# Is sell-side research more valuable in bad times?*

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Abstract

In bad times, uncertainty is high, so that investors find it more difficult to assess the prospects of the firms they invest in. Learning models suggest that in such times investors should, everything else equal, value informative signals such as analyst forecasts and recommendations more than in good times. However, the higher uncertainty in bad times and career concerns stemming from troubled employers may make the task of analysts harder, so that analyst output is noisier and hence less valuable in bad times. Consequently, whether analyst forecasts and recommendations are more valuable during bad times is an empirical matter. We examine a large sample of analyst output from 1983 to 2011. We find that analysts work harder in bad times, but their earnings forecasts accuracy is worse and that they disagree more. Despite more inaccurate earnings forecasts, revisions to earnings forecasts and stock recommendations have a more influential stock-price impact during bad times as predicted by a learning model.

*Keywords:* Security Analysts; Stock Recommendations; Earnings Forecasts; Crisis; Recessions; Uncertainty; Learning

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## 1. Introduction

There is a large literature on sell-side analysts' role as information intermediaries.[1] However, this literature mostly ignores the issue of whether the state of the economy affects analyst performance. There are good reasons to believe that the usefulness and performance of sell-side analysts should depend on the state of the economy. It is well-known that in recessions and crises (periods we call bad times) there is greater variation in outcomes across firms (greater uncertainty) and across time (greater volatility).[2] In other words, much more information is produced in bad times than in other times. To the extent that the role of analysts is to make sense of this new information about firms, their role becomes more important in bad times. At the same time, however, the faster arrival of information may degrade the signal-to-noise ratio and make it harder for analysts to perform their job, so that it is not clear whether their output is more valuable in bad times than at other times. In this paper, we show that the performance of analysts and the value of their output differ substantially in bad times from other times. While their forecasts are less accurate during bad times, analysts are more active and their forecast and recommendation revisions are more influential. Consequently, our evidence shows that analysts are more valuable in bad times.

We use a simple learning model from Pastor and Veronesi (2009) as a framework to derive implications of bad times for the value of analyst output. With this model, investors have a prior distribution of the prospects of a firm. They receive a signal, which we assume to be analyst output, that leads them to change their prior distribution. A signal that is more precise has a bigger impact on their estimate of the prospects of the firm. A signal of a given precision has more impact if the investors' a priori distribution is more volatile. In other words, a signal is more valuable if investors know less. In bad times, both investors and analysts know less. For analyst signals to be more valuable, bad times should

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

[2] See, for instance, Bloom (2009).

reduce the precision of analyst signals less than they increase investors' a priori uncertainty. To the extent that an analyst signal of a given precision is more valuable to investors in bad times, we would expect analysts to work harder in bad times, as more valuable signals build their reputation more effectively. Consequently, we expect (1) analysts to work harder in bad times, (2) analysts to produce noisier signals in bad times, and (3) analyst output to be more valuable in bad times. The effect of bad times on the impact of analyst recommendations may also be asymmetric depending on whether the recommendation was good or bad. For example, Veronesi (1999) shows that in a two-state economy, investors react more strongly to good news during bad times and vice versa. The logic is that when investors receive good news in the low state, they not only increase the present value of future dividends, but also increase the probability of transiting to a high state. This makes prices rise more than in a present value model.[3]

Several arguments in the literature on security analysts lead to predictions about the value of analyst output in bad times that are sharply different from our learning approach. First, Loh and Mian (2006) find that accurate earnings forecasts translate to more profitable stock recommendations. Because analysts have less accurate earnings forecasts during bad times, one might expect correspondingly poorer and hence less valuable stock recommendations. Second, analysts might be more focused on career concerns in bad times as their employer might be in difficulty or be cutting back its work force. While these career concerns might lead analysts to work harder, they might also lead them to spend time seeking new employment and hence become less productive. Third, because employment and profitability of broker-dealers is pro-cyclical, analysts might be rewarded less in bad times and, everything else equal, might choose not to work as hard. Finally, there is now solid evidence that investors pay less attention to firm-specific news when they receive more new information. For instance, Hirshleifer, Lim, and Teoh (2009) show that earnings announcements have less impact on days when there is more earnings news. During

[3] Beber and Brandt (2010) show that bad macroeconomic news impacts bond returns more than good news in expansionary periods while in recessionary periods, good news impacts bond returns more. Such asymmetry is also documented in Conrad, Cornell, and Landsman (2002) who find that the stock-price response to negative earnings surprises increases as the relative level of the market rises.

bad times, there is more news of every kind. Consequently, investors might pay less attention to analyst output so that this output has less impact.

We test our predictions using a sample of I/B/E/S Detail earnings forecasts from 1983-2011 and recommendations from 1993-2011. We define bad times in multiple ways. The most obvious approach is to use prominent crises that have occurred in the last two decades, such as the October 1987 crash, the LTCM crisis of 1998, and the credit crisis of 2007-2009. We also define bad times as recession periods marked by the National Bureau of Economic Research (NBER) or down market states (an ex ante bad times definition that relies on negative prior market returns following Cooper, Gutierrez, and Hameed (2004)).

Measuring the average two-day abnormal returns to recommendation changes, we find that analysts are more impactful during bad times as expected from the learning model. This result is strong for *both* downgrades and upgrades. In other words, there is no good news-bad news asymmetry to the increased impact of recommendations during bad times. Using the definition of influential recommendations in Loh and Stulz (2011), which effectively treats recommendation changes as influential if the stock-price reaction is statistically significant, we find robust evidence that both upgrades and downgrades are more likely to be influential during bad times compared to good times.

Not surprisingly, we find that analysts issue less accurate earnings forecasts in bad times compared to good times. This difference holds using different methods to scale forecast accuracy, and controls for forecast, analyst, and firm characteristics. We conclude that analysts are less able to evaluate near-term earnings during bad times, which are times when uncertainty is greater. However, as predicted from the learning model, forecast activity increases in bad times even after controlling for changes in the firm's information environment. Moreover, despite the fact that earnings forecasts are less accurate, we find that the market reacts more strongly to revisions in earnings forecasts during bad times as predicted by the learning model. The alternatives to the learning model predict that analysts are less influential in bad times and work less hard. These predictions are rejected. We also investigate whether our results can be explained by overreaction to analyst news in bad times. However, we find that in bad times the postrevision stock-price drift is insignificantly different from the drift in good times and there is no reversal in the stock-price impact afterwards. Overall, our evidence is strongly supportive of the learning model and inconsistent with the alternative hypotheses we put forward.

Some related papers have examined some aspects of the impact of crises on analyst output. However, none of these papers tests the theoretical predictions we focus on. Arand and Kerl (2012) examine analysts' earnings forecasts and recommendations in a short period around the credit crisis and find that, although forecast accuracy dropped, investors continued to react to revisions in recommendations. Hess, Kretzmann, Maaz, and Pucker (2012) 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, Landsman, Owens, and Stubben (2013) examine analyst forecast timeliness during periods of high market volatility and find that analysts are less timely and underreact to news in those periods. However, they also find that forecast revisions in these periods actually have more impact in reducing information asymmetry measured by bid-ask spreads.

The rest of the study is organized as follows. Section 2 discusses the hypotheses tested in more detail. Section 3 explains our data and our definitions of bad times. It also shows that ex ante volatility, measured using implied volatility, is sharply higher during bad times. Section 4 shows that analyst recommendations are more impactful in bad times. Section 5 examines the accuracy and impact of earnings forecasts in good and bad times. In Section 6, we check that our results cannot be explained by a pattern of overreaction to analyst reports and forecasts during bad times. Finally, Section 7 concludes.

## 2. A theory of the value of analyst signals in bad and good times

We now formulate in more detail a simple theory of how bad times and good times affect the value of analyst signals. Our starting point is a simple Bayesian updating model where the investor learns from signals about the value of the stock from analysts. The formal structure of such a model is described in Pastor and Veronesi (2009). Suppose that the value of the stock depends on $\theta$. The investor's prior beliefs about $\theta$ have mean $\theta_0$ and variance $\sigma_0^2$. The investor receives a signal from an analyst, $s = \theta + \varepsilon$, where $\varepsilon$

is normally distributed with zero mean and known variance $\sigma^2$. According to Bayes' rule, the investor's posterior belief is normally distributed with mean $\theta_P$ and variance $\sigma_P^2$, where:

$$\theta_P = \theta_0 \frac{\frac{1}{\sigma_0^2}}{\frac{1}{\sigma_0^2} + \frac{1}{\sigma^2}} + s \frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma_0^2} + \frac{1}{\sigma^2}} \tag{1}$$

$$\sigma_P^2 = \frac{1}{\frac{1}{\sigma_0^2} + \frac{1}{\sigma^2}} \tag{2}$$

It immediately follows from this, everything else equal, that an increase in the prior variance makes the analyst signal become more valuable because it changes the prior estimate of $\theta$ more. We would therefore expect the analyst signal, be it a recommendation change or an earnings forecast change, to have more of an impact on the stock price. Therefore, everything else equal, analyst signals are more valuable in bad times, which are times when investors' variance about their prior is high.

To make matters more complicated, however, we would expect the informativeness of analyst signals to be affected by bad times as well. In this framework, the value of the analyst signal, everything else equal, falls as the analyst's signal becomes noisier. Hence, if the rate at which the analyst's signal becomes noisier in bad times is worse than the rate at which the variance of the investor's prior increases, the value of the analyst's signal falls in bad times. If the precision of the signals produced by analysts does not degrade as much as the precision of investors' priors in bad times, the value of analyst signals will be higher in bad times. It follows that whether analyst signals are more valuable in bad times depends on the extent to which the quality of analyst signals degrades in bad times.

In bad times, news that could signal an end of bad times will have a strong positive impact on stock prices. Some models predict that signals in bad times have asymmetric effects, namely positive signals have more of an impact in absolute value than negative signals. Veronesi (1999) shows that in a two-state economy, investors may react more to good news during bad times because they update on the probability of transiting to the alternate state. Beber and Brandt (2010) find such asymmetry in the bond market's reaction to bad macroeconomic news during good times and reaction to good macroeconomic news during bad times. If such asymmetry exists, we expect upgrades to be more impactful during bad times.

With the learning model, an analyst's signal has the potential to be more valuable in bad times when market-wide uncertainty increases. We would therefore expect that an analyst can build his reputation more effectively in bad times because, keeping research output quality constant, his output has more impact on investors' beliefs in bad times. Suppose instead that the analyst keeps effort constant in bad and good times, the ratio of noise in the analyst's signal to the variance about the prior, $\sigma^2/\sigma_0^2$, will be constant. This ratio can be thought of as an analyst noise to market uncertainty ratio. But if the analyst exerts more effort in bad times, this means that the ratio $\sigma^2/\sigma_0^2$ is lower in bad times than in good times, so that an analyst signal has more value in bad times. A straightforward related hypothesis is that the analyst produces more output in bad times than in good times. However, the model does not necessarily predict that the noise in analyst signals is less in bad times. In fact, we would expect that in bad times, the greater uncertainty would make it unlikely that the analyst could produce signals with the same amount of noise as in good times even if the analyst wanted to. If analyst signals become noisier, we also would expect analysts to disagree more.

