direction as the revision and is 1.96 times larger than expected based on the prior three-month idiosyncratic volatility of the stock (following Loh and Stulz (2011)). Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *High Uncertainty* represents the highest tercile (over the period from 1983-2014) of the Baker et al. (2016) uncertainty index.