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Is Sell-Side Research More Valuable in Bad Times?

ROGER K. LOH and RENÉ M. STULZ*

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 whether 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, and analyst reports are more frequent and longer. The increased impact of analysts is also more pronounced for harder-to-value firms. These results are consistent with analysts working harder and investors relying more on analysts in bad times.

WHILE THERE IS A LARGE LITERATURE ON sell-side analysts' role as information intermediaries, this literature mostly ignores the question 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

*Roger K. Loh is at Lee Kong Chian School of Business at Singapore Management University. René M. Stulz is at Fisher College of Business at Ohio State University, NBER, and ECGI. We thank the Editor, Ken Singleton, an anonymous Associate Editor, and two anonymous referees for valuable comments and suggestions. We also thank Marcin Kacperczyk, Oguzhan Karakas, Jeff Kubik, Massimo Massa, Roni Michaely, Jay Ritter, Paola Sapienza, Siew Hong Teoh, Stijin Van Nieuwerburgh, Mitch Warachka, Kent Womack, Frank Yu, and Jialin Yu; participants at the Bank of America Merrill Lynch Asia Quant 2016 Conference, AFA 2014 Philadelphia meetings, SMU-SUFE Summer 2013 Institute of Finance Conference, and at a seminar at the University of Zurich for helpful comments. Brian Baugh, Andrei Gonçalves, David Hauw, Haoyuan Li, and Shuyu Xue provided excellent research assistance. Disclosures: Roger received financial support from the Sing Lun Fellowship and the Sim Kee Boon Institute for Financial Economics for data, research assistance, and travel costs related to the project. René received no funding related to this project. Over the last three years, he received consulting income from major banks that employ analysts, but none of that income was related in any way to issues concerning analysts and he had no discussion with any of these institutions concerning analysts over that period. He is not involved in any consulting involving analyst issues and does not anticipate such consulting in the foreseeable future.

[1] For example, Womack (1996), Barber et al. (2001), and Kecskés, Michaely, and Womack (2017) 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 lead to a large noticeable change in the firm's stock price and that these recommendations can impact the firm's information environment. Bradley et al. (2014) report that, compared to earnings announcements or company earnings guidance, recommendations are more likely to cause jumps in intraday stock prices. Others find that analyst coverage reduces information asymmetry and improves visibility (Kelly and Ljungqvist (2012)), disciplines credit rating agencies (Fong et al. (2014)), and affects corporate policies (Derrien and Kecskés (2013)).

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recessions and crises, there is greater variation in outcomes across firms and over time (see, for instance, Bloom (2009)). To the extent that the role of analysts is to make sense of firms amidst increased macro uncertainty, they should be more important and hence should work harder in bad times. Increased uncertainty, however, may make it more difficult for analysts to perform their job. Further, the decline in trading volume and hence broker profits in bad times may reduce performance rewards, leading to a decrease in analyst motivation. It is therefore 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 on analysts more in bad times.

We conduct our investigation using a sample of Institutional Brokers' Estimate System (I/B/E/S) Detail earnings forecasts from 1983 to 2014 and recommendations from 1993 to 2014. We define bad times in several ways. The most obvious approach is to use prominent crises that have occurred during the sample period, such as the October 1987 crash, the Long-Term Capital Management (LTCM) crisis of 1998, and the credit crisis of 2007 to 2009. We also define bad times as recessions marked by the National Bureau of Economic Research (NBER) and as high uncertainty periods in the Baker, Bloom, and Davis (2016) policy uncertainty index (from www.policyuncertainty.com). Our measure of the value of analyst output is the price impact, which captures the extent to which analyst signals affect investors' assessment of firm value and hence is a measure of analysts' contribution to firms' information environment.

Using average two-day abnormal returns to stock recommendation changes, we find that the stock-price impact of analysts is greater during bad times for both downgrades and upgrades. Further, using the definition of influential recommendations as defined by Loh and Stulz (2011), who classify recommendation changes as influential if the stock-price reaction is statistically significant, we find 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 controlling 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.

Notice that we focus on macro instead of firm-specific bad times. This is because macro bad times are economically important and are more likely to be exogenous to analysts. Prior studies such as Frankel, Kothari, and Weber (2006) and Loh and Stulz (2011) show that analysts are more informative when firm-level uncertainty is higher. While we already control for firm-level uncertainty, to ensure that it is macro uncertainty that drives our results, we conduct two sets of tests. First, 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 strongest 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 (2017) find that earnings announcement reactions are larger in recessions). Adapting the methodology in Frankel, Kothari, and Weber (2006), we regress a stock's daily absolute returns on a comprehensive set of dummy variables that capture important firm news events, in particular, recommendation changes, reiterations, earnings announcements, earnings guidance, dividend announcements, and insider trades. Interacting these news dummies with an indicator for bad times, we find that not all firm news events are associated with a greater impact in bad times. Importantly, the market continues to react more to recommendation changes (and reiterations) in bad times after taking into account all other news events and their interactions with bad times. Our finding that analysts' stock-price impact is greater in bad times is therefore novel and robust.

We next find that analysts' absolute forecast errors increase during bad times, which raises the question of how their output can have more of an impact on prices during these times. We show, however, that traditional measures of analyst precision are not appropriate for comparing precision across good and bad times. Rather, a relevant measure of precision is one that takes into account the underlying uncertainty. In a simple Bayesian model, the extent to which a new signal changes investors' priors depends on both the weight that investors put on the new signal and the weight that they put on their prior (e.g., 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 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 even 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. Thus, we can think of a relevant measure of forecast error as a measure of forecast error per unit of underlying 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 that we use to define influential recommendation changes). Importantly, however, the finding that analyst forecast precision increases when measured against the underlying uncertainty does not necessarily mean that analysts automatically become more useful to investors. Kacperczyk and Seru (2007) show that the extent to which investors rely on public information depends on the precision of their private information. Thus, if analysts' signals are public information, investors will rely less on analysts in bad times if investors themselves have better private information.

We develop and test five possible, nonmutually exclusive, explanations for why analysts might have more of an impact in bad times. First, we examine an analyst reliance hypothesis that builds on Kacperczyk and Seru (2007). This hypothesis predicts that investors rely on analyst information more during bad times. During bad times, investors have to understand how the increase in macro uncertainty affects firm prospects. Because of the increase in macro uncertainty, possible outcomes are more extreme, which can have more of an impact on firms than during good times. We would therefore expect greater demand for analyst output that helps investors sort out the potential impact of macro shocks during bad times compared to good times. If investors already know much about a stock however, analysts will have less to contribute. Consequently, when analyst output is more valuable, it will be particularly more valuable for more opaque stocks. The cross-sectional implication 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, thus, the value of analyst output increases relatively more for stocks of more opaque firms in bad times. We define opaque stocks as stocks with no company guidance, low institutional ownership, high idiosyncratic risk, small size, no options traded, or low coverage. Consistent with this argument, we find that the increased impact of analysts in bad times is indeed higher for more opaque stocks.

The analyst reliance hypothesis does not assume that analysts change what they do in bad times. Rather, it assumes that analysts become more important for investors because investors face challenges that they do not face in good times and analysts help them address these challenges. However, it is plausible that analysts change what they do during bad times. The next three hypotheses pertain to possible changes in analyst output in bad times.

Our second possible explanation for the increased impact of analysts in bad times is that analysts work harder in bad times due to career concerns. Glode (2011) argues that the better performance of mutual funds in bad times is due to investment managers working harder to produce better payoffs because investors have higher marginal utility in bad times. If the increase in uncertainty in bad times leads investors to value analyst signals more, analysts might also work harder to produce better signals in bad times.[2] If, however, rewards for better analyst performance are limited in bad times as a result of the reduction in the profits of analysts' employers and in turn in analysts' bonus pools, analysts may work less hard in bad times. Thus, there is no clear empirical prediction as to whether analysts work harder in bad times. We find that the stock-volatility-adjusted precision of analysts' earnings forecasts increases during bad times. This implies that analysts work harder to produce better forecasts in bad times. Consistent with this view, we find that analysts revise their earnings forecasts more frequently and write longer reports in bad times. Further, we find that analysts are more likely to leave the I/B/E/S database during bad times—this attrition risk could increase analysts' incentives to work harder during bad times. Since analysts produce better output in industries with more analyst competition (Merkley, Michaely, and Pacelli (2017)), we also expect analysts to work harder in industries with more analyst competition in bad times, with their impact increasing more in such industries. We find strong supportive results in the case of downgrades.

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

The third possible explanation for the increased impact of analysts in bad times considers 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 whether analysts also produce more sector/macro information in bad times that is common across firms when such information is more valued by investors. To address this question, we examine whether a recommendation revision on a single firm impacts peer firms. Such a spillover effect might occur if part of the information in the revision reflects the analyst's forecast of the common factor. We find some evidence that the spillover effect of downgrades on peer firms is larger in bad times than in good times; there is no difference for upgrades. Hence, part of the increased influence of analysts in bad times, particularly with respect to downgrades, might come from an increased effort to collect and distribute 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 conflicts from investment banking are less important in bad times because of lower deal flow, analyst output might become less distorted and, in turn, more valuable. To test this prediction, we examine whether forecast bias (i.e., the signed forecast error) is different in bad times from in good 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 or more optimistic in bad times. We also explore whether the increased impact of analysts in bad times is related to the type of broker the analyst works for. We find that the increased influence of analysts in bad times generally holds for both independent brokers and brokers with investment banking business. Overall, we do not find evidence consistent with the conflicts of interest hypothesis.

Our fifth and final potential explanation for the increased impact of analysts in bad times is that it has nothing to do with analyst output per se but rather is a result of overreaction by investors. Overreaction could be more likely in bad times due to lower liquidity, so that trading on analyst revisions causes temporary price pressure 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 in good times. To examine this possibility, we investigate whether the 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 cannot explain 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 (2016, p. 586) derive such a result for skilled fund managers, that is, managers who have access to valuable signals. They argue 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, Van Nieuwerburgh, and Veldkamp (2014) find empirical support for their prediction that skilled managers are better at market timing in bad times and at stock selection in good times.

A few prior papers examine how crises affect analyst output. However, none of them test the hypotheses that we focus on here or are as comprehensive in showing that analysts are more influential in bad times and 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. Kretzmann, Maaz, and Pucker (2015) find that recommendations have a larger impact in recessions than in boom periods but buy recommendations do not predict future stock returns in recessions. Amiram et al. (2017) examine analyst forecast timeliness during periods of high market uncertainty and find that analysts are less timely and underreact to news in these periods. However, investors still respond to forecasts in these periods even though these forecasts are more inaccurate. Hope and Kang (2005) also find that forecast errors are higher in bad times. While most of these papers conclude that investors incorrectly pay attention to analysts who appear more inaccurate in bad times, we show that, controlling for the underlying level of uncertainty, analysts are actually more precise in bad times and investors correctly react more strongly to analyst revisions in these periods.