Other factors can affect the value of analyst signals during bad times. First, during bad times, the employer of an analyst is more likely to face difficulties. The possibility that the employer of an analyst will face difficulties could lead the analyst to work harder to have better outside options, which would be another reason for the noise in analyst signals to increase less than the variance of investors' priors. However, the analyst may also be distracted by his employer's difficulties, so that the quality of his output could fall (analyst distraction hypothesis). Second, investors could pay less attention to analysts in bad times. Recent research shows that investors can be distracted when there is much new information (Hirshleifer et al. (2009)), so that news announcements about corporations, such as earnings announcements, have a less immediate impact on stock prices. Bad times are times with more information arriving to the market as they are more volatile times. Hence, investors could be more distracted in bad times, so that they would pay less attention to analyst reports and reports would have less of a contemporaneous impact (investor distraction hypothesis). Alternatively, investors could pay less attention to analysts simply because their forecasts are less precise in good times, which following Loh and Mian (2006) would also make their recommendations less valuable for investment purposes. Finally, the employers of analysts might value their output less during bad times, perhaps because business opportunities are pro-cyclical, so that analysts choose not to work as hard in bad times because of the limited upside to their compensation.

## 3. What are bad times?

In this section, we first present our sample and then we define bad times. Finally, we show that bad times are characterized by higher ex ante volatility.

### 3.1. *Earnings forecasts and recommendations sample*

The analyst data are from Thomson Financial's Institutional Brokers Estimate System's (I/B/E/S) U.S. Detail File. Earnings forecasts are one-quarter-ahead forecasts and actual earnings are taken from I/B/E/S from 1983-2011. The unadjusted file is used to mitigate the rounding problem in I/B/E/S (see, for instance, Diether, Malloy, and Scherbina (2002)). Using I/B/E/S' split-adjustment factors, we adjust the unadjusted forecast so that it is on the same per-share basis as the unadjusted actual earnings. As is common practice, financial firms are excluded from our analysis (we exclude group 29 of the Fama and French (1997) 30-industry definitions).

For stock recommendations, we rely on I/B/E/S individual analyst ratings from 1993-2011.[4] We define upgrades and downgrades using the analyst's current rating minus the prior rating by the same analyst. A prior rating is assumed to be outstanding if it has not been stopped (using the I/B/E/S Stopped file) and is less than one year old based on the I/B/E/S review date (following Ljungqvist et al. (2009)).

[4] Ljungqvist, Malloy, and Marston (2009) report that matched records in the I/B/E/S recommendations data were altered between downloads from 2000 to 2007. Thomson, in response to their paper, fixed the alterations in the recommendation history file as of February 12, 2007. The dataset we use is dated December 15, 2011 and hence reflects these corrections. However, there are still some large brokers missing from the current I/B/E/S files, such as Lehman Brothers and Merrill Lynch. When possible, we rely on old vintages of I/B/E/S available from WRDS (a 2008 vintage) or from our own old downloads (2001 and 2009 vintages) to reinstate such missing brokers.

We exclude anonymous analysts as well as observations with no outstanding prior rating from the same analyst (i.e., analyst initiations or re-initiations are excluded). We also remove revisions that occur on firm-news days following Loh and Stulz (2011). This step is important because we do not want recommendations that merely repeat the information contained in firm news releases. Firm-news days are defined as the three days centered on an earnings announcement date or around a company earnings guidance date (from First Call Guidelines), and days with multiple analysts issuing recommendations for the firm. These three filters are also used when we examine the stock-price impact of earnings forecast revisions. Stock returns are from the Center for Research in Security Prices (CRSP).

### 3.2. *Bad times definition*

We define bad times as periods of bad macroeconomic conditions and we have four proxies. The first two proxies focus on prominent financial crises. We set the indicator variable *Crisis* equal to one for the periods September-November 1987 (1987 crisis), August-December 1998 (LTCM crisis), and July 2007-March 2009 (credit crisis). Second, we consider separately the *Credit Crisis* period. Since this is an especially sharp crisis, it warrants a separate investigation. The third definition uses NBER-defined recessions, which are the periods July 1990-March 1991, March-November 2001, and December 2007-June 2009. The last measure is based on poor market returns, where we define a *Down Market* as one where the prior three-month buy-and-hold market return is negative. This is similar in spirit to the market state measure in Cooper et al. (2004) and will label more periods as bad times than the earlier definitions. Further, unlike the earlier definitions which are ex post-defined measures, *Down Market* is an ex-ante measure of bad times. In our 1983-2011 sample, 8.5%, 6.2%, 10.9%, and 32.3% of the months are classified as *Crisis*, *Credit Crisis*, *Recession*, and *Down Market* respectively.

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

Our learning theory requires that the variance of the investors' prior increases in bad times. This variance is an ex ante variance. We show that with our definition of bad times, it is indeed the case that there is more ex ante uncertainty about the market and about individual stocks.

In Panel A of Table 1, we report daily estimates of the VIX collected by the CBOE for bad times as well as for other times. This data starts from 1986 and so it overlaps most of our 1983-2011 sample. The typical daily VIX in *Crisis* periods is 33.569, while in other times it is 20.271. The VIX in *Crisis* periods is therefore more than 50% greater than in other times. The increase is statistically significant at the 1% level. The increase in the VIX is almost as high for the *Credit Crisis* period and for the *Recession* periods. It is smaller for the *Down Market* periods but is still significant. It follows that for all our classifications of bad times, the ex ante volatility of the market increases sharply.

We turn now to ex ante volatility for the common stock of individual firms. Panel B of Table 1 reports the annualized implied volatilities of the stocks five days before they are subject to a recommendation change for bad times and other times. The implied volatility data is from Option Metrics' Volatility Surface file, using the average of the interpolated volatility from puts and calls with 30-days to expiration and a delta of 50. Data for implied volatility is not available for all firms in our sample but we are able to match 72% of the recommendation changes in our sample with an implied volatility for the period 1993-2011. We focus on implied volatilities before recommendation changes because they are the relevant ex ante volatilities for our learning theory. We separate downgrades from upgrades since we discussed the possibility of an asymmetric reaction to downgrades and upgrades associated with the resolution of uncertainty. Starting with the *Crisis* definition of bad times, we see that the option implied volatility is 60.964% in bad times and 49.429% in other times. The difference of 11.535 percentage points is statistically significant at the 1% level. When we turn to upgrades, the implied volatilities are very similar to what they are for downgrades. For all our definitions of bad times, we find similar results. It follows from this that there is clear evidence of higher ex ante volatility even at the firm level during bad times.

## 4. Are analyst recommendations more influential in bad times?

The key focus of our study is whether analyst output is more valuable in bad times. Our learning model predicts that analyst output is more valuable in bad times. In contrast, the analyst distraction and investor distraction hypotheses predict the opposite. In this section, we focus on whether analyst recommendations changes are more influential during bad times.

### 4.1. *Comparisons of recommendation change CAR*

Because recommendation levels can be biased, recommendation changes are more reliable than levels as a setting to evaluate the impact of analysts. Boni and Womack (2006) for instance, show that rating changes contain more information for returns than rating levels. To estimate the stock-price impact of the recommendation change, we use the cumulative abnormal return of the day of the recommendation change and the following trading day, i.e., a day [0,1] event window. If the recommendation is issued after trading hours, day 0 of the recommendation is defined as the next trading day. The CAR is the cumulative return of the stock less that on an equally-weighted characteristics-matched size, book-to-market (B/M), and momentum portfolio (following Daniel, Grinblatt, Titman, and Wermers (1997), thereafter DGTW). Table 2 reports the average CAR of recommendation changes issued in bad times and in good times with statistical significance based on standard errors clustered by calendar day. We separate the recommendation change sample into upgrades and downgrades. As predicted by the learning model, we see that CARs for downgrades and upgrades are larger during bad times. The differences are stark. Starting with the *Crisis* definition of bad times, we see that the average two-day CAR is -2.560% for a recommendation downgrade in bad times and is -1.602% in other times. Both CARs are significant at the 1% level. The difference is -0.958% and is significant at the 1% level. The CAR for upgrades in bad times is 2.635%, while in other times the CAR is 2.036%. These CARs are statistically significant at the 1% level as well. The difference in these CARs is 0.599% and is again significant at the 1% level. For the *Crisis* definition, the absolute value of the CAR difference is larger for downgrades than for upgrades.

We now turn to the other definitions of bad times. The results are very similar for the *Credit Crisis* definition and for the *Recession* definition. For the *Down Market* definition, the downgrades have more impact during bad times, but the difference is smaller than for the other definitions of bad times. However, the upgrades do not have a stronger impact during *Down Market* periods.

Our evidence shows that recommendation changes have more impact during bad times than they do during good times across almost all definitions of bad times. We conclude there is little evidence for the analyst and investor distraction hypotheses, but that there is strong support for the learning model. If information uncertainty increases in bad times, the signal provided by analysts may become more important in such an environment.

We now examine whether analysts are more influential in bad times using the influential definition of Loh and Stulz (2011). Loh and Stulz show that it is important to assess whether a recommendation change results in a stock-price reaction that is noticed by investors, i.e. that the rating change results in a reaction that is significant at the firm level based on the firm's prior stock-price volatility.[5] We show in Panel B Table 2 the fraction of recommendation changes that are influential during bad times compared to other times.

The results are striking. For all definitions of bad times, a recommendation downgrade is significantly more likely to be influential during bad times than during good times. The difference is especially large when we use the *Crisis* definition or the *Credit Crisis* definition of bad times. For these definitions, a recommendation downgrade has a probability of being influential that is almost 50% higher during bad times (14.902% versus 10.863%). The difference is smaller for the *Recession* and *Down Market* definitions. Turning to recommendation upgrades, we find that a recommendation upgrade is significantly more likely to be influential in all definitions of bad times except for the *Down Market* definition. The results for the fraction of influential recommendations are, therefore, similar to the CAR results.

We plot in Figure 1 the summary of our main results in Table 2, i.e. the average mean CAR as well as the influential probability of the recommendation downgrades and upgrades. We can see that upgrades and downgrades are both associated with stronger stock-price reactions and are more likely to be influential in bad times compared to good times.

[5] Specifically, we check if the CAR is in the same direction as the recommendation change and the absolute value CAR exceeds $1.96 \times \sqrt{2} \times \sigma_{\varepsilon}$. We multiply by $\sqrt{2}$ since the CAR is a two-day CAR. $\sigma_{\varepsilon}$ 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-French factors. This measure roughly captures recommendation changes that are associated with noticeable abnormal returns that can be attributed to the recommendation changes.