The rest of the study is organized as follows. Section I summarizes the hypotheses that we test. Section II describes our sample and reports our main result, that analysts' impact is more pronounced in bad times. Section III reports results of several robustness tests. Section IV examines how forecast precision differs in good and bad times using different measures to scale forecast errors. Section V investigates potential explanations for the greater impact of analyst output in bad times. Section VI concludes.

I. Hypotheses

We examine whether the stock-price impact of analyst revisions differs across good and bad times. Below, we develop three hypotheses predicting why analysts might have *less* of an impact in bad times, and five hypotheses predicting why analysts might have *more* of an impact in bad times.

A. Why Analysts Might Have Less of an Impact in Bad Times

A.1. Difficult Environment Hypothesis

In bad times, the forecasting environment is more difficult, which makes it harder for analysts to make accurate forecasts. Consistent with this view, Jacob

(1997), Chopra (1998), and Hope and Kang (2005) find that earnings forecasts are less accurate during bad times. This hypothesis thus predicts that analyst revisions have a smaller stock-price impact in bad times due to greater forecast inaccuracy.

A.2. Shirking Hypothesis

Investment banking deal flow, equity market capitalization, and trading volume shrink in bad times, which can reduce brokerage business profits and in turn the bonus pool for analysts. Facing fewer rewards for good performance, analysts might be less motivated to provide quality research in bad times. Moreover, the greater amount of noise in the information environment can provide cover for poorer-performing analysts, making their lack of effort or skill less noticeable. This hypothesis thus predicts less accurate forecasts and less impactful revisions in bad times due to increased incentives to shirk. This argument is similar to that in Bertrand and Mullainathan (2001), who describe the difficulty that investors have in evaluating manager quality when firm performance is reduced by poor macroeconomic conditions.

A.3. Inattention Hypothesis

Hirshleifer, Lim, and Teoh (2009) show that when a lot of news hits the market, investors tend to react less to firm news events. In bad times, information uncertainty increases, and hence there is a lot more news to digest. This hypothesis predicts that the stock-price impact of analyst revisions is lower in bad times due to distracted investors underreacting to analyst revisions.

B. Why Analysts Might Have More of an Impact in Bad Times

Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) show that information about payoffs with a given precision is more valuable in bad times because of higher uncertainty. Analyst revisions are signals about firm prospects that 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 priors, 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 (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 in analyst signals relative to prior uncertainty can decrease because (1) analysts take steps to ensure that the noise in their signals increases less than the uncertainty in investors' priors, or (2) the uncertainty in investors' priors increases more than the noise in analyst signals as investors' alternative sources of information, such as private information, dry up in bad times. The latter situation forms the basis of our first hypothesis below. The former situation then forms the basis for our next two hypotheses.

B.1. Analyst Reliance Hypothesis

Investors have multiple sources of information. For opaque firms, the availability of public information may be limited, but for other firms, investors have access to many public information signals that compete with the information provided by analysts. It follows that when uncertainty increases due to macro shocks, investor demand for analyst output increases more for more opaque firms. However, for analysts to be more valuable to investors in bad times, investors' other sources of information cannot become more precise in bad times compared to analyst information. Kacperczyk and Seru (2007) show that if investors' private information becomes noisier, or if their ability to process public information accurately becomes noisier, investors will rely more on public information such as analyst signals. Bad times can be a regime change, where the advantage of some investors at processing data is 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.

In our context, the Kacperczyk and Seru (2007) model suggests that the impact of analyst signals on investors' priors is greater in bad times, when investors' private information or information processing ability becomes noisier, which 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. Analyst output thus becomes more valuable because competing sources of information become less valuable to investors precisely when macro shocks can have more of an impact on firm prospects. The cross-sectional prediction is that the increase in uncertainty about the effect of macro shocks for firm prospects is most pronounced for more opaque firms.

B.2. Analyst Effort Hypothesis

Our next hypothesis predicts that analysts work harder in bad times to produce signals that are of better quality and hence have a greater impact. Glode (2011) finds that fund managers perform better in bad times to satisfy investors' higher marginal utility in those 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 work for analysts through attrition risk. This hypothesis also predicts a higher frequency of reports and more accurate earnings forecasts after accounting for the increase in uncertainty in bad times. Further, this hypothesis predicts analyst effort to increase more in industries with more analyst competition, as more analyst competition in an industry leads to better analyst output (Merkley, Michaely, and Pacelli (2017)).

B.3. Analyst Expertise Hypothesis

A related hypothesis predicts that if analysts have expertise in helping investors understand the implications of bad times, they can employ this expertise only during bad times. For example, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) show that fund managers have market-timing skills during bad times but stock-picking skills 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 analysts' revisions might have more of an impact in bad times as they contain more industry information during these times, consistent with the finding that analysts have expertise to predict industry returns (e.g., Howe, Unlu, and Yan (2009), Kadan et al. (2012)).

B.4. Conflicts of Interest Hypothesis

In bad times, analysts in brokerages with investment banking divisions are likely to face less deal-related pressure to bias their research. To the extent that investment banking conflicts lead analysts to display an optimistic bias in their research (see, for example, Michaely and Womack (1999)), this bias might be lower in bad times when investment banking revenue drops. As a result, research might be of higher quality and hence have more of an impact in bad times due to reduced conflicts of interest.

B.5. Overreaction Hypothesis

Prior studies show evidence that in bad times, investors might react more strongly to news, such as earnings announcements (see, for example, Schmalz and Zhuk (2017)). Motivated by this result, our last hypothesis predicts that analyst revisions have more of an impact in bad times due to investor overreaction, which we capture by looking at the future drift of stock prices. Overreaction may be more likely to occur in bad times because, during those times, arbitrageurs are more constrained and cannot counteract inefficient reactions to revisions.

II. Main Analysis

A. Bad Times Measures

We employ four proxies for bad times. The first two focus on prominent financial crises: *Crisis* equals one for the periods September to November 1987 (1987 crisis), August to December 1998 (LTCM crisis), and July 2007 to March 2009 (credit crisis), and *Credit Crisis* equals one for the credit crisis period, since this especially sharp and prolonged crisis warrants separate investigation. Our third proxy for bad times, *Recession*, equals one for NBER-defined recessions, specifically July 1990 to March 1991, March to November 2001, and December 2007 to June 2009. Our fourth proxy for bad times is the Baker, Bloom, and Davis (2016) policy uncertainty index. *High Uncertainty* equals one when the U.S. historical index is in the top tercile of available values (August 1983 to

February 2014). This measure classifies more months as bad times compared to the three prior measures—7.7%, 5.6%, 9.8%, and 33.4% of the sample months are classified as bad times using *Crisis*, *Credit Crisis*, *Recession*, and *High Uncertainty*, respectively.

B. Earnings Forecast and Recommendation Data

We obtain data from Thomson Financial's I/B/E/S U.S. Detail file.[3] Specifically, one quarter-ahead earnings forecasts issued from August 1983 to December 2014 and actual earnings (announced from September 1983 to April 2015) are taken from I/B/E/S. We use the unadjusted file to mitigate the rounding problem in I/B/E/S (Diether, Malloy, and Scherbina (2002)). Using the I/B/E/S split-adjustment factors, we adjust the unadjusted forecast to be on the same per-share basis as the unadjusted actual earnings. Financial firms (group 29 of the Fama and French (1997) 30-industry classifications) are excluded from our main analysis (but included in robustness tests) because many crises began in the financial sector, making it hard to separate macro from industry bad times.

We obtain individual analyst stock recommendations from the I/B/E/S Detail file for the period 1993 to 2014. We define upgrades and downgrades using an 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 according to 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, Malloy, and Marston (2009)). We exclude anonymous analysts, observations with no outstanding prior rating from the same analyst (i.e., analyst initiations and reinitiations are excluded), and recommendation changes for which the lagged stock price is less than one dollar. We also remove revisions that occur on firm-news days (following Loh and Stulz (2011)) because we do not want to consider ratings 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 the I/B/E/S Guidance file thereafter), as well as days with multiple analysts issuing a recommendation for the firm.[4] We employ similar filters when we examine

[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. In response to their paper, Thomson fixed the alterations in the recommendation history file as of February 12, 2007. The data set we use is dated December 17, 2015 and hence reflects these corrections. However, some large brokers are still missing from the current I/B/E/S files. To reinstate the missing years for these brokers, we use Capital IQ estimates to extract recommendations and earnings forecasts issued by the missing brokers and splice the collected data into our I/B/E/S sample. Spliced observations make up about 1.05% of the observations in the forecasts sample and 0.45% of the observations in the recommendations sample.

[4] One concern with these filters is that if analysts piggyback on firm news more in bad times, a larger fraction of poor-quality recommendations might be removed in bad times, making the remaining sample of recommendations appear "better" in bad times than in good times. We find, however, that analysts piggyback more in good times. For example in non-*Crisis* periods, 37.7%

the stock-price impact of earnings forecast revisions. Stock returns come from CRSP.

C. Evidence of Large Increases in Uncertainty during Bad Times

In this section, we examine the variance of investors' priors in 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 I, we report daily estimates of the VIX from Chicago Board Options Exchange (CBOE) as a proxy for ex ante uncertainty. These data start in 1990 and overlap most of our 1983 to 2014 sample period. The typical daily VIX (quoted as an annualized standard deviation) in *Crisis* periods is 31.339, while in good times it is 18.865. Therefore, the VIX in *Crisis* periods is more than 60% greater than in non-*Crisis* periods, with this difference being statistically significant. The increase in the VIX is similar for *Credit Crisis* and *Recession* periods. The increase in the VIX is smaller for the *High Uncertainty* periods although it is still sizable. Hence, using all of our measures of bad times, ex ante market volatility increases sharply in bad times, showing that investors' priors become less precise in bad times.

In Panel B of Table I, we report the annualized implied volatilities of stocks five trading days before they are subject to a recommendation change. The implied volatility data come 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* measure of bad times, we see that for downgrades the option-implied volatility is 61.820% in bad times and 47.319% in good times, with the difference of 13.501% being statistically significant. For upgrades, the difference in implied volatilities is very similar. We find similar results using other measures of bad times. Hence, using all of our measures of bad times, we find that ex ante volatility at the firm level is higher just before recommendation changes in bad times compared to good times.

D. Stock-Price Impact of Recommendation Changes

We now address the question of whether the stock-price impact of analyst output is greater in bad times. We take the view that if analyst output moves stock prices, it changes investors' priors and hence is valuable to investors. We first examine 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 analyst impact (e.g., Boni and

(30.3%) of downgrades (upgrades) are removed by the filters compared to 33.8% (27.0%) in *Crisis* periods. We also examine whether recommendation changes that occur on firm-news days are more impactful in bad times. We find strong evidence for downgrades (all four measures of bad times) but mixed evidence for upgrades (only two of four measures). Because it is hard to determine 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.