## 4.2. *Multiple regressions*

Thus far we have only shown univariate results which support the learning hypothesis. Because recommendation impact can be determined by other characteristics besides bad times, it is important to examine if our results are robust to controlling for such characteristics. In Table 3, we report estimates of OLS regressions where we control for firm, analyst, and recommendation characteristics. We use the following control variables from the existing literature that are known to be related to the impact of recommendations. *LFR* is the analyst's prior year leader-follower ratio constructed following Cooper, Day, and Lewis (2001).[6] Leader analysts have been shown to exert more impact on the stock price when they issue reports. *Star Analyst* is an indicator variable for analysts elected to the All-American team (whether as first-, second-, third-team, or runner-up statuses) in the latest October *Institutional Investor* annual poll following Fang and Yasuda (2013), who show that stars have better performance. Mikhail, Walther, and Willis (1997) show that analyst experience impacts performance and so we add proxies for analyst experience. *Relative Experience* is the difference between the analyst's number of quarters on I/B/E/S and the average experience of all analysts covering the firm. Prior forecast accuracy can also be a proxy for skill in both forecasting earnings as well as issuing stock recommendations. We define *Accuracy Quintile* as the average forecast accuracy quintile of the analyst based on the firms covered in the past year where the quintile rank is increasing in forecast accuracy. Log *Broker Size* is the number of analysts employed by the broker since broker size has been used as a proxy for analyst ability and availability of resources. We also add the following firm characteristics: Log # *Analysts* (specifically 1+the number of analysts covering the firm), Log *Size* (last June's market cap), Log *BM* (book-to-market equity ratio, where *Size* and *BM* are computed and aligned following Fama and French (2006)), *Momentum* (buy-and-hold return from month *t*-12 to *t*-2), and *Stock Volatility* (measured as the standard

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

deviation of daily stock returns in the prior three months) as firm-level control variables so that we can check if changing firm characteristics from good to bad times drive our results.

The first eight regressions shown in Table 3 estimate whether downgrades are more impactful during bad times. For each definition of bad times, we estimate the regression first using a constant and an indicator variable for bad times. We then estimate the regression controlling for firm, analyst, forecast characteristics, and industry fixed effects. Standard errors are clustered by calendar day to account for cross-sectional correlation of returns that occur on the same date. In all cases for downgrades, the indicator variable for bad times is statistically significant at the 1% level. Recommendations by analysts with a greater leader-follower ratio have a larger impact in absolute value. Not surprisingly in light of the earlier literature, we see that recommendation changes by Star analysts have a greater impact. So do the recommendations of analysts from larger brokers. In contrast, and also in line with the literature, recommendation changes have less impact when a firm is followed by more analysts or when the firm is larger. Lastly, the impact of analyst downgrades is greater when the firm's stock is more volatile.

Turning to recommendation upgrades, we find that upgrades have a significantly higher stock-price reaction during bad times for regressions (9) through (14), which are the regressions corresponding to the *Crisis*, *Credit Crisis*, and *Recession* definitions of bad times. However, for the *Down Market* definition, the coefficient on the indicator variable is significant at the 10% level, but has the opposite sign.

Table 4 repeats the analysis of Table 3 for the fraction of recommendations that are influential. We estimate probit models and report the marginal effects with *z*-statistics in parentheses (based on standard errors clustered by calendar day). Recommendation downgrades are more likely to be influential in bad times irrespective of the definition of bad times. Surprisingly, the coefficient on the bad times indicator variables are higher when we control for analyst, firm and recommendation characteristics. For example, in regression 1 of Table 4, a *Crisis* coefficient indicates that bad times increase the likelihood that a recommendation change is influential by 4% when we do not control for firm, analyst, and recommendation characteristics, but the marginal effect increases to 7% when we do. Turning to recommendation upgrades, we find that upgrades are more likely to be influential during bad times for all definitions except for the *Down Market* definition. When we control for firm, analyst, and recommendation characteristics, we see that the economic magnitude of these results is even stronger.

These findings are consistent with the learning hypothesis. We find strong evidence that changes in recommendations are more impactful during bad times for almost all of our definitions. Some of the literature suggests that good news have more impact during bad times (e.g. Beber and Brandt (2010) and Veronesi (1999)). We find no evidence supportive of such an asymmetry since there is no case where the increased impact of recommendations in bad times compared to good times is limited only to upgrades.

An important caveat for our results is that the credit crisis period forms a large fraction of the bad times observations in our sample for all our definitions of bad times.[7] As a result, when we exclude the credit crisis from our sample, our results are much weaker and typically insignificant.

## 5. Earnings forecasts in good and bad times

The learning model implies that analyst output is more valuable in bad times even though the earnings forecasts underlying the analyst reports are expected to be less precise than in good times. In this section, we first show that analyst forecasts are less precise in bad times and that analysts agree less among themselves in bad times. We then show that analyst forecast revisions have more impact in bad times as predicted by the learning model and that analysts indeed exert more effort in bad times by revising their forecasts more.

### 5.1. *Forecast accuracy in bad times*

We begin our analysis by examining earnings forecast accuracy. For each analyst, the final unrevised one-quarter-ahead forecast for the forecasting quarter is used to compute forecast error, defined as the actual earnings minus the forecast. A positive forecast error means that the analyst was too pessimistic (actuals were too high compared to the forecast) and a negative value shows that the analyst was too optimistic (actuals were much lower). The literature uses two different approaches to scale forecast errors.

[7] 72%, 43%, and 14% of all the months denoted as bad times by the *Crisis*, *Recession*, and *Down Market* definitions respectively occur during the *Credit Crisis*.

The first approach scales by the absolute value of actual earnings and the second scales by the stock price. We focus on results that scale forecast errors by the absolute value of actual earnings because many bad times periods have lower stock prices, so that forecast errors are magnified when scaled by stock prices. When scaling forecast error by the absolute value of actual earnings, denominator values smaller than 0.25 are set to 0.25 to limit the impact of small denominators. Scaled forecast errors are then winsorized at the extreme 1% each year.

Table 5 formally tests whether the average absolute forecast error of analysts in bad times is larger. All results use the absolute forecast error scaled by the absolute value of actual earnings. When we scale forecast errors by price, we typically get stronger results. Standard errors are clustered by industry-quarter where the industry definition is the Fama and French (1997) 30-industry groupings. As in Tables 3 and 4, for each definition of bad times, we estimate a regression with a constant and a bad times indicator variable as well as a regression where we add controls for analyst, firm, and forecast characteristics. We use the control variables in Tables 3 and 4, but also add control variables that are relevant for predicting the accuracy of analyst forecasts from the literature. Lim (2001) shows that analysts trade off optimism and accuracy because optimism facilitates access to private information from the covered firm's management. We add optimism as a control where *Optimistic* is a dummy variable that equals one when the forecast is in the top half among all final unrevised forecasts in that quarter. Clement (1999) stresses the importance of controlling for forecast recency because forecasts closer to the actual earnings announcement date will obviously be more accurate. Log *Days to Annc* is the number of days that the forecast date is before the announcement date of actual earnings and serves as a control for forecast recency. As Bradley, Jordan, and Ritter (2008) suggest, days with activity from multiple analysts most likely are caused by a corporate news release. Forecast accuracy may be different when the forecast is made in response to a corporate news release. *Multiple Forecast Day* is an indicator variable representing days where the forecast falls on a day on which more than one analyst issues a forecast on the firm. To control for differences of opinion among analysts, we include the *Dispersion* of forecasts measured as the standard deviation of quarterly forecasts making up the final consensus scaled by the mean estimate.

We see in Table 5 that absolute forecast errors are significantly larger in bad times. Further, when we control for analyst, firm, and forecast characteristics, these results become stronger. For example, regressions (1) and (2) use the *Crisis* definition of bad times. Regression (1) shows that the absolute forecast error is 15.38% higher in bad times. In regression (2), the coefficient on the *Crisis* indicator is higher by almost 50%. It follows that the increase in the absolute forecast error is larger after taking into account analyst, firm and forecast characteristics. The same results hold for the *Credit Crisis* and for the *Recession* definitions of bad times. When we turn to the *Down Market* definition of bad times, the absolute forecast error is not significantly higher without control variables, but it is with the controls.

One possible explanation for the greater forecast inaccuracy could be that analysts are more biased during bad times. We examine this possibility in regressions (9) through (16) of Table 5 where the dependent variable is now the signed forecast error, defined as actual earnings minus forecasted earnings so that negative errors denote forecast optimism. We find no evidence of greater bias during bad times. Regression (9) has only a constant and an indicator variable for the *Crisis* definition of bad times. The constant is significant and negative, indicating that analysts are optimistic during good times, which is consistent with the literature documenting optimistic forecasts by analysts on average. However, the coefficient on the indicator variable is not significant, so that there is no evidence that analysts are more biased in bad times. The same result holds when we control for analyst, firm, and forecast characteristics. The only regression that is consistent with a difference in bias during bad times is regression (11), which uses the *Credit Crisis* definition of bad times. That regression does not have control variables. The coefficient on the indicator variable is positive and significant, indicating that analysts are less biased during bad times. All other coefficients of the indicator variables are insignificant.[8]

[8] When we use forecast errors scaled by price, there is some evidence of a greater optimistic bias by analysts in bad times. This could be due to the fact the price-scaled forecast errors get magnified by smaller stock prices in bad times so that any slight optimistic slant in bad times gets accentuated.

### 5.2. *Forecast dispersion*

To understand better why analyst forecasts are noisier during bad times, we now turn to forecast dispersion. The dispersion of earnings forecasts comingles two effects—the first is the disagreement between analysts and the second is the underlying information uncertainty of the covered firm. Dispersion (×100) is defined as the standard deviation of the final unrevised forecast of analysts within the firm-quarter divided by the absolute value of the mean quarterly estimate. A minimum of two analysts is needed to compute dispersion and we winsorize the dispersion each year at the top 1%. Standard errors are clustered by industry-quarter.

Table 6 reports our regression estimates where the dependent variable is the dispersion of analyst forecasts. We use the same control variables as before, except that now we cannot have analyst-level control variables because analyst dispersion is a firm-level measure. We find that analyst dispersion increases sharply during bad times. To see this, note that regression (1) implies that the analyst dispersion is higher by 30.63% (7.569/24.706) during bad times. When we control for firm characteristics, the indicator variable falls but is still highly significant. One can interpret the coefficient on the indicator variable in regression (2) as the component related to disagreement or analyst noise since the firm characteristics related to uncertainty such as size, B/M, stock volatility, etc. have been controlled for. Though our results hold for the *Crisis*, *Credit Crisis*, and *Recession* definitions of bad times, they do not for the *Down Market* definition. For that definition, while forecast dispersion is higher in bad times for univariate comparisons, it falls in bad times once we add the control variables to the regression.

### 5.3. *Market reactions to forecast revisions*

We now investigate whether earnings forecasts are more or less useful to investors during bad times than during good times by measuring their impact on the firm's stock price. We use two definitions of impact. The first is the two-day cumulative abnormal return (CAR) from day 0 to day 1 of the revision date. As with our analysis of recommendation changes, the CAR is the cumulative return of the stock less that on a characteristics-matched DGTW portfolio. The second is the definition of influential recommendations of Loh and Stulz (2011), which essentially considers forecasts to be influential if the stock-price reaction is in the same direction as the forecast revision and is statistically significant at the 5% level (see discussion earlier on influential recommendations). A forecast revision is defined using the analyst's own prior forecast of quarterly earnings, provided that the prior forecast has not been stopped and is still active (less than one year old) using its review date in I/B/E/S. The revision is then scaled by the lagged CRSP stock price and we call this the *Forecast Revision* variable. Because we are measuring the stock-price impact, we remove forecast revision dates that coincide with corporate events so that we do not falsely give credit to the analyst for company announcement-driven stock-price changes. Following Loh and Stulz (2011), we remove revision days that fall within a trading day of earnings announcement days (from Compustat) and company earnings guidance days (from First Call Guidelines). We also remove days where multiple analysts issue forecasts since these clustered forecasts likely reflect a collective response to a company announcement.

Figure 2 (first two charts on the left) reports the univariate results where the average forecast revision CAR is plotted in bar charts. We see clear evidence that forecast revisions have more stock-price impact in bad times. Table 7 then estimates regressions using the same control variables as for the regressions on forecast errors. We add an important variable, *Forecast Revision* itself, as a control for the stock-price impact because one naturally expects larger-magnitude revisions to be associated with larger stock-price changes. Table 7 reports the regressions of forecast revision CARs on indicators for bad times and controls where the standard errors are clustered by calendar day. Regression (1) has no control variables. It shows that the forecast revision CAR is much larger in bad times for downward revisions. The intercept of the regression is -0.299% while the coefficient on the indicator variable is -0.384%, so that the stock-price reaction to a downward revision during bad times is more than twice the reaction during good times. Adding the control variables to the regression does not change the coefficient on the indicator variable meaningfully. Similar results hold for the other definitions of bad times. When we turn to upward revisions, the CAR is significantly higher for the *Crisis* and for the *Credit Crisis* definition of bad times, but not for the other definitions. Further, the impact of bad times on the CAR is smaller. For instance, for the *Crisis* definition, the intercept is 0.459% and the estimate of the coefficient on the indicator variable is 0.182%, so that the impact of an upward revision in bad times is 39.65% higher than in bad times, which contrasts with an impact which is 128.42% higher in bad times.

Figure 2 (right two charts) and Table 8 examine whether a revision is more likely to be influential in bad times. For the multivariate analysis in Table 8, we use a probit specification since the dependent variable is an indicator variable that equals one when the forecast is deemed to be influential. The results are stronger than in the earlier table with almost all coefficients statistically significant. Essentially, an analyst's forecast revision is more likely to be influential in bad times compared to good times. The economic effect is also large. For example, in good times, the fraction of influential downward revisions (see Figure 2 plot) is about 4.5%. The coefficient in model 2 of Table 8 shows a marginal effect of 0.034 which means in *Crisis* times a downward revision is 3.4% ($z$ =5.92) more likely to be influential, almost doubling the base influential probability of 4.5%.

Overall, the earnings forecast accuracy and impact results strongly support the learning model. The results are most impressive for the multivariate analysis, which controls for various determinants of forecast accuracy and price impact. There, all the definitions of bad times show that analysts make more inaccurate forecasts but yet those very forecasts produce a more influential impact on stock returns.

5.4. *Analyst forecast activity in bad times versus good times*

Our evidence so far is inconsistent with the alternative hypotheses about the value of analyst output in bad times. These alternatives predict that the value of analyst output is lower in bad times and we have seen strong evidence to the contrary. However, the hypothesis that analysts are distracted in bad times also suggests that analysts produce less output in bad times. We now test this hypothesis by investigating whether forecast activity increases or decreases in bad times. We define forecast activity as the number of forecasts made by the analyst for a firm-quarter pair. For each firm, we assume that the period of a particular analyst's coverage starts with the first quarter and stops with the last quarter that the analyst features in I/B/E/S for that firm. We then count the number of forecasts that the analyst makes in each of the coverage quarters. Quarters within the coverage period that have no forecast from the analyst are assigned a forecast activity of zero.

We estimate regressions explaining forecast activity in Table 9 where the dependent variable is the log of one plus the number of analyst's forecasts. The regressions are at the firm-quarter-analyst level. The forecast-level control variables are now simply averages of the analyst, firm, and forecast characteristic within the quarter. For the bad times definitions, when part of a calendar quarter is defined as a bad times period, we treat that quarter as a bad times quarter. We see from the bad times dummies that there is indeed more analyst activity even after controlling for all other variables. This holds true irrespective of the definition of bad times. In all cases adding control variables reduces the magnitude of the coefficient on the bad times indicator variable substantially, but the coefficient is always significant at the 1% level after including the control variables.

## 6. Can overreaction explain our results?

Our main result is that after analyst revisions of recommendations or earnings forecasts, the market reacts more strongly in bad times than in good times and that this is consistent with our learning model. One alternative interpretation is that the market overreacts to analysts in bad times. If this is true, there will be a subsequent reversal in stock prices. We find that this is not the case.

In untabulated results, we examine whether the stock-price drift exhibits any reversal. To do this, we form daily-rebalanced calendar-time portfolios which buy stocks revised by analysts from day 2 of the revision to day 21, i.e. a one-month drift. We follow the standard approach in Barber, Lehavy, and Trueman (2007) when computing average daily returns, in which one dollar is placed in each revision and the weight of the revised stock varies from day 2 to day 21 according to its cumulative return. 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 the four factors to allow for factor exposures to vary according to bad times. The intercept measures the revision drift in good times, and the bad times dummy identifies whether the drift in bad times is statistically different from the good times drift. For each bad times definition we have four portfolios—recommendation downgrades, recommendation upgrades, downward forecast revisions, and upward forecast revisions—and so a total of 16 portfolios.

We find that the intercepts of the regressions are all significantly negative for negative revisions and significantly positive for positive revisions indicating that investors underreact to analyst revisions in good times. Of interest is the coefficient on the bad times dummies and we find that this coefficient is statistically insignificant for 14 of 16 portfolios. This is clear evidence that the drift from bad times is statistically indistinguishable from the good times drift. In two exceptions, negative downgrades and downward revisions in *Recession* periods, the coefficient on bad times is statistically positive, but adding up the intercept and the coefficient on bad times yields a coefficient indistinguishable from zero, indicating no evidence of any reversal (i.e. positive drift after negative revisions) in returns after negative revisions. Overall, we do not find evidence that the larger stock-price impact of analysts in bad times is due to investor overreaction.

## 7. Conclusion

We assemble a large sample of analysts' earnings forecasts and recommendations from 1983-2011 and examine the value of sell-side equity research in bad times. We propose a learning model that predicts that analyst output is more valuable in bad times even if analyst output is noisier because of increased uncertainty. The reason for this prediction is that the increase in uncertainty means that analyst output of given precision has a greater impact on investors' priors than in good times which are associated with less uncertainty. We formulate two alternative hypotheses that predict that analyst output is less valuable in bad times. One hypothesis predicts that analysts are distracted and do not work as hard as in good times. The other hypothesis predicts that investors are distracted and pay less attention to analysts in bad times due to the deluge of news.

Using various definitions of bad times, we find that analysts' forecast accuracy deteriorates during bad times. Despite the reduction in earnings forecast accuracy, we show that analysts' earnings forecast revisions and recommendation changes in bad times are more influential than those issued during good times. There is also no reversal in the stock-price impact when we examine the post-event returns. Analysts' role in financial markets hence appears to increase in importance during bad times. This is consistent with the learning model. Because of the heightened market uncertainty in bad times, analyst signals are more valuable to investors even though they are noisier than in good times.

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## Table 1: Change in uncertainty during bad times

Panel A reports the average daily VIX over bad times from 1986-2011. Panel B reports the average annualized implied volatility for the recommendation change sample measured five days before the recommendation event. About 72% of the recommendation change sample has implied volatility data from Option Metrics. Implied volatility is from the 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. In Panel B, the recommendations change sample is shorter, from 1993-2011. Recommendation changes are based on the individual analyst's prior outstanding recommendation (i.e., initiations are excluded). Recommendation changes made on earnings announcement days, earnings guidance days, and multiple-recommendation days are excluded. Bad times are defined in four ways. *Crisis* is when the forecast is announced in any of the periods: Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *Down Market* is when the prior 3-month buy-and-hold market return is negative. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A: VIX

| Bad times definition | Average daily VIX (%) | | |
|---|---|---|---|
| | Bad times | Not | Diff. |
| Crisis | 33.569*** | 20.271*** | 13.298*** |
| | (49.67) | (221.12) | (19.51) |
| | 610 | 5939 | |
| Credit Crisis | 32.553*** | 20.712*** | 11.841*** |
| | (44.55) | (199.37) | (16.06) |
| | 441 | 6108 | |
| Recession | 31.307*** | 20.200*** | 11.107*** |
| | (71.70) | (192.78) | (24.75) |
| | 772 | 5777 | |
| Down Market | 26.621*** | 19.174*** | 7.446*** |
| | (103.98) | (188.36) | (27.03) |
| | 2054 | 4495 | |

## Table 1 (Cont'd)

Panel B: Implied volatility before recommendation changes

| Bad times definition | Rec-change | Variable | Option implied volatility (annualized) | | |
|---|---|---|---|---|---|
| | | | Bad times | Not | Diff. |
| Crisis | Downgrade | Implvol | 60.964*** | 49.429*** | 11.535*** |
| | | t-stat | (64.09) | (144.63) | (11.42) |
| | | #obs | 8758 | 40763 | |
| | Upgrade | Implvol | 58.011*** | 47.402*** | 10.609*** |
| | | t-stat | (63.00) | (209.17) | (11.20) |
| | | #obs | 8098 | 39373 | |
| Credit Crisis | Downgrade | Implvol | 61.448*** | 49.757*** | 11.691*** |
| | | t-stat | (54.42) | (150.49) | (9.95) |
| | | #obs | 7251 | 42270 | |
| | Upgrade | Implvol | 58.400*** | 47.654*** | 10.747*** |
| | | t-stat | (55.00) | (213.36) | (9.91) |
| | | #obs | 6881 | 40590 | |
| Recession | Downgrade | Implvol | 67.282*** | 47.999*** | 19.283*** |
| | | t-stat | (81.78) | (144.29) | (21.74) |
| | | #obs | 8912 | 40609 | |
| | Upgrade | Implvol | 63.851*** | 46.391*** | 17.460*** |
| | | t-stat | (81.93) | (221.12) | (21.65) |
| | | #obs | 7668 | 39803 | |
| Down Market | Downgrade | Implvol | 60.262*** | 45.344*** | 14.919*** |
| | | t-stat | (110.88) | (178.17) | (24.87) |
| | | #obs | 20333 | 29188 | |
| | Upgrade | Implvol | 55.906*** | 45.325*** | 10.581*** |
| | | t-stat | (106.25) | (197.65) | (18.44) |
| | | #obs | 17435 | 30036 | |