Table I

Change in Uncertainty during Bad Times

Panel A reports the average daily VIX over bad times from 1990 to 2014. Panel B reports the average annualized implied volatility (*Implvol*, from 1996 to 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 the analyst's current rating minus their prior outstanding rating (initiations and reiterations are excluded); changes made around earnings announcement and guidance days, and changes on multiple-recommendation days, are excluded. Bad times measures are as follows. *Crisis*: September to November 1987 (1987 crisis), August to December 1998 (LTCM), and July 2007 to March 2009 (*Credit Crisis*). *Recession* (NBER recessions): July 1990 to March 1991, March to November 2001, and December 2007 to June 2009. *High Uncertainty* represents the highest tercile (over the period 1983 to 2014) of the Baker, Bloom, and Davis (2016) uncertainty index. t-statistics (in absolute values and based on standard errors clustered by calendar day) are in parentheses. *, **, and *** denote statistical significance of the differences in VIX/implied volatility at the 10%, 5%, and 1% levels, respectively. Panel C reports descriptive statistics for 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 whether 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 covered firms over the past year (quintile 5 = most accurate), *Broker Size* is the number of analysts employed, # *Analysts* is the number of analysts covering the firm, *Size* is the firm's market cap in the prior June, *BM* is the book-to-market ratio, *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

		Average Daily VIX (%)		
Bad Times Measure	Variable	Bad Times	Good Times	Difference
Crisis	VIX	31.339	18.865	12.474***
	#Obs	547	5,752	(21.56)
Credit Crisis	VIX	31.261	19.096	12.165***
	#Obs	441	5,858	(17.39)
Recession	VIX	29.899	18.558	11.341***
	#Obs	772	5,527	(26.50)
High Uncertainty	VIX	24.172	17.870	6.302***
	#Obs	2205	3,882	(27.01)

Panel B: Implied Volatility before Recommendation Changes

			Option-Implied Volatility in Annualized%		
Bad Times Measure	Rec-Change	Variable	Bad Times	Good Times	Difference
Crisis	Downgrade	Implvol	60.820	47.319	13.501***
		#Obs	8,481	44,841	(13.62)
	Upgrade	Implvol	57.949	45.923	12.027***
		#Obs	7,796	44,660	(12.73)
Credit Crisis	Downgrade	Implvol	61.264	47.671	13.593***
		#Obs	7,042	46,280	(11.71)
	Upgrade	Implvol	58.307	46.176	12.130***
		#Obs	6,633	45,823	(11.23)

(*Continued*)

Table I—*Continued*

Panel B: Implied Volatility before Recommendation Changes

			Option-Implied Volatility in Annualized%		
Bad Times Measure	Rec-Change	Variable	Bad Times	Good Times	Difference
Recession	Downgrade	Implvol	67.104	46.083	21.021***
		#Obs	8,581	44,741	(24.37)
	Upgrade	Implvol	63.834	45.076	18.758***
		#Obs	7,367	45,089	(23.46)
High Uncertainty	Downgrade	Implvol	52.392	47.783	4.609***
		#Obs	22,687	28,983	(7.58)
	Upgrade	Implvol	50.112	46.624	3.488***
		#Obs	21,302	29,295	(6.49)

Panel C: Descriptive Statistics for the Recommendation Change Sample

	Full Sample			Bad Times: Crisis Periods			Good Times: Non-Crisis Periods		
Variable	Mean	Stdev	#Obs	Mean	Stdev	#Obs	Mean	Stdev	#Obs
				Downgrade 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	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 ($m)	7,940	25,124	71,070	9,372	27,443	9,648	7,716	24,733	61,422
BM	0.512	0.636	71,070	0.454	0.436	9,648	0.521	0.661	61,422
Momentum	0.132	0.671	71,070	−0.048	0.530	9,648	0.160	0.686	61,422
Stock Volatility	0.031	0.022	71,069	0.041	0.026	9,648	0.029	0.020	61,421
				Upgrade Sample					
CAR(%)	2.123	6.095	67,425	2.658	6.768	8,688	2.044	5.985	58,737
LFR	2.379	2.771	63,493	2.310	2.859	8,203	2.389	2.757	55,290
Star Analyst	0.139	0.346	67,425	0.116	0.320	8,688	0.143	0.350	58,737
Experience (#qtrs)	27.89	20.78	67,425	28.57	20.17	8,688	27.79	20.87	58,737
Accuracy Quintile	2.981	0.417	60,759	2.989	0.390	7,838	2.980	0.420	52,921
Broker Size	51.86	48.96	67,425	50.57	53.28	8,688	52.05	48.29	58,737
# Analysts Per Firm	10.083	6.344	67,425	9.640	5.736	8,688	10.149	6.426	58,737
Size ($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

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, that is, over the [0,1] event window. If the recommendation is issued on a nontrading day or after trading hours, day 0 is defined as the next trading day. We compute the CAR as the cumulative return on the common stock less the cumulative return on an equally weighted characteristics-matched size, book-to-market (B/M), and momentum portfolio (following Daniel et al. (1997, DGTW)). Panel A of Table II, 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 a larger impact during bad times. The differences are stark—for example, the average two-day CAR for a recommendation downgrade is −2.678% in *Crisis* periods and −1.687% in non-*Crisis* periods. Both CARs are significant at the 1% level, indicating that analysts have an impact in both good and bad times. However, the significant difference of −0.991% shows that downgrades have a larger impact in bad times. The same is true for upgrades: the CAR for upgrades is 2.658% in *Crisis* periods and 2.044% in non-*Crisis* periods, with the difference in CARs of 0.614% again significant at the 1% level. We continue to find evidence of a larger impact of recommendations in bad times using our other measures of bad times.[5]

We next examine whether analysts are more influential in bad times using the definition of influential recommendations in Loh and Stulz (2011). Loh and Stulz (2011) show that it is important to account for whether a recommendation change results in a stock-price reaction that is noticed by investors, that is, whether 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 II reports the fraction of recommendation changes that are influential during bad times compared to good times.

The results are striking. Using all of our measures of bad times, we find that a recommendation downgrade is significantly more likely to be influential during bad times than during good times. The difference is especially large

[5] Using a bad times dummy means that the baseline group is nonbad times, which we refer to as good times. This approach is consistent with, say, how the NBER defines recessions and labels other periods as expansions. In tests reported in the Internet Appendix (available in the online version of the article on the *Journal of Finance* website), we use monthly market returns to sort nonbad times into two groups, normal times and good times. Using normal times as the baseline group, we continue to find a stronger CAR impact of recommendation changes in bad times. We find little change in the CAR in good times compared to normal times, except for upgrades, which have a slightly larger impact in good times compared to normal times.

[6] Specifically, we check whether the CAR is in the same direction as the recommendation change and the absolute value of the 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 associated with noticeable abnormal returns that can be attributed to the recommendation changes.

Table II

Recommendation Change Impact and Influential Likelihood in Bad Times

In this table, we present the two-day CAR (in percent), which is the average day [0,1] cumulative abnormal return, and influential probability, which is the percentage of influential recommendation changes. Influential changes are those whose two-day CAR is 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 to 2014. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initiations and reiterations are excluded); changes made around earnings announcement and guidance days, and changes on multiple-recommendation days, are excluded. Bad times measures are as follows. *Crisis*: September to November 1987 (1987 crisis), August to December 1998 (LTCM), and July 2007 to March 2009 (*Credit Crisis*). *Recession* (NBER recessions): July 1990 to March 1991, March to November 2001, and December 2007 to June 2009. *High Uncertainty* represents the highest tercile (over the period 1983 to 2014) of the Baker, Bloom, and Davis (2016) uncertainty index. t-statistics (in absolute values and based on standard errors clustered by calendar day) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Bad Times Measure	Rec-Change	Variable	Two-Day CAR (%) Bad Times	Two-Day CAR (%) Good Times	Two-Day CAR (%) Difference	Influential Probability (%) Bad Times	Influential Probability (%) Good Times	Influential Probability (%) Difference
Crisis	Downgrade	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	9,648	61,422		9,648	61,422	
	Upgrade	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	8,688	58,737		8,688	58,737	
Credit Crisis	Downgrade	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	7,792	63,278		7,792	63,278	
	Upgrade	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	7,262	60,163		7,262	60,163	
Recession	Downgrade	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	9,714	61,356		9,714	61,356	
	Upgrade	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	8,147	59,278		8,147	59,278	
High Uncertainty	Downgrade	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	26,292	43,059		26,292	43,059	
	Upgrade	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	24,038	41,478		24,038	41,478	

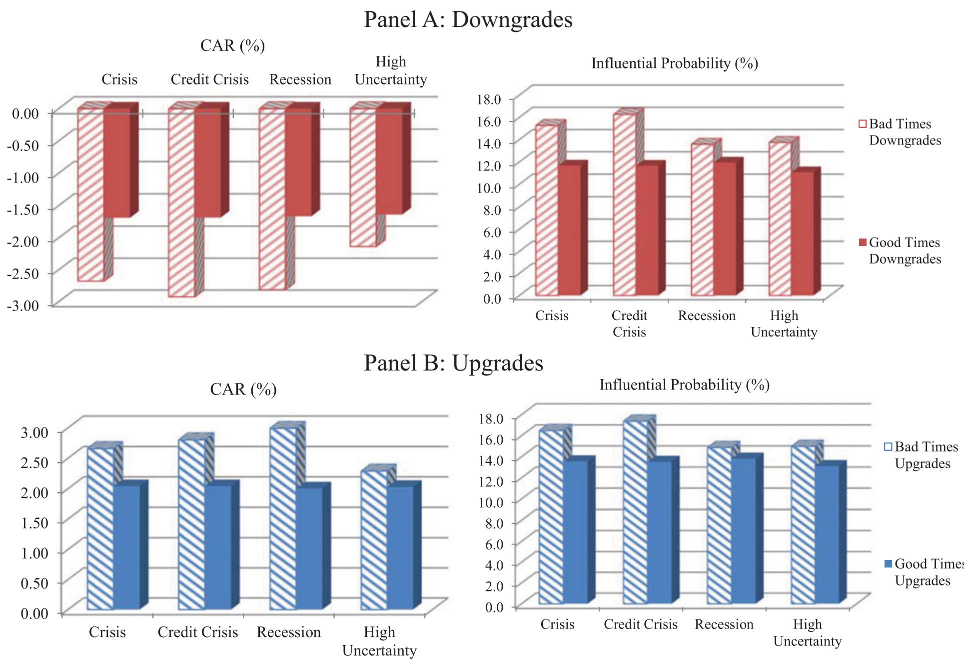

Figure 1. Impact of recommendation changes in bad times. This figure plots the mean two-day CAR and the influential probability of recommendation changes (in percent). Panel A shows downgrades and Panel B shows upgrades. The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1993 to 2014. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initiations and reiterations are excluded); changes made around earnings announcement and guidance days, and changes on multiple-recommendation days, are excluded. Influential changes are those whose two-day CAR is 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 measures are as follows. *Crisis*: September to November 1987 (1987 crisis), August to December 1998 (LTCM), and July 2007 to March 2009 (*Credit Crisis*). *Recession* (NBER recessions): July 1990 to March 1991, March to November 2001, and December 2007 to June 2009. *High Uncertainty* represents the highest tercile (over the period 1983 to 2014) of the Baker, Bloom, and Davis (2016) uncertainty index. (Color figure can be viewed at wileyonlinelibrary.com)

when we use the *Crisis* or *Credit Crisis* measures of bad times. Using these measures, a recommendation downgrade's probability of being influential is one-third higher during bad times (e.g., 15.278% versus 11.681% using *Crisis*). The differences are smaller using the *Recession* and *High Uncertainty* measures of bad times. Turning to recommendation upgrades, we find that they are also significantly more likely to be influential using all of our measures of bad times. The results for the fraction of influential recommendations are therefore similar to the CAR results.

In Figure 1, we plot the summary of our results in Table II. As can be seen, both upgrades and downgrades are associated with stronger stock-price reactions and are more likely to be influential in bad times.

Thus far, we have only presented univariate results. Because analysts' recommendation impact can also be affected by characteristics other than bad times, it is important to examine whether our results are robust to controlling for such characteristics. In Table III, we report estimates of OLS panel regressions in which 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. First, we control for *LFR*, the analyst's leader-follower ratio in the previous year, constructed following Cooper, Day, and Lewis (2001), who show that reports from leader analysts have greater stock-price impact.[7] Second, we control for *Star Analyst*, an indicator variable for analysts elected to the All-American team (with first, second, third team status, or as runner-up) in the most recent *Institutional Investor* annual (in October) poll, as Fang and Yasuda (2014) show that star analysts have better performance. Mikhail, Walther, and Willis (1997) further show that analyst experience impacts performance, and thus we control for *Relative Experience*, the difference between analyst experience (number of quarters since appearance on I/B/E/S) and the average experience of all analysts covering the firm. Next, because forecast accuracy can proxy for skill in picking stocks (Loh and Mian (2006)), we control for *Accuracy Quintile*, the average forecast accuracy quintile (relative to other analysts covering the firm) of the analyst based on the firms covered in the past year, where the quintile rank is increasing in forecast accuracy. We also control for *Broker Size*, the number of analysts employed by the broker as a proxy for the resources available to analysts. Turning to firm characteristics, we include the following controls: # *Analysts*, which is the number of analysts covering the firm; *Size*, last June's market cap; *BM*, the book-to-market equity ratio (computed and aligned following Fama and French (2006)); *Momentum*, the buy-and-hold return from month $t-12$ to $t-2$; and *Stock Volatility*, the standard deviation of daily stock returns in the prior month. Adding these controls allows us to determine whether our univariate results are robust to controlling for changing firm and analyst characteristics from good to bad times.

Descriptive statistics for these variables are reported in Panel C of Table I for the full sample, as well as separately for good and bad times based on one of our measures of bad times, namely, *Crisis*. These statistics represent averages of the characteristics across all of the recommendation change observations within the downgrade or upgrade sample. As can be seen, most analyst characteristics look similar between good and bad times, with the exception that there appears to be a smaller fraction of star analysts in bad times. With respect to the firm characteristics, we find that the average *Size*, *Momentum*, *BM*, and

[7] To compute *LFR*, the gaps between the current recommendation and the previous two recommendations from other brokers are computed and summed. We repeat this calculation for the next two recommendations. The leader-follower ratio is then defined as 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.

Table III

Panel Regression of Recommendation Change CARs in Bad Times

In this table, we estimate the effect of bad times on recommendation two-day CARs (in percent) controlling for firm, analyst, and recommendation characteristics, from 1993 to 2014. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initiations and reiterations are excluded); changes made around earnings announcement and guidance days, and changes on multiple-recommendation days, are excluded. Bad times measures are described in Table I. For the control variables, *LFR* is the analyst's prior-year leader-follower ratio, *Star Analyst* is a dummy indicating whether the analyst is a star in the most recent *Institutional Investor* poll, *Relative Experience* is the difference between the analyst's experience (in quarters) against the average of peers who cover the same firm, *Accuracy Quintile* is the average forecast accuracy quintile of the analyst's covered firms over the past year (quintile 5 = most accurate), *Broker Size* is the number of analysts employed, *# Analysts* is the number of analysts covering the firm, *Size* is the firm's market cap in the prior June, *BM* is the book-to-market ratio, *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. For the count variables *Broker Size* and *# Analysts*, we add one before taking logs. t-statistics (in absolute values and based on standard errors clustered by calendar day) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Industry fixed effects (F.E.) use the Fama and French (1997) 30-industry classification.

	Dependent Variable: CAR of Downgrades								Dependent Variable: CAR of Upgrades							
Variable	(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)

(*Continued*)

Table III—*Continued*

	Dependent Variable: CAR of Downgrades								Dependent Variable: CAR of Upgrades							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
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	71,070	59,511	71,070	59,511	71,070	59,511	69,351	58,163	67,425	56,901	67,425	56,901	67,425	56,901	65,516	55,395
Adj. R^2	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

Analysts per firm decrease in bad times, while *Stock Volatility* is markedly higher in bad times.

Table III reports results of the regressions that include these controls. For each measure of bad times, we first estimate the CAR regression using a constant and a bad times indicator. The coefficient on the intercept is the CAR impact of good times and that on the bad times indicator is the additional impact of downgrades in bad times (equivalent to the univariate CAR difference in Table II). We then add the controls for firm, analyst, and forecast characteristics, as well as industry fixed effects (Fama and French (1997) 30-industry classification). For the count variables *Broker Size* and # *Analysts*, we add one before taking logs. Standard errors are clustered by calendar day to account for cross-sectional correlation of returns on the same day (clustering by firm or by analyst typically leads to similar or statistically stronger results). When we focus on downgrades in models (1) to (8), we see that, regardless of whether we include the control variables, the coefficients on all of the measures for bad times are negative and statistically significant at the 1% level. This shows that the stock-price impact of analyst downgrades is greater in bad times compared to good times. To gauge the economic significance 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%, which means that the CAR impact is about 1.57 times ($\frac{-0.998\,+\,(-1.761)}{-1.761}$) higher in bad times, an effect that is similar to the case without the controls.

Looking at the coefficients on the controls, we see that recommendations by analysts with a greater leader-follower ratio have a larger impact. Not surprisingly in light of earlier literature, we also see that recommendation changes by larger brokers have more of an impact, as do the downgrades of star analysts. Also in line with the literature, recommendation changes have less of an 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 the controls, upgrades also have a significantly larger stock-price reaction regardless of the measure of bad times that we employ.

Table IV repeats the analysis in Table III by estimating probit models for whether a recommendation change is influential. The table reports the marginal effects, which measure the change in probability when changing the variable by one standard deviation centered around its mean (or a zero to one change for a dummy variable), with z-statistics in parentheses (based on standard errors clustered by calendar day). We see that downgrades are more likely to be influential using all of our measures of bad times. Interestingly, the marginal effects of the bad times indicator variables are more pronounced when we control for analyst, firm, and recommendation characteristics as well as industry fixed effects. For example, in regression (1) of Table IV, the marginal effect on *Crisis* indicates that the univariate increase in the probability of a

Table IV

Probit of Recommendation Change Influential Probability in Bad Times

In this table, we estimate probit regressions of the marginal effect (in percent) of bad times on the influential probability of the CAR for recommendation changes controlling for firm, analyst, and recommendation characteristics. Influential changes are those whose two-day CAR is 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 to 2014. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initiations and reiterations are excluded); changes made around earnings announcement and guidance days, and changes on multiple-recommendation days, are excluded. Definitions of bad times measures and control variables are described in Tables I and III, respectively. z-statistics (in absolute values and based on standard errors clustered by calendar day) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Industry fixed effects (F.E.) use the Fama and French (1997) 30-industry classification.

	Dependent Variable: Influential Dummy for Downgrades								Dependent Variable: Influential Dummy for Upgrades							
Variable	(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	71,070	59,511	71,070	59,511	71,070	59,511	69,351	58,163	67,425	56,901	67,425	56,901	67,425	56,901	65,516	55,395
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

downgrade being influential in *Crisis* periods is 3.6% (compared to the predicted probability of a downgrade being influential, labeled "Predicted Prob.," of 12.1%). When we add the control variables, the coefficient on *Crisis* increases to 6.5% (compared to the predicted probability of 11.7%). Turning to recommendation upgrades, we find that upgrades are also more likely to be influential during bad times using all of our bad times measures, with the effect also stronger when we add the control variables.

Overall, we find strong evidence that the impact of recommendation changes is greater in bad times. Some researchers 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 that the increased impact of recommendation changes in bad times applies to both upgrades and downgrades, although the magnitudes are larger for downgrades. Importantly, the result that analysts have more of an impact in bad times is inconsistent with the difficult environment hypothesis, the shirking hypothesis, and the inattention hypothesis, all of which predict that analyst research quality should be lower in bad times. Instead, our result supports the hypotheses that predict better-quality analyst output in bad times.[8]

E. Stock-Price Impact of Earnings Forecast Revisions

Our analysis thus far looks at stock recommendations, which are essentially the analyst's summary measure of the future prospects of a firm's stock. We now focus on analyst 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 as larger-magnitude revisions are likely to be associated with larger stock-price reactions. A 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. We then scale by the lagged stock price and call this variable *Forecast Revision*. We remove revisions on dates that coincide with corporate events (in particular, the three trading days around earnings announcements and guidance dates, as well as multiple-forecast dates) so that we do not incorrectly give credit to the analyst for stock-price changes driven by company announcements.

We examine multivariate regressions of forecast revision CARs and probits of forecast revision influential probability. Both sets of tests show that the impact

[8] A caveat with our results is that the credit crisis overlaps with a sizable fraction of our bad times measures. Specifically, 72% and 43% of the *Crisis* and *Recession* months, respectively, occur during 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 of an impact in *Crisis* or *Recession* periods. However, this issue is mitigated for the *High Uncertainty* measure of bad times as only 12% of *High Uncertainty* months occur during the credit crisis. Using the *High Uncertainty* measure of bad times, excluding credit crisis observations does not affect the finding of increased analyst impact in bad times. These results are reported in the Internet Appendix.

of earnings forecast revisions is higher in bad times. For brevity, we report only the probit results here; the CAR results are reported in the Internet Appendix. In Table V, we estimate probits where the dependent variable is an indicator variable that equals one when the forecast is classified as influential. All the marginal effects are 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 rises by 3.6%, which is a large increase from the 4.5% predicted influential probability in the probit model. The coefficient on *Forecast Revision* itself is statistically significant but does not remove the statistical significance of bad times, meaning that it is not the case that larger-magnitude revisions in bad times explain their greater influential probability.

Taken together, our results provide strong evidence 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 short-term fundamentals (quarterly earnings), we find that analysts' impact on stock prices is more influential in bad times.

III. Robustness Tests

In this section, we conduct several robustness tests to examine whether our finding of greater analyst impact in bad times is new to the literature and whether it is robust.