## Table 2: Recommendation impact and influential likelihood in bad times

2-day CAR (in percent) is the average two-day day [0,1] cumulative abnormal return. Influential Probability is the percentage of influential recommendation changes. Influential changes are those whose two-day day CARs are in the same direction as the recommendation change and is 1.96 times larger than expected based on the prior three-month idiosyncratic volatility of the stock (following Loh and Stulz, 2011). The benchmark return is the return from a characteristics-matched DGTW portfolio. The sample is from 1993-2011. Recommendation changes are based on the individual analyst's prior outstanding recommendation (i.e., initiations are excluded). Recommendation changes made on earnings announcement days, earnings guidance days, and multiple-recommendation days are excluded. Bad times are defined in four ways. *Crisis* is when the forecast is announced in any of the periods: Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *Down Market* is when the prior 3-month buy-and-hold market return is negative. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

| Bad times definition | Rec-changes | Variable | 2-day CAR (%) | | | Influential Probability | | |
|---|---|---|---|---|---|---|---|---|
| | | | Bad times | Not | Diff. | Bad times | Not | Diff. |
| Crisis | Downgrades | Percent | -2.560*** | -1.602*** | -0.958*** | 14.902*** | 10.863*** | 4.038*** |
| | | t-stat | (-20.16) | (-43.92) | (-7.25) | (30.80) | (58.41) | (7.80) |
| | | #obs | 10114 | 58233 | | 10113 | 58233 | |
| | Upgrades | Percent | 2.635*** | 2.036*** | 0.599*** | 16.231*** | 13.182*** | 3.050*** |
| | | t-stat | (27.04) | (62.32) | (5.83) | (24.97) | (71.81) | (4.52) |
| | | #obs | 9075 | 53794 | | 9075 | 53794 | |
| Credit Crisis | Downgrades | Percent | -2.810*** | -1.599*** | -1.210*** | 15.826*** | 10.869*** | 4.957*** |
| | | t-stat | (-20.24) | (-43.91) | (-8.44) | (29.45) | (59.35) | (8.74) |
| | | #obs | 8165 | 60182 | | 8164 | 60182 | |
| | Upgrades | Percent | 2.778*** | 2.032*** | 0.746*** | 17.020*** | 13.156*** | 3.865*** |
| | | t-stat | (25.19) | (63.01) | (6.50) | (22.60) | (72.71) | (4.99) |
| | | #obs | 7585 | 55284 | | 7585 | 55284 | |
| Recession | Downgrades | Percent | -2.687*** | -1.577*** | -1.110*** | 13.156*** | 11.160*** | 1.996*** |
| | | t-stat | (-21.57) | (-43.51) | (-8.56) | (29.12) | (58.39) | (4.07) |
| | | #obs | 10285 | 58062 | | 10284 | 58062 | |
| | Upgrades | Percent | 2.936*** | 1.994*** | 0.942*** | 14.533*** | 13.479*** | 1.054* |
| | | t-stat | (23.40) | (65.74) | (7.30) | (25.59) | (70.18) | (1.76) |
| | | #obs | 8546 | 54323 | | 8546 | 54323 | |
| Down Market | Downgrades | Percent | -2.073*** | -1.538*** | -0.536*** | 12.193*** | 11.002*** | 1.190*** |
| | | t-stat | (-25.16) | (-43.89) | (-5.99) | (34.52) | (57.15) | (2.96) |
| | | #obs | 26320 | 42027 | | 26319 | 42027 | |
| | Upgrades | Percent | 2.161*** | 2.101*** | 0.061 | 13.205*** | 13.849*** | -0.644 |
| | | t-stat | (39.60) | (55.14) | (0.91) | (40.28) | (63.57) | (-1.64) |
| | | #obs | 22166 | 40703 | | 22166 | 40703 | |

## Table 3: Recommendation CAR in bad times controlling for recommendation, analyst, and firm characteristics

The panel regressions estimate the effect of bad times on recommendation downgrade and upgrade 2-day day CARs (in percent) controlling for recommendation, firm, and analyst characteristics. The benchmark return is the return from a characteristics-matched DGTW portfolio. The sample is from 1993-2011. Recommendation changes are based on the individual analyst's prior outstanding recommendation (i.e., initiations excluded). Recommendation changes made on earnings announcement days, earnings guidance days, and multiple-recommendation days are excluded following Loh and Stulz (2011). Bad times are defined in four ways. *Crisis* is when the forecast is announced in any of the periods: Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *Down Market* is when the prior 3-month buy-and-hold market return is negative. *LFR* is the analyst's prior-year leader-follower ratio (computed from recommendations), *Star Analyst* is from the *Institutional Investor* poll, *Relative Experience* is the difference between the analyst's experience (in quarters) against the average of peers covering the same firm, *Accuracy Quintile* is the average forecast accuracy quintile of the analyst's past-year's covered firms (quintile 5=most accurate), *Broker Size* is the number of analysts employed, *# Analysts* is 1+ the number of analysts covering the firm, *Size* is last June's market cap, *BM* is the book-to-market ratio, and *Momentum* is the month *t*-12 to *t*-2 buy-and-hold return, and *Stock Volatility* is based on last 3 months of daily stock returns. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects rely on the Fama-French 30-industry groupings.

| Variables | Downgrades | | | | | | | | Upgrades | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Crisis | -0.958*** | -1.050*** | | | | | | | 0.599*** | 0.475*** | | | | | | |
| | (7.25) | (9.52) | | | | | | | (5.83) | (4.12) | | | | | | |
| Credit Crisis | | | -1.210*** | -1.257*** | | | | | | | 0.746*** | 0.591*** | | | | |
| | | | (8.44) | (11.05) | | | | | | | (6.50) | (4.57) | | | | |
| Recession | | | | | -1.110*** | -0.914*** | | | | | | | 0.942*** | 0.461*** | | |
| | | | | | (8.56) | (7.34) | | | | | | | (7.30) | (3.80) | | |
| Down Market | | | | | | | -0.536*** | -0.289*** | | | | | | | 0.061 | -0.122* |
| | | | | | | | (5.99) | (3.41) | | | | | | | (0.91) | (1.69) |
| LFR | | -0.047*** | | -0.047*** | | -0.046*** | | -0.044*** | | 0.028*** | | 0.028*** | | 0.028*** | | 0.028*** |
| | | (4.67) | | (4.68) | | (4.56) | | (4.34) | | (3.03) | | (3.06) | | (3.03) | | (3.00) |
| Star Analyst | | -0.180** | | -0.183** | | -0.177** | | -0.173** | | 0.172** | | 0.173** | | 0.173** | | 0.168** |
| | | (2.10) | | (2.15) | | (2.08) | | (2.01) | | (2.18) | | (2.19) | | (2.19) | | (2.14) |
| Relative Experience | | -0.001 | | -0.001 | | -0.001 | | -0.000 | | -0.001 | | -0.001 | | -0.001 | | -0.001 |
| | | (0.60) | | (0.71) | | (0.53) | | (0.26) | | (0.57) | | (0.48) | | (0.63) | | (0.75) |
| Accuracy Quintile | | -0.042 | | -0.041 | | -0.036 | | -0.034 | | 0.050 | | 0.050 | | 0.046 | | 0.042 |
| | | (0.68) | | (0.67) | | (0.59) | | (0.55) | | (0.91) | | (0.91) | | (0.84) | | (0.77) |
| Log Broker Size | | -0.414*** | | -0.422*** | | -0.405*** | | -0.391*** | | 0.453*** | | 0.456*** | | 0.445*** | | 0.441*** |
| | | (11.77) | | (11.98) | | (11.51) | | (10.89) | | (13.00) | | (12.96) | | (12.92) | | (13.01) |
| Log # Analysts | | 0.372*** | | 0.366*** | | 0.398*** | | 0.442*** | | -0.553*** | | -0.545*** | | -0.552*** | | -0.594*** |
| | | (4.21) | | (4.16) | | (4.51) | | (5.06) | | (6.59) | | (6.49) | | (6.56) | | (7.14) |
| Log Size | | 0.256*** | | 0.261*** | | 0.256*** | | 0.227*** | | -0.362*** | | -0.366*** | | -0.366*** | | -0.337*** |
| | | (9.37) | | (9.60) | | (9.29) | | (8.33) | | (14.39) | | (14.56) | | (14.40) | | (13.52) |
| Log BM | | 0.034 | | 0.044 | | 0.024 | | 0.016 | | -0.056 | | -0.060 | | -0.055 | | -0.054 |
| | | (0.70) | | (0.91) | | (0.50) | | (0.33) | | (1.29) | | (1.39) | | (1.26) | | (1.23) |
| Momentum | | -0.171** | | -0.175** | | -0.201*** | | -0.135* | | -0.163** | | -0.160** | | -0.151** | | -0.183*** |
| | | (2.46) | | (2.53) | | (2.88) | | (1.95) | | (2.49) | | (2.45) | | (2.31) | | (2.80) |
| Stock Volatility | | -19.020*** | | -18.948*** | | -17.728*** | | -21.539*** | | 23.688*** | | 23.560*** | | 22.658*** | | 26.840*** |
| | | (5.34) | | (5.36) | | (4.82) | | (6.03) | | (7.53) | | (7.49) | | (7.05) | | (8.42) |
| Intecept | -1.602*** | -4.182*** | -1.599*** | -4.209*** | -1.577*** | -4.357*** | -1.538*** | -4.053*** | 2.036*** | 6.325*** | 2.032*** | 6.345*** | 1.994*** | 6.464*** | 2.101*** | 6.168*** |
| | (43.93) | (10.06) | (43.91) | (10.15) | (43.51) | (10.37) | (43.89) | (9.74) | (62.32) | (16.43) | (63.01) | (16.50) | (65.74) | (16.69) | (55.15) | (15.99) |
| #Obs | 68347 | 32760 | 68347 | 32760 | 68347 | 32760 | 68347 | 32760 | 62869 | 32637 | 62869 | 32637 | 62869 | 32637 | 62869 | 32637 |
| Adj R-Sq | 0.0019 | 0.0325 | 0.0026 | 0.0339 | 0.0026 | 0.0311 | 0.0011 | 0.0280 | 0.0011 | 0.0477 | 0.0014 | 0.0482 | 0.0026 | 0.0475 | 0.0000 | 0.0467 |
| Industry fixed effects | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

## Table 4: Recommendation influential probability in bad times controlling for recommendation, analyst, and firm characteristics

The probit regressions estimate the marginal effect of bad times on influential probability of the CAR for downgrades and upgrades controlling for recommendation, firm, and analyst characteristics. Influential is the dependent variable and is defined following Loh and Stulz (2011). The sample is from 1993-2011. Recommendation changes are based on the individual analyst's prior outstanding recommendation (i.e., initiations are excluded). Recommendation changes made on earnings announcement days, earnings guidance days, and multiple-recommendation days are excluded. Bad times are defined in four ways. *Crisis* is when the forecast is announced in any of the periods: Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *Down Market* is when the prior 3-month buy-and-hold market return is negative. *LFR* is the analyst's prior-year leader-follower ratio (computed from recommendations), *Star Analyst* is from the *Institutional Investor* poll, *Relative Experience* is the difference between the analyst's experience (in quarters) against the average of peers covering the same firm, *Accuracy Quintile* is the average forecast accuracy quintile of the analyst's past-year's covered firms (quintile 5=most accurate), *Broker Size* is the number of analysts employed, *# Analysts* is 1+ the number of analysts covering the firm, *Size* is last June's market cap, *BM* is the book-to-market ratio, and *Momentum* is the month $t$-12 to $t$-2 buy-and-hold return, and *Stock Volatility* is based on last 3 months of daily stock returns. In parentheses are $t$-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects rely on the Fama-French 30-industry groupings.

| Variables | Downgrades | | | | | | | | Upgrades | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Crisis | 0.040*** | 0.070*** | | | | | | | 0.030*** | 0.048*** | | | | | | |
| | (8.37) | (10.41) | | | | | | | (4.78) | (6.64) | | | | | | |
| Credit Crisis | | | 0.050*** | 0.078*** | | | | | | | 0.039*** | 0.051*** | | | | |
| | | | (9.54) | (10.76) | | | | | | | (5.36) | (6.35) | | | | |
| Recession | | | | | 0.020*** | 0.050*** | | | | | | | 0.011* | 0.028*** | | |
| | | | | | (4.23) | (7.22) | | | | | | | (1.80) | (3.88) | | |
| Down Market | | | | | | | 0.012*** | 0.029*** | | | | | | | -0.006 | 0.006 |
| | | | | | | | (3.01) | (5.97) | | | | | | | (1.63) | (1.13) |
| LFR | | 0.003*** | | 0.003*** | | 0.003*** | | 0.003*** | | 0.001* | | 0.001* | | 0.001* | | 0.001* |
| | | (5.48) | | (5.47) | | (5.36) | | (5.04) | | (1.93) | | (1.95) | | (1.90) | | (1.86) |
| Star Analyst | | 0.011** | | 0.011** | | 0.010* | | 0.009* | | -0.002 | | -0.002 | | -0.002 | | -0.003 |
| | | (2.00) | | (2.04) | | (1.93) | | (1.75) | | (0.39) | | (0.36) | | (0.41) | | (0.48) |
| Relative Experience | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 |
| | | (1.01) | | (1.08) | | (0.88) | | (0.79) | | (0.49) | | (0.55) | | (0.35) | | (0.22) |
| Accuracy Quintile | | 0.005 | | 0.005 | | 0.005 | | 0.004 | | 0.006* | | 0.006* | | 0.006 | | 0.006 |
| | | (1.39) | | (1.35) | | (1.28) | | (1.21) | | (1.73) | | (1.72) | | (1.58) | | (1.53) |
| Log Broker Size | | 0.026*** | | 0.026*** | | 0.025*** | | 0.025*** | | 0.031*** | | 0.032*** | | 0.031*** | | 0.031*** |
| | | (11.73) | | (11.90) | | (11.51) | | (11.00) | | (13.44) | | (13.42) | | (13.24) | | (13.22) |
| Log # Analysts | | -0.008*** | | -0.008*** | | -0.007*** | | -0.006*** | | -0.062*** | | -0.062*** | | -0.063*** | | -0.065*** |
| | | (4.50) | | (4.52) | | (4.24) | | (3.79) | | (10.98) | | (10.94) | | (11.18) | | (11.55) |
| Log Size | | -0.008*** | | -0.008*** | | -0.007*** | | -0.006*** | | -0.013*** | | -0.013*** | | -0.012*** | | -0.011*** |
| | | (4.50) | | (4.52) | | (4.24) | | (3.79) | | (7.18) | | (7.18) | | (6.81) | | (6.10) |
| Log BM | | -0.001 | | -0.001 | | -0.001 | | -0.000 | | -0.001 | | -0.001 | | -0.001 | | -0.001 |
| | | (0.34) | | (0.53) | | (0.27) | | (0.09) | | (0.42) | | (0.52) | | (0.41) | | (0.38) |
| Momentum | | 0.012*** | | 0.012*** | | 0.012*** | | 0.010*** | | -0.011*** | | -0.011*** | | -0.011*** | | -0.013*** |
| | | (4.19) | | (4.24) | | (4.36) | | (3.40) | | (3.19) | | (3.20) | | (3.25) | | (3.72) |
| Stock Volatility | | -1.452*** | | -1.420*** | | -1.467*** | | -1.397*** | | -1.987*** | | -1.957*** | | -1.958*** | | -1.793*** |
| | | (7.89) | | (7.88) | | (8.02) | | (7.70) | | (11.51) | | (11.43) | | (11.46) | | (10.32) |
| #Obs | 68346 | 32760 | 68346 | 32760 | 68346 | 32760 | 68346 | 32760 | 62869 | 32637 | 62869 | 32637 | 62869 | 32637 | 62869 | 32637 |
| Industry fixed effects | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

## Table 5: Forecast error and bias in bad times controlling for forecast, analyst, and firm characteristics

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

| Variables | Dependent variable: Absolute forecast error | | | | | | | | Dependent Variable: Signed forecast error | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Crisis | 2.421*** | 3.440*** | | | | | | | 0.345 | -0.084 | | | | | | |
| | (5.88) | (9.90) | | | | | | | (0.81) | (0.21) | | | | | | |
| Credit Crisis | | | 2.901*** | 3.921*** | | | | | | | 0.857* | 0.355 | | | | |
| | | | (6.26) | (10.20) | | | | | | | (1.81) | (0.82) | | | | |
| Recession | | | | | 2.832*** | 3.723*** | | | | | | | -0.158 | -0.053 | | |
| | | | | | (6.38) | (10.54) | | | | | | | (0.36) | (0.13) | | |
| Down Market | | | | | | | 0.121 | 0.674*** | | | | | | | 0.321 | 0.094 |
| | | | | | | | (0.54) | (3.33) | | | | | | | (1.38) | (0.42) |
| Optimistic Forecast | | 0.411*** | | 0.401*** | | 0.417*** | | 0.437*** | | 0.175*** | | 0.175*** | | 0.175*** | | 0.175*** |
| | | (3.88) | | (3.79) | | (3.93) | | (4.14) | | (13.71) | | (13.68) | | (13.66) | | (13.66) |
| LFR | | -0.174*** | | -0.176*** | | -0.169*** | | -0.170*** | | -1.833*** | | -1.815*** | | -1.831*** | | -1.827*** |
| | | (16.89) | | (17.01) | | (16.47) | | (16.34) | | (14.00) | | (13.90) | | (13.92) | | (13.88) |
| Star Analyst | | 1.291*** | | 1.311*** | | 1.241*** | | 1.171*** | | 0.009*** | | 0.009*** | | 0.009*** | | 0.009*** |
| | | (12.00) | | (12.21) | | (11.50) | | (10.78) | | (8.39) | | (8.35) | | (8.42) | | (8.38) |
| Relative Experience | | -0.006*** | | -0.006*** | | -0.006*** | | -0.005*** | | -0.138** | | -0.138** | | -0.138** | | -0.138** |
| | | (6.90) | | (6.98) | | (6.86) | | (6.52) | | (1.97) | | (1.98) | | (1.98) | | (1.97) |
| Accuracy Quintile | | -1.030*** | | -1.030*** | | -1.020*** | | -1.027*** | | -0.620*** | | -0.620*** | | -0.620*** | | -0.619*** |
| | | (19.09) | | (19.10) | | (18.88) | | (18.97) | | (9.70) | | (9.69) | | (9.70) | | (9.65) |
| Log Days toAnnc | | 1.130*** | | 1.134*** | | 1.168*** | | 1.144*** | | 1.256*** | | 1.245*** | | 1.255*** | | 1.251*** |
| | | (21.34) | | (21.34) | | (21.31) | | (21.41) | | (13.69) | | (13.54) | | (13.67) | | (13.65) |
| Mutiple Forecast Day | | -1.235*** | | -1.260*** | | -1.251*** | | -1.176*** | | 0.907*** | | 0.904*** | | 0.907*** | | 0.905*** |
| | | (15.38) | | (15.77) | | (15.64) | | (14.50) | | (14.48) | | (14.44) | | (14.43) | | (14.42) |
| Log Broker Size | | -0.577*** | | -0.576*** | | -0.590*** | | -0.559*** | | 0.598** | | 0.616** | | 0.601** | | 0.605** |
| | | (11.68) | | (11.65) | | (11.67) | | (10.99) | | (2.35) | | (2.41) | | (2.36) | | (2.37) |
| Log # Analysts | | 1.592*** | | 1.577*** | | 1.547*** | | 1.446*** | | 0.598** | | 0.616** | | 0.601** | | 0.605** |
| | | (6.72) | | (6.65) | | (6.53) | | (6.04) | | (2.35) | | (2.41) | | (2.36) | | (2.37) |
| Log Size | | -2.079*** | | -2.083*** | | -2.069*** | | -2.034*** | | 0.657*** | | 0.650*** | | 0.656*** | | 0.654*** |
| | | (32.81) | | (33.00) | | (32.86) | | (31.73) | | (8.93) | | (8.85) | | (8.94) | | (8.88) |
| Log BM | | 2.871*** | | 2.855*** | | 2.920*** | | 2.840*** | | -0.665*** | | -0.661*** | | -0.665*** | | -0.661*** |
| | | (18.85) | | (18.75) | | (19.79) | | (18.97) | | (4.96) | | (4.92) | | (4.95) | | (4.93) |
| Momentum | | -1.985*** | | -1.969*** | | -1.804*** | | -2.141*** | | 2.511*** | | 2.534*** | | 2.510*** | | 2.520*** |
| | | (10.74) | | (10.69) | | (10.27) | | (11.18) | | (15.78) | | (15.85) | | (16.36) | | (15.76) |
| Dispersion | | 0.000** | | 0.000** | | 0.000** | | 0.000** | | -0.000 | | -0.000 | | -0.000 | | -0.000 |
| | | (2.18) | | (2.17) | | (2.19) | | (2.16) | | (0.59) | | (0.59) | | (0.59) | | (0.59) |
| Intercept | 15.739*** | 45.703*** | 15.743*** | 45.793*** | 15.626*** | 45.440*** | 15.979*** | 45.452*** | -0.371** | -12.563*** | -0.413*** | -12.544*** | -0.309** | -12.558*** | -0.440*** | -12.582*** |
| | (114.75) | (58.44) | (115.40) | (58.75) | (116.32) | (58.88) | (110.28) | (58.03) | (2.50) | (13.97) | (2.81) | (13.98) | (2.11) | (13.95) | (2.74) | (13.91) |
| Observations | 1268404 | 888414 | 1268404 | 888414 | 1268404 | 888414 | 1268404 | 888414 | 1268404 | 888414 | 1268404 | 888414 | 1268404 | 888414 | 1268404 | 888414 |
| Adj R-sq | 0.0011 | 0.0656 | 0.0013 | 0.0659 | 0.0017 | 0.0664 | 0.0000 | 0.0631 | 0.0000 | 0.0120 | 0.0001 | 0.0121 | 0.0000 | 0.0120 | 0.0000 | 0.0120 |
| Industry fixed effects | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