A. Does Marketwide or Firm-Specific Uncertainty Drive Our Results?

Our measures of bad times are based on changes in aggregate economic activity. We use a marketwide definition instead of a firm-specific definition because marketwide bad times are more likely to be exogenous to the analyst and the industry. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), for example, show that in recessions, an average stock's aggregate risk increases substantially but the change in idiosyncratic risk is not statistically different from zero. This means that bad times likely introduce an exogenous change in uncertainty in the average firm. Several previous studies examine how firm-level uncertainty affects analysts' output. Frankel, Kothari, and Weber (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 earnings forecast dispersion. Although our analyses already control for firm-specific uncertainty, to further mitigate concerns, we employ a different approach here.

We first decompose the variance of a firm's stock returns over the prior month into macro, industry (Fama and French (1997) 30-industry classification), and residual (firm-specific) components by regressing daily returns on market (CRSP value-weighted) returns and market-purged industry returns. Defining high uncertainty as the highest tercile of the relevant variance

Table V

Probit of Earnings Forecast Revision Influential Probability in Bad Times

In this table, we estimate probit regressions of the marginal effect (in percent) of bad times on the influential probability of the CAR for earnings forecast revisions controlling for firm, analyst, and forecast characteristics. Influential revisions are those whose two-day CAR is 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 to 2014. A forecast revision is defined as the analyst's current one-quarter-ahead earnings forecast minus their prior outstanding forecast (i.e., initiations are excluded) scaled by price; revisions made around earnings announcement and guidance days, and revisions on multiple-forecast days, are excluded. Definitions of bad times measures and control variables are described in Tables I and III, respectively. An additional control here is *Forecast Revision*, which is the analyst's current forecast minus prior forecast, scaled by the stock price. z-statistics (in absolute values and based on standard errors clustered by calendar day) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Industry fixed effects (F.E.) use the Fama and French (1997) 30-industry classification.

	Dependent Variable: Influential Dummy for Downward Revisions								Dependent Variable: Influential Dummy for Upward Revisions							
Variable	(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)

(*Continued*)

Table V—*Continued*

	Dependent Variable: Influential Dummy for Downward Revisions								Dependent Variable: Influential Dummy for Upward Revisions							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Accuracy		0.002		0.002		0.002		0.001		0.003*		0.003*		0.003*		0.003*
Quintile		(1.36)		(1.40)		(1.43)		(0.71)		(1.92)		(1.93)		(1.91)		(1.76)
Log Broker		0.003***		0.003***		0.003***		0.004***		0.004***		0.004***		0.004***		0.004***
Size		(3.92)		(4.00)		(4.04)		(4.64)		(4.07)		(4.06)		(4.16)		(3.93)
Log #		−0.001*		−0.001**		−0.001		−0.001		−0.015***		−0.015***		−0.016***		−0.018***
Analysts		(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		−0.501***		−0.504***		−0.501***		−0.326***		−0.601***		−0.588***		−0.557***		−0.480***
Volatility		(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	172,481	105,097	172,481	105,097	172,481	105,097	164,256	99,663	112,147	69,773	112,147	69,773	112,147	69,773	107,045	66,470
Industry F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

component over the firm's history, in Panel A of Table VI we regress recommendation change CAR on these three high uncertainty dummies. Using the highest quintile instead of tercile or cross-sectional sorts instead of time-series sorts does not affect our results (see the Internet Appendix). We find that all three high uncertainty dummies are related to significantly larger CAR impact in a univariate setting. When we consider all three uncertainty dummies together and add analyst control variables (we do not include firm controls since they may be highly correlated with firm-level uncertainty), we find that only the coefficient on the marketwide uncertainty dummy remains statistically significant across all specifications, particularly for downgrades. Hence, we believe that our results are new in that we show it is marketwide uncertainty rather than firm-specific uncertainty that drives analysts' greater impact during periods of high uncertainty.

B. Do Reports that Reiterate Recommendations Have More of an Impact?

Although we find that the impact of analyst reports containing revisions is greater in bad times, it could be the case that analysts have fewer recommendation changes and more reiterations, in which case analysts might actually be less useful in bad times. We therefore examine 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)). We infer reiterations outside of those recorded on I/B/E/S 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. In the Internet Appendix, we find that in non-*Crisis* periods, the average number of recommendation changes per month for a firm (across all analysts covering it) is 0.183, whereas in *Crisis* times, this figure rises to 0.238 (a 30% increase). We similarly find across our other measures of bad times that the number of recommendation changes goes up in bad times. Hence, we find 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* periods and 0.903 in *Crisis* periods (a 17% increase). The finding that the number of reiterations goes up holds using our other measures of bad times (see the Internet Appendix). There is no evidence that the number of reiterations goes up at the expense of the number of revisions as the number of recommendations increases just like the number of reiterations does. Rather, the evidence simply shows that analysts act more often.

In Panel B of Table VI, we investigate whether these more numerous reiterations in bad times have differential impact. We find that the impact of unfavorable reiterations (reiterated sell or reiterated hold since most of the literature considers holds unfavorable) is higher in bad times across all specifications, similar to our findings on revisions. Hence, analysts have more of an impact when issuing reiterations in bad times. We find less evidence of

Table VI

Robustness Tests

In Panel A, we estimate the effect of high firm, industry, and market uncertainty on the two-day CAR (in percent) of recommendation changes. Control variables for analyst characteristics are included in even specifications but not reported. Definitions of bad times measures and control variables are described in Tables I and III, respectively. The total variance of a firm's daily stock returns in the prior month is decomposed into market, industry, and firm components by regressing daily returns on market returns and market-purged industry returns (Fama and French (1997) 30-industry classification). *High Uncertainty* equals one when the relevant component is in the top tercile of the firm's time-series of monthly variance components. In Panel B, we estimate the effect of bad times on the two-day CAR (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 to 2014. A recommendation reiteration is either an explicit reiteration from the I/B/E/S recommendation file or an assumed reiteration—the analyst's outstanding rating is assumed to be reiterated when there is a quarterly earnings or target price forecast with no new rating issued. A reiteration is defined as unfavorable (favorable) if the outstanding rating is a hold or sell (buy). Control variables (in even specifications but not reported) are the same as in Table III 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 reiterations on multiple-reiteration days, are excluded. In Panel C, we regress the daily absolute returns of firms in the CRSP file from 1993 to 2014 on firm news event dummies and bad times dummies, excluding observations for which the lagged price is less than one dollar. Event dummies equal one for day 0 of the announcement, or day 1 if the announcement occurs after trading hours (for cases in which we have time stamps to verify this). 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 trades are from the Thomson Insider Form 4 file. *Size*, *BM*, and *Momentum* are defined in Table III. The control variables *Lag Return*, *Idio. Volatility*, *Turnover*, and *Inst. Ownership* are measured in the prior month. t-statistics (in absolute values and based on standard errors clustered by calendar day) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Industry fixed effects (F.E.) use the Fama and French (1997) 30-industry classification.

Panel A: Panel Regression of Recommendation Change CAR on Different Measures of High Uncertainty

	Dependent Variable: CAR of Downgrades								Dependent Variable: CAR of Upgrades							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
High Firm Uncertainty	−0.171***	−0.208***					−0.036	−0.067	0.523***	0.509***					0.472***	0.446***
	(2.74)	(3.05)					(0.57)	(0.96)	(8.36)	(7.45)					(7.56)	(6.61)
High Ind. Uncertainty			−0.167***	−0.162***			−0.074	−0.051			0.130**	0.149**			−0.038	−0.016
			(3.01)	(2.67)			(1.31)	(0.82)			(2.37)	(2.43)			(0.71)	(0.27)
High Mkt Uncertainty					−0.457***	−0.505***	−0.434***	−0.479***					0.362***	0.388***	0.267***	0.294***
					(7.48)	(7.54)	(6.91)	(6.95)					(6.77)	(6.66)	(4.73)	(4.75)
Good Times $\hat{Y}$	−1.764	−1.838	−1.760	−1.850	−1.649	−1.718	−1.618	−1.686	1.953	2.064	2.076	2.176	1.989	2.086	1.885	1.981
#Obs	71,067	60,699	71,067	60,699	71,067	60,699	71,067	60,699	67,424	58,030	67,424	58,030	67,424	58,030	67,424	58,030
Adj. R^2	0.0001	0.0068	0.0001	0.0067	0.0010	0.0079	0.0010	0.0079	0.0016	0.0134	0.0001	0.0121	0.0008	0.0129	0.0020	0.0139
Controls, Ind. F.E.	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

(Continued)

Table VI—*Continued*

Panel B: Panel Regression of Reiteration CAR in Bad Times

	Dependent Variable: CAR of Unfavorable Recommendation Reiterations								Dependent Variable: CAR of Favorable Recommendation Reiterations							
Variables	(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)
Good 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
#Obs	248,676	243,190	248,676	243,190	248,676	243,190	237,063	231,964	347,922	339,883	347,922	339,883	347,922	339,883	334,452	326,827
Adj. R^2	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

Panel C: Regression of Firm-Day Absolute Returns on Firm News Events and Bad Times

	Bad Times: Crisis			Bad Times: Credit Crisis			Bad Times: Recession			Bad Times: High Uncertainty		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
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)

(*Continued*)

Table VI—*Continued*

Panel C: Regression of Firm-Day Absolute Returns on Firm News Events and Bad Times

	Bad Times: Crisis			Bad Times: Credit Crisis			Bad Times: Recession			Bad Times: High Uncertainty		
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
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)
#Obs	21,139,679	20,120,657	20,120,657	2,113,9679	20,120,657	20,120,657	21,139,679	20,120,657	20,120,657	20,495,984	19,525,767	19,525,767
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0158	0.1344	0.1344	0.0144	0.1338	0.1339	0.0163	0.1343	0.1344	0.0148	0.1326	0.1327

this for favorable reiterations (reiterated buy), with mostly lower impact in bad times. Overall, there is no evidence that analysts reiterate more in bad times at the expense of revising less. Moreover, analysts' reiterations, especially of unfavorable ratings, are more informative in bad times compared to those in good times.

C. Does the Market React More to All Types of Firm News in Bad Times?

We now examine whether the impact of all firm news is greater in bad times. If there is something systematic about how the market reacts to news in bad times, the heightened reaction to analyst output in bad times may be explained by the fact that the market reacts more to all news. Schmalz and Zhuk (2017), for instance, find that the market also reacts more to earnings announcements in bad times. To examine this possibility, we adapt the methodology in Frankel, Kothari, and Weber (2006) and estimate a panel regression of individual daily absolute stock returns on dummy variables for important firm news events, namely, recommendation changes, reiterations, earnings announcements, earnings guidance, dividend announcements, and insider trades. Following Frankel, Kothari, and Weber (2006), 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 come from the Thomson Insider Form 4 files. The insider trade date is the date when the insider trade occurs and the filing date is the date when it is reported to the Securities and Exchange Commission (SEC) and hence becomes publicly known.

We expect the coefficients on the firm news dummies to be positive and the coefficients on recommendation-related dummies to remain positive in the presence of the other firm news dummies. As controls, we include our firm characteristics variables (size, B/M, momentum, idiosyncratic volatility, etc.) as well as industry fixed effects. We also add bad times indicators, whose coefficients are expected to be positive if the market in general is more volatile in bad times, and interactions between the firm news dummies and the bad times indicators, whose coefficients are expected to be positive if the market reacts more to any news in bad times. Of particular interest is whether the recommendation-related interactions with the bad times indicator variables remain significantly positive in the presence of the other firm news dummies and their interactions. If so, then this would mean that the market's heightened reaction to recommendations in bad times is robust to controlling for the market's differential reaction to news in general in bad times.

In Panel C of Table VI, we find that the recommendation change and reiteration dummies are always statistically significant both alone and in the presence of the other firm news dummies (based on standard errors clustered by calendar day). These results indicate that both recommendation changes and reiterations are more informative in bad times, in line with our earlier results. When we include all of 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 consistent with Bradley et al. (2014)). Thus, our main findings are robust to controlling for the differential impact of firm news in bad times. We also find that the market does *not* react more to all types of firm news in bad times: Earnings announcements do elicit greater reactions in bad times, but guidance announcements elicit lower reactions, and evidence on reactions to dividend announcements and insider trades is mixed.

D. Alternative Specifications and Samples

Differences in analyst characteristics could spuriously explain our results if analyst performance is 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 would be large enough to explain our findings, which already control for analyst characteristics, we nonetheless conduct two further sets of tests. First, we repeat our tests above on the subsample of analysts who are present before and after the longest bad times period we consider, namely, the credit crisis. These analysts, who appear in I/B/E/S before 2007 and continue to issue reports after March 2009, are responsible for almost half of the recommendations in our sample. These tests allow us to ascertain the performance differential between good and bad times for an identifiable set of seasoned analysts. Second, we augment the tests on this subsample with analyst fixed effects. Under 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. Results reported in the Internet Appendix show that the impact of recommendation changes continues to be higher in bad times compared to good times when analyst fixed effects are added, and in many cases the results are stronger. For example, in the model with the control variables, the marginal effect of a *Crisis* period on the probability of a downgrade being influential is 0.059 without analyst fixed effects. After adding analyst fixed effects, the marginal effect becomes 0.067. For upgrades, the increased probability of the recommendation change being influential in a *Crisis* period is 0.043, and this is unchanged with analyst fixed effects added. We also tried broker fixed effects instead of analyst fixed effects with this subsample and find similar results (see the Internet Appendix).

In another set of tests reported in the Internet Appendix, we control for whether an analyst's career starts during bad times. Analysts who begin their careers during bad times may have more experience with such times and hence might do better in such periods. Alternatively, brokers may hire analysts with special expertise when bad times strike. To account for such possibilities, we construct a dummy variable that is equal to one for analysts who began their careers in any of the bad times periods. We also consider another dummy variable that is equal to one for analysts who began their careers during the credit crisis. When we add these dummy variables to our main regressions, we find that these coefficients are mostly statistically insignificant and all of our main findings are unaffected. We conclude that analysts who join brokerages during bad times are unlikely to be driving our finding that analysts produce better research in bad times.

Finally, recall that we exclude financial firms from our baseline analysis because many of the macro bad times periods that we consider started in the financial sector, for example, the credit crisis and most of the recessions. Thus, for the financial sector, the periods that we define as macro bad times are often also industry bad times. Industry bad times might also not be as exogenous to analysts as macro bad times are. For robustness, however, we repeat our analysis on financial firms (group 29 of the Fama and French (1997) 30-industry classification). We find that recommendation changes made on financial firms also have significantly greater CAR impact in bad times. For example, as reported in the Internet Appendix, the mean recommendation downgrade CAR for financial firms in non-*Crisis* periods is –1.087% while in bad times it elicits an additional –2.118% abnormal return. For upgrades, the non-*Crisis* CAR is 1.315% but the *Crisis* CAR is 1.473% larger. The results are similarly strong using our other measures of bad times and after adding the 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. Importantly, for this set of firms it is hard to distinguish whether the results are triggered by industry or macro bad times.

IV. Are Analyst Signals More Precise in Bad Times?

Having established that analyst output is more influential in bad times, we now investigate why this is so. Analysts may be more influential because their signals are more precise in bad times. If so, their forecast errors should be lower. The literature typically measures forecast errors using the absolute difference between actual and forecasted earnings per share, scaled by the absolute value of actual earnings or price. It would be surprising if such a measure of forecast errors were lower in bad times because earnings become harder to forecast in bad times. Indeed, we find that, according to this traditional measure of absolute forecast errors, analysts are less precise in bad times, consistent with Jacob (1997), Chopra (1998), and Hope and Kang (2005). We argue that this traditional measure is not appropriate for investigating why analysts are more influential in bad times as 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 firm prospects, analyst signals that have a small amount of noise are useless. Hence, to compare the usefulness of analyst forecasts over time, the precision of analyst signals has to be evaluated relative to firm uncertainty. This is similar in spirit to the way we define influential recommendations by scaling recommendation CARs by prior stock return volatility. Under this new approach, we find that analysts are actually *more* precise in bad times.

A. Using a Traditional Measure of Forecast Errors

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 that 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 are by definition associated with lower stock prices, so forecast errors would be 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. We then winsorize scaled forecast errors at the extreme 1% before we take absolute values.[9]

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

We see in Table VII that traditional absolute forecast errors are significantly larger in bad times. Model (1) shows that in non-*Crisis* periods the absolute forecast error is 14.835% of actual earnings, while in *Crisis* periods, the absolute forecast error is 2.775% higher. This increase in absolute forecast error holds

[9] 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 reported in the Internet Appendix, 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 other control variables. We find that our results are similar.

Table VII
Absolute Forecast Errors in Bad Times

In this table, we estimate the effect of bad times on an analyst's absolute forecast error (in percent). Absolute forecast error is actual minus forecasted quarterly earnings, divided by the absolute value of actual earnings in models (1) to (8) (denominators less than \$0.25 are set to \$0.25), or by the daily stock return volatility (annualized) in the month before the forecast in models (9) to (16). Forecast errors are winsorized at the extreme 1% before taking absolute values. Only forecasts that are revisions of prior forecasts are included. Definitions of bad times measures are provided in Table I. Control variables definitions are similar to those in Table III. Additional controls specific to forecasts are also included. *Optimistic Forecast* is an indicator variable equal to one if the forecast is above the final consensus, *Days to Annc* is the number of days from the forecast to the next earnings announcement date, *Multiple Forecast Day* is a dummy indicating whether more than one analyst issued a forecast on that day, and *Dispersion* is the dispersion of forecasts making up the final consensus. For the count variables *Broker Size*, *# Analysts*, and *Days to Annc*, we add one before taking logs. t-statistics (in absolute values and based on standard errors clustered by industry-quarter) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Industry fixed effects (F.E.) use the Fama and French (1997) 30-industry classification.

	Dependent Variable: Absolute Forecast Error Scaled by Absolute Value of Actual Earnings								Dependent Variable: Absolute Forecast Error Scaled by Stock Volatility							
Variable	(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)

(*Continued*)

Table VII—*Continued*

	Dependent Variable: Absolute Forecast Error Scaled by Absolute Value of Actual Earnings								Dependent Variable: Absolute Forecast Error Scaled by Stock Volatility							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
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)
Multiple 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
#Obs	406,644	334,974	406,644	334,974	406,644	334,974	388,570	318,887	406,642	334,973	406,642	334,973	406,642	334,973	388,568	318,886
Adj. R^2	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

after taking into account analyst, firm, and forecast characteristics. The same results obtain using our other measures of bad times, which suggests that analysts are more imprecise during bad times.

B. Absolute Forecast Errors Scaled by Stock Volatility

We now examine whether analyst forecast errors are larger in bad times after accounting for the increased uncertainty that investors face in bad times. To do so, we normalize absolute forecast errors by the stock's daily return volatility (annualized) in the prior month. This 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. 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 VII report results using this new measure of adjusted forecast precision. We see that the intercept in model (9) is 26.852, which can be interpreted as the percentage absolute forecast error per unit (100%) of stock volatility. Hence, the coefficient of –6.667 on *Crisis*, which describes the difference in the uncertainty-adjusted absolute forecast error during bad times compared to good times, tells us that precision improves by 25% (from $\frac{-6.667}{26.852}$) in bad times. We see that this percentage improvement is similar after including the controls and using our other measures of bad times. We also tried using the implied volatility (when available) five trading days before the forecast as a proxy for the uncertainty facing the firm and find similar results (see the Internet Appendix).

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

V. Why is the Impact of Analyst Output Greater in Bad Times?

So far we have shown that the impact of analyst output is greater in bad times and that analysts offer more precise signals during bad times after taking into account the uncertainty that investors face. In this section, we explore possible explanations for these results. We presented various potential explanations in Section I. Clearly, we find no support for the hypotheses in Section I that predict analysts will have less of an impact in bad times. We therefore investigate the hypotheses that predict analysts to have more of an impact in bad times, namely, the analyst reliance 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 hypothesis that the market overreacts to analysts in bad times.

A. Analyst Reliance Hypothesis

The analyst reliance hypothesis predicts that analyst output becomes more valuable in bad times, especially for more opaque stocks. To proxy for stocks that are more opaque and for which investors might rely more on analysts, we use stocks with no company guidance, low institutional ownership, high idiosyncratic volatility to total volatility, small size, no traded options (a proxy for less informed trading), and low analyst coverage.[10] We then 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. Specifically, *NoGuidance* equals one when the firm has had no earnings guidance in the last month, *LowIO* equals one for the lowest quintile of firms sorted by the most recent Thomson 13F-reported fraction of shares owned by institutions, *HighIVOLfrac* equals one for the highest quintile of stocks sorted on the prior-quarter fraction of firm-specific daily return volatility over 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 (New York Stock Exchange (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), and *LowCoverage* equals one for the lowest analyst coverage quintile based on the number of analysts issuing recommendations in the prior quarter. We use dummy variables in these cross-sectional tests for ease of interpreting the coefficients.

In Table VIII, we report the coefficients on the bad times dummies, the firm characteristics dummies, and their interactions with and without controls. We find that for most of the proxies for opacity, increased 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 that the increase in the impact of analysts in bad times is stronger 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.[11]

[10] In the uncertainty literature, an increase in idiosyncratic volatility proxies for an increase in uncertainty (Bloom (2009)). Idiosyncratic volatility has also been viewed as evidence of informed trading (in Roll (1988)), as a proxy for skewness (Bali, Cakici, and Whitelaw (2011)), and as a proxy for illiquidity (Han and Lesmond (2011)). Ultimately, whether analysts have more or less impact on high idiosyncratic volatility stocks during bad times is an empirical question. Under the analyst reliance hypothesis, if idiosyncratic volatility is a proxy for uncertainty, everything else equal analyst output should 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 is an empirical question.