## Table 6: Analyst forecast dispersion controlling for firm characteristics

The panel regressions estimate the effect of bad times on forecast dispersion. *Dispersion* (×100) is defined as the standard deviation of forecasts divided by the absolute value of the mean consensus estimate. Each analyst's final unrevised forecast of the firm-quarter is used. At least two forecasts are required and *Dispersion* is winsorized at the top 1%. I/B/E/S one-quarter-ahead individual analyst forecasts are used and the time period is from 1983-2011. Periods of bad times are as defined in Table 1 using the date of the last final unrevised forecast for that quarter's earnings. Firm characteristics include firm size, BM, momentum, analyst forecast dispersion, and the prior 3-month stock volatility. In parentheses are *t*-statistics based on standard errors clustered by industry-quarter, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects rely on the Fama-French 30-industry groupings.

| Variables | Dependent Variable: Forecast Dispersion | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Crisis | 7.569*** | 4.932*** | | | | | | |
| | (8.52) | (6.36) | | | | | | |
| Credit Crisis | | | 9.874*** | 7.572*** | | | | |
| | | | (9.92) | (9.44) | | | | |
| Recession | | | | | 8.732*** | 3.960*** | | |
| | | | | | (10.73) | (5.41) | | |
| Down Market | | | | | | | 1.673*** | -0.789* |
| | | | | | | | (3.54) | (1.85) |
| Log # Analysts | | 6.992*** | | 6.922*** | | 6.938*** | | 6.919*** |
| | | (18.19) | | (18.03) | | (18.06) | | (17.99) |
| Log Size | | -5.238*** | | -5.269*** | | -5.224*** | | -5.082*** |
| | | (31.88) | | (32.24) | | (31.80) | | (30.65) |
| Log BM | | 4.576*** | | 4.549*** | | 4.538*** | | 4.577*** |
| | | (16.52) | | (16.40) | | (16.43) | | (16.58) |
| Momentum | | -6.086*** | | -6.014*** | | -6.025*** | | -6.291*** |
| | | (16.59) | | (16.49) | | (16.36) | | (17.04) |
| Stock Volatility | | 291.876*** | | 290.246*** | | 288.141*** | | 312.244*** |
| | | (14.20) | | (14.11) | | (13.76) | | (14.63) |
| Intercept | 24.706*** | 79.512*** | 24.693*** | 79.973*** | 24.414*** | 79.514*** | 24.970*** | 77.787*** |
| | (106.05) | (36.84) | (106.85) | (37.21) | (106.51) | (36.80) | (93.77) | (35.78) |
| Observations | 180609 | 176757 | 180609 | 176757 | 180609 | 176757 | 180609 | 176757 |
| Adj R-sq | 0.0015 | 0.0460 | 0.0020 | 0.0466 | 0.0023 | 0.0459 | 0.0002 | 0.0455 |
| Industry fixed effects | No | Yes | No | Yes | No | Yes | No | Yes |

## Table 7: Forecast revision CAR in bad times controlling for forecast, analyst, and firm characteristics

The panel regressions estimate the effect of bad times on downward earnings forecast revisions and upward revisions on the 2-day day CARs (in percent) controlling for forecast, firm, and analyst characteristics. The benchmark return is the return from a characteristics-matched DGTW portfolio. The sample is from 1983-2011. Recommendation changes are based on the individual analyst's prior outstanding Q1 forecast (i.e., initiations are excluded) and scaled by price. Forecasts revisions made on earnings announcement, earnings guidance, and multiple-forecast days are excluded. Bad times are defined in four ways. *Crisis* is when the forecast is announced in any of the periods: Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *Down Market* is when the prior 3-month buy-and-hold market return is negative. *Forecast Revision* is analyst's current forecast minus his prior forecast, scaled by the stock price. Other controls are as defined in Table 5. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects rely on the Fama-French 30-industry groupings.

| Variables | Downward revisions | | | | | | | | Upward revisions | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Crisis | -0.384*** | -0.409*** | | | | | | | 0.182** | 0.180** | | | | | | |
| | (5.97) | (5.51) | | | | | | | (2.42) | (2.10) | | | | | | |
| Credit Crisis | | | -0.512*** | -0.553*** | | | | | | | 0.198** | 0.171* | | | | |
| | | | (7.28) | (6.93) | | | | | | | (2.37) | (1.84) | | | | |
| Recession | | | | | -0.307*** | -0.254*** | | | | | | | 0.099 | 0.054 | | |
| | | | | | (5.27) | (3.52) | | | | | | | (1.36) | (0.62) | | |
| Down Market | | | | | | | -0.199*** | -0.162*** | | | | | | | 0.031 | -0.067 |
| | | | | | | | (5.38) | (3.87) | | | | | | | (0.81) | (1.51) |
| Forecast Revision | | 9.273** | | 9.288** | | 8.913** | | 9.112** | | 2.054 | | 1.936 | | 1.852 | | 1.750 |
| | | (2.12) | | (2.13) | | (2.04) | | (2.09) | | (0.24) | | (0.23) | | (0.22) | | (0.21) |
| LFR | | -0.023*** | | -0.022*** | | -0.025*** | | -0.025*** | | 0.045*** | | 0.045*** | | 0.045*** | | 0.045*** |
| | | (3.52) | | (3.39) | | (3.79) | | (3.77) | | (5.85) | | (5.84) | | (5.91) | | (5.91) |
| Star Analyst | | 0.030 | | 0.025 | | 0.041 | | 0.043 | | -0.113*** | | -0.113*** | | -0.118*** | | -0.120*** |
| | | (0.75) | | (0.63) | | (1.02) | | (1.08) | | (2.73) | | (2.74) | | (2.85) | | (2.89) |
| Relative Experience | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | -0.000 | | -0.000 | | -0.000 | | -0.000 |
| | | (0.22) | | (0.19) | | (0.23) | | (0.24) | | (0.16) | | (0.15) | | (0.14) | | (0.14) |
| Accuracy Quintile | | -0.009 | | -0.010 | | -0.008 | | -0.007 | | 0.040 | | 0.040 | | 0.040 | | 0.039 |
| | | (0.30) | | (0.32) | | (0.27) | | (0.23) | | (1.28) | | (1.28) | | (1.26) | | (1.24) |
| Log Broker Size | | -0.058*** | | -0.058*** | | -0.060*** | | -0.060*** | | 0.050** | | 0.050** | | 0.051** | | 0.052** |
| | | (2.84) | | (2.85) | | (2.93) | | (2.96) | | (2.30) | | (2.30) | | (2.35) | | (2.40) |
| Log # Analysts | | 0.114** | | 0.106** | | 0.128*** | | 0.140*** | | -0.092* | | -0.095* | | -0.102** | | -0.109** |
| | | (2.33) | | (2.17) | | (2.60) | | (2.84) | | (1.83) | | (1.88) | | (2.02) | | (2.15) |
| Log Size | | 0.031** | | 0.038** | | 0.025 | | 0.019 | | -0.083*** | | -0.082*** | | -0.078*** | | -0.074*** |
| | | (1.96) | | (2.43) | | (1.59) | | (1.21) | | (5.03) | | (4.99) | | (4.78) | | (4.51) |
| Log BM | | -0.025 | | -0.021 | | -0.024 | | -0.023 | | 0.016 | | 0.016 | | 0.014 | | 0.014 |
| | | (0.91) | | (0.77) | | (0.90) | | (0.83) | | (0.61) | | (0.58) | | (0.53) | | (0.54) |
| Momentum | | -0.025 | | 0.022 | | 0.030 | | 0.055 | | 0.081** | | 0.080** | | 0.077** | | 0.072* |
| | | (0.57) | | (0.43) | | (0.59) | | (1.11) | | (2.13) | | (2.11) | | (2.00) | | (1.89) |
| Stock Volatility | | 0.029 | | -1.069 | | -2.145 | | -2.812 | | 2.858 | | 3.015 | | 3.298 | | 4.281 |
| | | (0.65) | | (0.43) | | (0.83) | | (1.10) | | (1.04) | | (1.10) | | (1.16) | | (1.54) |
| Intecept | -0.299*** | -0.633*** | -0.292*** | -0.713*** | -0.302*** | -0.579** | -0.285*** | -0.487** | 0.459*** | 1.420*** | 0.460*** | 1.413*** | 0.467*** | 1.380*** | 0.469*** | 1.336*** |
| | (20.19) | (2.64) | (19.56) | (3.00) | (20.35) | (2.41) | (17.56) | (2.07) | (27.51) | (5.47) | (27.81) | (5.45) | (28.23) | (5.30) | (24.44) | (5.18) |
| #Obs | 143879 | 82895 | 143879 | 82895 | 143879 | 82895 | 143879 | 82895 | 92161 | 54912 | 92161 | 54912 | 92161 | 54912 | 92161 | 54912 |
| Adj R-Sq | 0.0009 | 0.0034 | 0.0014 | 0.0041 | 0.0006 | 0.0027 | 0.0004 | 0.0026 | 0.0002 | 0.0059 | 0.0002 | 0.0058 | 0.0000 | 0.0057 | 0.0000 | 0.0057 |
| Industry fixed effects | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

## Table 8: Forecast revision influential probability in bad times controlling for forecast, analyst, and firm characteristics