[11] In the Internet Appendix, we also examine whether some types of analysts are more likely to have a greater impact in bad times. To do so, we look at large brokers (top quintile based on analysts issuing ratings in the prior quarter), star analysts, experienced analysts (top quintile based on number of quarters in I/B/E/S as of the current quarter), and highly influential analysts

Table VIII
Cross-Sectional Tests of CAR Impact of Recommendation Changes in Bad Times

In this table, we estimate panel regressions of the effect of bad times on the two-day CAR (in percent) of recommendation downgrades (in models (1) to (8)) and upgrades (in models (9) to (16)) with firm characteristics interactions. The benchmark return for the CAR is the return from a characteristics-matched DGTW portfolio. The sample is from 1993 to 2014. A recommendation change is defined as the analyst's current rating minus their prior outstanding rating (initiations and reiterations are excluded); changes made around earnings announcement and guidance days, and changes on multiple-recommendation days, are excluded. Definitions of bad times measures are provided in Table I. 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 stocks sorted on the prior month's fraction of firm-specific daily return volatility over total volatility (estimated by regressing daily returns on market returns and market-purged industry returns). *SmallSize* (Panel D) equals one for the lowest NYSE-breakpoint quintile rank of the firm's market cap in the prior June. *NoOptions* (Panel E, 1996 to 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 (coefficients unreported) are the same as in Table III, except that the relevant control is dropped when it is related to the firm characteristic dummy (e.g., *Size* is dropped in the *SmallSize* panel). t-statistics (in absolute values and based on standard errors clustered by calendar day) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Industry fixed effects (F.E.) use the Fama and French (1997) 30-industry classification.

	Dependent Variable: CAR of Downgrades								Dependent Variable: CAR of Downgrades							
	Crisis		Credit Crisis		Recession		High Uncertainty		Crisis		Credit Crisis		Recession		High Uncertainty	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: No Guidance Firms Interacted with Bad Times																
BadTimes	−0.515***	−0.485**	−0.670***	−0.749***	−0.485***	−0.254	−0.163	−0.117	0.525***	0.487***	0.509***	0.464***	0.577***	0.252	−0.116	−0.055
	(2.89)	(2.47)	(3.73)	(3.87)	(2.93)	(1.36)	(1.45)	(0.94)	(3.21)	(2.81)	(3.05)	(2.62)	(3.45)	(1.40)	(1.15)	(0.52)
NoGuidance	−0.466***	−0.388***	−0.475***	−0.392***	−0.443***	−0.340***	−0.399***	−0.277***	0.262***	0.083	0.249***	0.057	0.225***	0.014	0.086	−0.108
	(7.35)	(5.46)	(7.41)	(5.46)	(6.92)	(4.73)	(5.05)	(3.11)	(4.52)	(1.36)	(4.30)	(0.94)	(4.05)	(0.24)	(1.17)	(1.41)
BadTimes × NoGuidance	−0.561***	−0.605***	−0.682***	−0.758***	−0.805***	−0.925***	−0.405***	−0.525***	0.115	0.184	0.326	0.510**	0.510**	0.716***	0.462***	0.526***
	(2.59)	(2.60)	(3.09)	(3.22)	(3.94)	(4.20)	(3.10)	(3.65)	(0.60)	(0.89)	(1.62)	(2.28)	(2.28)	(2.94)	(3.95)	(4.21)
Good Times $\hat{Y}$	−1.752	−1.831	−1.748	−1.815	−1.756	−1.861	−1.764	−1.860	2.055	2.159	2.068	2.172	2.053	2.191	2.167	2.247
#Obs	71,087	59,524	71,087	59,524	71,087	59,524	69,368	58,176	67,436	56,908	67,436	56,908	67,436	56,908	65,527	55,402
Adj. R^2	0.0032	0.0205	0.0040	0.0220	0.0043	0.0208	0.0021	0.0201	0.0014	0.0432	0.0018	0.0440	0.0031	0.0440	0.0008	0.0429

(*Continued*)

Table VIII—*Continued*

	Dependent Variable: CAR of Downgrades								Dependent Variable: CAR of Downgrades							
	Crisis		Credit Crisis		Recession		High Uncertainty		Crisis		Credit Crisis		Recession		High Uncertainty	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel B: Low Institutional Ownership Firms Interacted with Bad Times																
BadTimes	−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)
BadTimes × 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	70,688	59,224	70,688	59,224	70,688	59,224	69,083	57,959	67,092	56,657	67,092	56,657	67,092	56,657	65,265	55,213
Adj. R^2	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																
BadTimes	−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)
BadTimes × 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	71,084	59,523	71,084	59,523	71,084	59,523	69,365	58,175	67,435	56,908	67,435	56,908	67,435	56,908	65,526	55,402
Adj. R^2	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
Panel D: Small Size Firms Interacted with Bad Times																
BadTimes	−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)
SmallSize	−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)
BadTimes × SmallSize	−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	71,087	59,524	71,087	59,524	71,087	59,524	69,368	58,176	67,436	56,908	67,436	56,908	67,436	56,908	65,527	55,402
Adj. R^2	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

(*Continued*)

Table VIII—*Continued*

	Dependent Variable: CAR of Downgrades								Dependent Variable: CAR of Downgrades							
	Crisis		Credit Crisis		Recession		High Uncertainty		Crisis		Credit Crisis		Recession		High Uncertainty	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel E: No Options Firms Interacted with Bad Times																
BadTimes	−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)
BadTimes × 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	63,540	52,969	63,540	52,969	63,540	52,969	61,821	51,621	60,619	50,964	60,619	50,964	60,619	50,964	58,710	49,458
Adj. R^2	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																
BadTimes	−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)
BadTimes × 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	61,280	51,950	61,280	51,950	61,280	51,950	59,869	50,831	59,384	50,527	59,384	50,527	59,384	50,527	57,814	49,264
Adj. R^2	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

B. Analyst Effort Hypothesis

We next examine the role of analyst incentives as an explanation for why analysts have more of an impact during bad times. Prior studies argue 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 incentives, they might exert more effort to produce better research in bad times. For fund managers, investors can reward the manager directly with fund flows. For analysts, investors can reward the analyst only indirectly though the analyst reputation channel. Further, during bad times, analysts might face career concerns due to increased attrition risk and lower compensation. The higher likelihood of job loss conditional on effort might therefore motivate analysts to work harder.

In Table IX, we examine whether analysts are more likely to disappear from the profession during bad times using probit regressions of analyst attrition. For the recommendations sample, *Disappear* is a dummy variable that equals one for the analyst-year in which the analyst makes no recommendation in I/B/E/S across all firms in the following year. 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 following year contains one of the bad times periods of interest. Control variables are averaged for each analyst-year and standard errors are clustered by analyst.

We see that across the different bad times periods, analysts are 1% to 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% to 13% in these models. An important independent variable in the regressions is the probability that an analyst is influential that year, which is computed as the fraction of the analyst's recommendation changes that are influential. This influential probability is typically negatively related to analyst attrition—issuing high-impact recommendation changes reduces analyst attrition. When we interact this influential probability with bad times, we see that the likelihood of attrition is even lower. Taken together, these results suggest that analysts work harder to avoid attrition in bad times since attrition is more likely in bad times and research impact reduces the likelihood of attrition.[12]

Having established that the likelihood of attrition is related to performance, we examine two additional measures of analyst output quantity to assess whether the increased analyst impact and precision are accompanied by more effort in bad times. Above, we see that the number of recommendation changes

(top quintile of fraction of influential recommendations in the previous year). While there is some evidence that the last characteristic is associated with a greater impact in bad times (highly influential analysts have more of an impact for downgrades in bad times using the credit crisis and recession measures of bad times), this is not the case for the other characteristics.

[12] In the Internet Appendix, we estimate the attrition probits on the quarterly earnings forecasts sample and find weaker results. Hence, career concerns are a plausible explanation for why analysts work harder in bad times, with influential recommendation changes being more important than accurate earnings forecasts in reducing attrition risk.

Table IX

Analyst Attrition in Bad Times

In this table, we estimate probits of analyst attrition for the recommendations sample (1993 to 2014). Variables are averaged within each analyst-year. *Disappear* equals one when the analyst makes no recommendation in I/B/E/S in the next year. Bad times measures are as follows. *Crisis*: September to November 1987 (1987 crisis), August to December 1998 (LTCM), and July 2007 to March 2009 (*Credit Crisis*). *Recession* (NBER recessions): July 1990 to March 1991, March to November 2001, and December 2007 to June 2009. *High Uncertainty* represents the highest tercile (over the period 1983 to 2014) of the Baker, Bloom, and Davis (2016) uncertainty index. Definitions of control variables included here are in Table III. A new control variable *Rec Influ Prob* is the fraction of influential recommendation changes made by the analyst that year. z-statistics (in absolute values and based on standard errors clustered by analyst) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Recommendations Sample, Disappear from I/B/E/S Next Year							
Variable	(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)				

(*Continued*)

Table IX—*Continued*

	Dependent Variable: Recommendations Sample, Disappear from I/B/E/S Next Year							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	38,546	35,508	38,546	35,508	38,546	35,508	38,546	35,508

and reiterations increases. Here, we first look at analyst activity as proxied by the number of forecasts that the analyst makes for a firm-quarter. Assuming that a particular analyst's coverage of a firm starts with the first quarter and stops with the last quarter that analyst is featured in I/B/E/S for that firm, we count for each firm the number of forecasts that the analyst makes in each of the coverage quarters. Quarters in the coverage period with no forecast from the analyst are assigned an analyst activity value of zero.

In Table X, we estimate regressions explaining analyst activity where the dependent variable is the log of one plus the number of analyst forecasts, which are computed at the firm-quarter-analyst level. The control variables are now averages of the given characteristic within the analyst-firm-quarter. The relevant bad times indicator variables equal one when any part the given quarter is defined as bad times according to the bad times measure used. We see that there is indeed more analyst activity in bad times even after including all of the control variables. Given the dependent variable is the log of one plus the number of analyst forecasts, the *Crisis* coefficient of 0.063 and non-*Crisis* coefficient of 0.642 in model (1) imply about a 14% increase in analyst activity. This evidence of increased activity holds regardless of the measure of bad times used and whether we include the control variables.[13]

We next use the number of pages in the analyst report to proxy for analyst effort. Unfortunately, this information is not recorded by I/B/E/S. We therefore hand-collect these data from Thomson ONE from 1994 to September 2011, and from Thomson Eikon from October 2011 to December 2014 (Thomson recently migrated users of T1.com to Eikon, but both draw from the database formerly known as Investext). Without downloading the actual reports, one can download a spreadsheet of headlines (restricted to 50 observations at a time) that contain the broker name, covered firm name, report title, date, and number of pages in the report. To keep the data collection effort manageable, we download all the headlines for one large broker, Morgan Stanley, 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, using this sample, we regress the number of pages in these reports on a bad times dummy and the following firm-level control variables: market *Beta*, *Size* quintile (based on NYSE breakpoints), *Momentum* quintile, *BM* quintile, and *Stock Volatility* (standard deviation of last month's daily returns).[14] We also add dummy variables indicating whether the report

[13] Increased analyst activity means there is less time between the reports that analysts issue. If becoming busier affects their performance, it may be important to control for analyst busyness. However, when we add a control for busyness, namely, the log of the number of firms covered by the analyst, our result that analyst recommendation changes have more of an impact is unaffected (see the Internet Appendix).

[14] This number of reports from 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 exclude 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

Table X
Panel Regression of Analyst Activity in Bad Times

In this table, we estimate the effect of bad times on analyst forecast activity (log of one plus the number of forecasts an analyst makes per firm-quarter) controlling for firm, analyst, and forecast 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 that the analyst makes for each calendar quarter. Bad times measures equal one whenever any month in the quarter is defined as bad times according to the relevant measure: *Crisis*: September to November 1987 (1987 crisis), August to December 1998 (LTCM), and July 2007 to March 2009 (*Credit Crisis*). *Recession* (NBER recessions): July 1990 to March 1991, March to November 2001, and December 2007 to June 2009. *High Uncertainty* represents the highest tercile (over the period 1983 to 2014) of the Baker, Bloom, and Davis (2016) uncertainty index. Analyst and forecast characteristics (variables described in Table VII) are the averages within the analyst-firm-quarter. t-statistics (in absolute values and based on standard errors clustered by industry-quarter) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Industry fixed effects (F.E.) use the Fama and French (1997) 30-industry classification.

	Dependent Variable: Log (1 + #Forecasts Per Firm-Quarter)							
Variable	(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)

(Continued)

Table X—*Continued*

	Dependent Variable: Log (1 + #Forecasts Per Firm-Quarter)							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Days to Annc		−0.019***		−0.020***		−0.019***		−0.020***
		(9.45)		(9.63)		(9.12)		(9.70)
Multiple 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
#Obs	1,916,213	1,250,891	1,916,213	1,250,891	1,916,213	1,250,891	1,850,104	1,201,285
Adj. R^2	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

is issued within a trading day associated with an earnings announcement or earnings guidance event. Such reports might be of a different length because they contain additional information about the announcement in addition to the analyst's own analysis.

Table XI reports the results. Looking at model (1), we find that the average report length is 10.237 pages. In *Crisis* periods, however, the report length increases by 1.336 pages, or 13%. This shows that reports issued in bad times typically contain more information. When we add the control variables in model (2), we find that reports are 1.552 pages longer than the good times predicted number of pages of 10.220. Note that this result controls for the firm's recent volatility of daily stock returns. This implies that the longer report length is not due to an increase in firm-specific volatility but rather to the macroeconomic bad times. We see similar evidence of longer reports using the other measures of bad times, except for recessions. The overall evidence of longer reports is consistent with analysts exerting more effort in incorporating information in their reports, and hence provides an explanation for why analyst reports have more of an impact, in bad times.[15,16]

We also look at analyst competition. The literature shows that analyst output quality increases with competition (e.g., Hong and Kacperczyk (2010) and Merkley, Michaely, and Pacelli (2017)). If analysts have incentives to work harder in bad times, this means that competition should be more intense, particularly for industries with more competition. We define an industry as competitive if it is in the highest quintile based on the prior-quarter number of analysts in the industry over the total market cap of the industry. In the Internet Appendix, we find that high competition is associated with a significantly greater impact of downgrades across all of our measures of bad times and irrespective of whether we include controls (and industry fixed effects). We do not find a significant impact of competition for upgrades.

occur on earnings announcement dates and earnings guidance dates (about one-third of the sample) and we continue to find that reports in bad times are longer (see the Internet Appendix).

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

[16] We also test whether analysts more actively incorporate changes in the business cycle into their reports in bad times by using Thomson Eikon's advanced search to manually count the fraction of reports from this broker that contain the words "macro" or "macroeconomic" in the 1994 to 2014 period. We choose a neutral business cycle word like "macro" because negative words like "recession" or "crisis" will mechanically be more frequent in bad times. We find that 16.5% of reports in *Crisis* periods have such words compared to 11.4% in non-*Crisis* periods, with the difference statistically significant. The other bad times measures usually see larger economic and statistical differences (e.g. bad times versus good times fractions for each bad times measures are, respectively, 21.2% versus 10.9% for *Credit Crisis*, 20.7% versus 11.2% for *Recession*, and 19.4% versus 7.2% for *High Uncertainty*). These results, though anecdotal, support the view that analyst behavior does indeed change over the business cycle.

Table XI

Analyst Report Length in Bad Times

The list of all U.S. analyst company reports issued by Morgan Stanley from 1994 to 2014 is downloaded from Thomson ONE (until September 2011) and Thomson Eikon (from October 2011 onwards) and the number of pages in each report is regressed against a bad times dummy and control variables. Bad times measures are defined in Table I. *Beta* is the stock's market beta based on three years of past monthly returns. *Size Quintile* is based on the stock's market cap in the prior June using NYSE breakpoints. *Momentum Quintile* is based on the month $t-12$ to $t-2$ buy-and-hold stock return sorted in 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. t-statistics (in absolute values and based on standard errors clustered by the date of the analyst report) are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Industry fixed effects (F.E.) use the Fama and French (1997) 30-industry classification.

	Dependent Variable: Number of Pages in an Analyst Report							
Variable	(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)

(*Continued*)

Table XI—*Continued*

	Dependent Variable: Number of Pages in an Analyst Report							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	85,525	84,707	85,525	84,707	85,525	84,707	81,583	80,806
Adj. R^2	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

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

C. Analyst Expertise Hypothesis

Recent work in the mutual fund literature shows that managers use different skills in bad times compared to good times (see Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016)). 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. If analysts also demonstrate this change of skill in bad times, they might produce more of the type of information that is valuable across firms in bad times. There is some evidence that analysts can predict industry returns (e.g., Howe, Unlu, and Yan (2009) and Kadan et al. (2012)) and that analyst coverage at the industry level has spillover effects to the firm level (Merkley, Michaely, and Pacelli (2017)). To detect the presence of common information in analyst reports, we examine whether analyst recommendation revisions on a firm spill over to other covered firms more in bad times compared to good times.

For each recommendation change, we form a portfolio of peer firms that consist of firms that the analyst has issued a recommendation on in the last year. We then measure the two-day CAR of these peer firms (equally weighting the CAR for all peers) around the recommendation change, excluding peers that receive a recommendation from the same analyst on the same date. A typical recommendation change is associated with about 10 peer firms in our sample. Using this average peer CAR as the dependent variable, in the Internet Appendix we find in good times that downgrades are associated with a negative CAR for peer firms, which implies that revisions do spill over to other firms covered by the same analyst. When we consider whether this spillover increases in bad times, we find that the coefficients on *Crisis*, *Credit Crisis*, and *Recession* indeed show evidence that there is a greater spillover of downgrades to peer firms in bad times. For upgrades, however, we do not find that bad times increase the spillover effect of recommendations to peer firms. Overall, we find that only the negative information produced by analysts during bad times contains a common component. This evidence offers some support for the hypothesis that analysts display different skills in bad times.

D. Conflicts of Interest Hypothesis

Another possible explanation for the greater impact of analysts in bad times is that potential conflicts of interest are less important in these times. We first examine the impact of bad times on an analyst's optimism bias. If bad times reduce investment banking conflicts and if the optimism bias can be attributed to conflicts of interest, analyst forecast optimism should be lower in bad times. We capture an analyst's optimism bias using the signed forecast error, which is the signed version of our absolute forecast error in Table VII. In the Internet Appendix, we find that the signed forecast error scaled by the absolute value of actual earnings is mostly insignificantly different in bad times from that in good times. However, when we scale the signed forecast error by prior volatility, we find that analysts are actually more optimistic in bad times than in good times. Hence, we find little evidence for the conflicts of interest prediction that analysts are less optimistic in bad times.

Next, we identify the subset of brokers that have no investment banking business and compare the bad times impact of their analysts to the bad times impact of analysts employed by brokers with underwriting business. Using the I/B/E/S broker translation file to obtain broker names, we search for information about analyst's broker online to construct the 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 only about 10% of the recommendation changes in our sample. If a reduction in conflicts of interest is responsible for the increase in 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. To test this prediction, we interact the bad times dummies with *Underwriter* and reestimate the downgrade and upgrade CAR impact regressions. In the Internet Appendix, we find that in almost all cases, the coefficients on the bad times dummies are still strong and significant, which suggests that independent brokers also have more of an impact in bad times. This is inconsistent with the conflicts of interest hypothesis. For the interaction terms between the underwriter indicator and bad times, there is some evidence that brokers with underwriting business have more of an impact in bad times than independent brokers (about half of the specifications). While this seems to support the conflicts story, underwriter brokers also have more of an impact in good times than independent brokers. Taken together, these results imply that brokers with underwriting business generally have a greater impact than independent brokers, perhaps due to their larger size and more extensive resources. Consequently, there seems to be little support for the conflicts of interest explanation for why analysts have more of impact during bad times.

E. Overreaction Hypothesis

Another explanation for analysts' seemingly greater impact in bad times is that analysts do not really have more of an impact but rather investors simply overreact to analysts. Such overreaction might stem from the reduction in liquidity provision during bad times so investors have more of a price price impact when they trade in response to recommendations. Alternatively, overreaction could stem from arbitrageurs being more constrained in bad times, in which case they cannot trade against the overreaction by some investors.

To investigate this hypothesis, we form daily-rebalanced calendar-time portfolios that buy stocks from trading day 2 following the revision to day 21, that is, a one-month drift. We follow the standard approach in Barber, Lehavy, and Trueman (2007) when computing average daily returns, in which we place one dollar in each revision, and the weight of the revised stock varies 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 of our bad times measures, we have four portfolios—recommendation downgrades, recommendation upgrades, downward forecast revisions, and upward forecast revisions—for a total of 16 portfolios.

In the Internet Appendix, we find that the intercepts are all significantly negative for negative revisions and significantly positive for positive revisions, indicating that there is stock-price drift in response to analyst revisions in good times. However, the coefficients on the bad times dummies are statistically insignificant for almost all portfolios, which suggests that the bad times drift is statistically indistinguishable from the good times drift. When we add the intercept and the coefficients on bad times dummies to measure the stock-price drift of revisions in bad times, we do not find significant drift that is in the opposite 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.

VI. Conclusion

We assemble a large sample of analyst earnings forecasts and recommendations from 1983 to 2014 to examine the value of sell-side research in bad times. Using various measures of bad times, we find that analyst stock recommendation changes and earnings forecast revisions have more of an impact during bad times compared to good times. When we investigate the precision of analyst earnings forecasts, we find that, while forecasts are more imprecise using a traditional measure of forecast accuracy, a new measure of forecast accuracy that adjusts for the underlying uncertainty shows that analyst forecasts are actually more precise in bad times. We investigate various potential explanations for 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 component in bad times. Alternative possible explanations related to conflicts of interest or overreaction cannot account for our results.

In sum, we show that the role of analysts in financial markets increases in importance during bad times because it is during these times when investors rely more on them and they work harder. The effect we document is economically significant. To gauge the change in firm value brought about by the increased impact of recommendations, we can use the typical recommendation change, which is associated with a market cap of approximately $8 billion (Panel C of Table I). The average increased CAR impact in *Crisis* times compared to good times is 1% for downgrades (0.6% for upgrades), which is equivalent to an $80 million increase in the impact of downgrades ($48 million for upgrades) on market cap.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.