The probit regressions estimate the marginal effect of bad times on influential probability of the CAR for downward earnings forecast revisions and upward revisions controlling for forecast, firm, and analyst characteristics. Influential is the dependent variable and is defined following Loh and Stulz (2011). The sample is from 1983-2011. Forecast revisions changes are based on the individual analyst's prior outstanding Q1 earnings forecast (i.e., initiations are excluded) and are scaled by price. Revisions made on earnings announcement days, earnings guidance days, and multiple-forecast days are excluded. Bad times are defined in four ways. *Crisis* is when the forecast is announced in any of the periods: Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *Down Market* is when the prior 3-month buy-and-hold market return is negative. *Forecast Revision* is analyst's current forecast minus his prior forecast, scaled by the stock price. Other controls are as defined in Table 5. In parentheses are *t*-statistics based on standard errors clustered by calendar day, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively. Industry fixed effects rely on the Fama-French 30-industry groupings.

| Variables | Downward revisions | | | | | | | | Upward revisions | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| Crisis | 0.024*** | 0.034*** | | | | | | | 0.015*** | 0.022*** | | | | | | |
| | (8.97) | (10.67) | | | | | | | (5.00) | (6.02) | | | | | | |
| Credit Crisis | | | 0.028*** | 0.039*** | | | | | | | 0.017*** | 0.023*** | | | | |
| | | | (9.33) | (11.19) | | | | | | | (5.37) | (6.05) | | | | |
| Recession | | | | | 0.017*** | 0.028*** | | | | | | | 0.002 | 0.009** | | |
| | | | | | (6.61) | (8.95) | | | | | | | (0.84) | (2.46) | | |
| Down Market | | | | | | | 0.016*** | 0.023*** | | | | | | | 0.003 | 0.005** |
| | | | | | | | (9.39) | (11.90) | | | | | | | (1.54) | (2.19) |
| Forecast Revision | | -0.189* | | -0.183* | | -0.169* | | -0.209** | | 0.148 | | 0.136 | | 0.120 | | 0.148 |
| | | (1.95) | | (1.91) | | (1.74) | | (2.12) | | (0.50) | | (0.46) | | (0.40) | | (0.49) |
| LFR | | 0.001*** | | 0.001*** | | 0.001*** | | 0.001*** | | 0.002*** | | 0.002*** | | 0.002*** | | 0.002*** |
| | | (5.89) | | (5.78) | | (6.49) | | (6.35) | | (5.86) | | (5.80) | | (6.02) | | (6.04) |
| Star Analyst | | -0.000 | | -0.000 | | -0.001 | | -0.001 | | -0.002 | | -0.002 | | -0.003 | | -0.003 |
| | | (0.11) | | (0.08) | | (0.52) | | (0.58) | | (0.76) | | (0.74) | | (0.96) | | (1.00) |
| Relative Experience | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 |
| | | (0.41) | | (0.47) | | (0.39) | | (0.35) | | (0.70) | | (0.71) | | (0.73) | | (0.72) |
| Accuracy Quintile | | 0.001 | | 0.001 | | 0.001 | | 0.001 | | 0.003 | | 0.003 | | 0.003 | | 0.003 |
| | | (0.47) | | (0.51) | | (0.52) | | (0.40) | | (1.64) | | (1.64) | | (1.61) | | (1.57) |
| Log Broker Size | | 0.003*** | | 0.003*** | | 0.003*** | | 0.003*** | | 0.004*** | | 0.004*** | | 0.004*** | | 0.004*** |
| | | (3.39) | | (3.46) | | (3.48) | | (3.50) | | (3.11) | | (3.10) | | (3.19) | | (3.24) |
| Log # Analysts | | -0.002** | | -0.002** | | -0.002** | | -0.001* | | -0.013*** | | -0.013*** | | -0.014*** | | -0.014*** |
| | | (2.32) | | (2.55) | | (2.08) | | (1.80) | | (4.08) | | (4.13) | | (4.41) | | (4.48) |
| Log Size | | -0.002** | | -0.002** | | -0.002** | | -0.001* | | -0.004*** | | -0.004*** | | -0.004*** | | -0.004*** |
| | | (2.32) | | (2.55) | | (2.08) | | (1.80) | | (4.40) | | (4.38) | | (3.96) | | (3.83) |
| Log BM | | -0.001 | | -0.002 | | -0.001 | | -0.002 | | -0.002* | | -0.002* | | -0.003* | | -0.003* |
| | | (1.23) | | (1.46) | | (1.37) | | (1.59) | | (1.72) | | (1.75) | | (1.90) | | (1.96) |
| Momentum | | 0.005*** | | 0.005*** | | 0.006*** | | 0.004*** | | 0.003** | | 0.003** | | 0.003** | | 0.002 |
| | | (4.06) | | (4.12) | | (4.52) | | (2.64) | | (2.27) | | (2.29) | | (2.02) | | (1.60) |
| Stock Volatility | | -0.391*** | | -0.394*** | | -0.403*** | | -0.394*** | | -0.507*** | | -0.498*** | | -0.473*** | | -0.452*** |
| | | (5.91) | | (6.06) | | (5.79) | | (5.63) | | (5.52) | | (5.47) | | (5.03) | | (4.86) |
| #Obs | 143866 | 82887 | 143866 | 82887 | 143866 | 82887 | 143866 | 82887 | 92159 | 54911 | 92159 | 54911 | 92159 | 54911 | 92159 | 54911 |
| Industry fixed effects | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

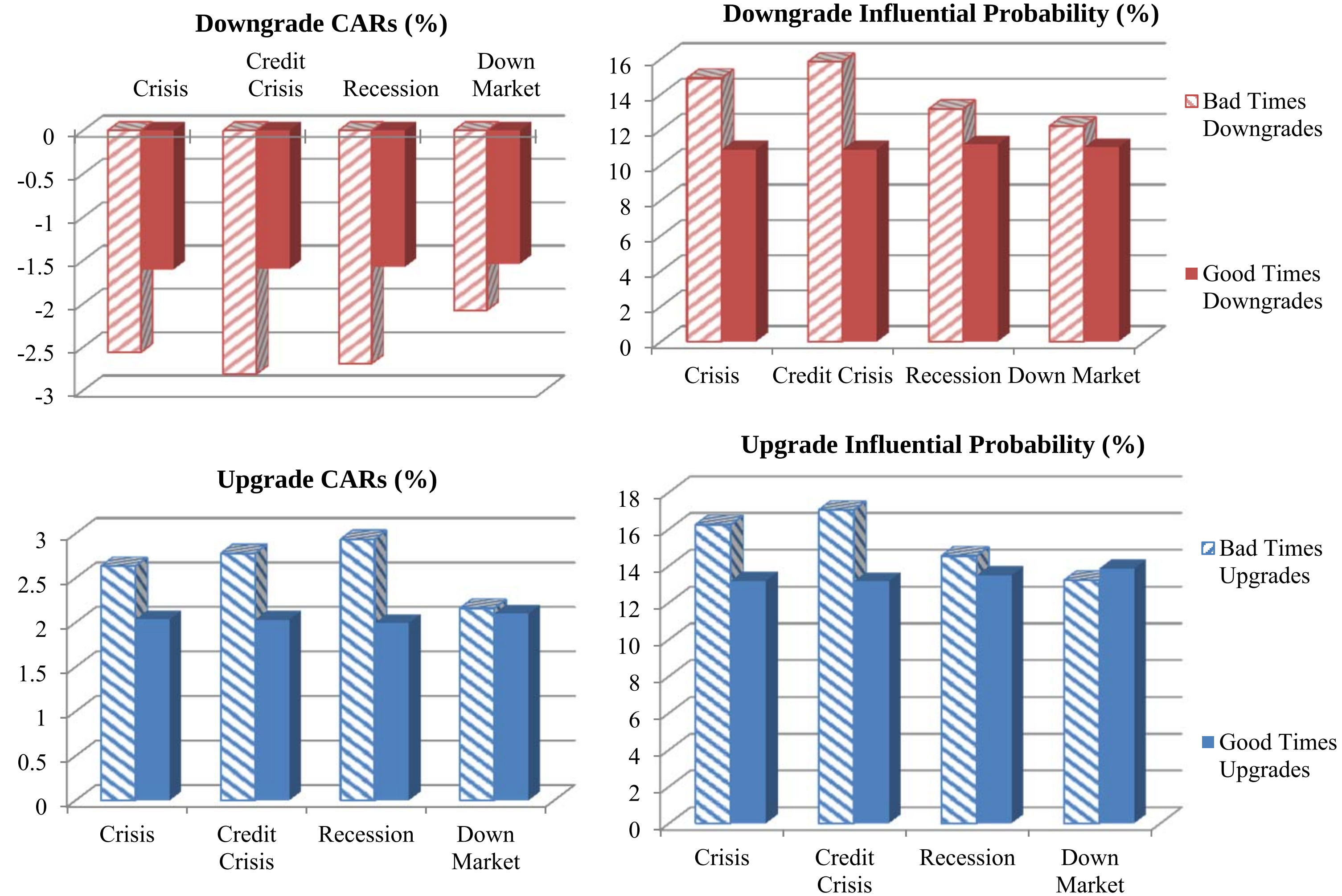
## Table 9: Analyst activity controlling for analyst and firm characteristics

The panel regressions estimate the effect of bad times on Log forecast activity (1+an analyst's # of forecasts per firm-quarter) controlling for forecast, analyst, and firm characteristics. The first eight specifications use the financial firm sample (group 29 of Fama-French 30-industry groups) and the rest are for all other firms. We define the starting and ending quarter of coverage using the first and last Q1 forecast of the analyst-firm-broker combination. We then count the number of forecasts per quarter for each calendar quarter. Analyst and forecast characteristics are the averages within the analyst-firm quarter. Bad times definitions are as defined in Table 2. Controls include an *Optimistic* indicator, *LFR*, *Star Analyst*, *Relative Experience*, *Accuracy Quintile*, *Days to Annc*, *Multiple Forecast Day*, *Broker Size*, *# Analysts*, firm *Size*, *BM*, *Momentum*, and analyst forecast *Dispersion*. In parentheses are *t*-statistics based on standard errors clustered by industry-quarter, where *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

| Variables | Dependent variable: Log (1 + # forecasts per firm-quarter) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Crisis | 0.068*** | 0.029*** | | | | | | |
| | (7.49) | (5.70) | | | | | | |
| Credit Crisis | | | 0.096*** | 0.035*** | | | | |
| | | | (8.84) | (5.73) | | | | |
| Recession | | | | | 0.075*** | 0.037*** | | |
| | | | | | (9.70) | (8.63) | | |
| Down Market | | | | | | | 0.032*** | 0.013*** |
| | | | | | | | (5.63) | (5.25) |
| Optimistic Forecast | | 0.011*** | | 0.010*** | | 0.010*** | | 0.011*** |
| | | (11.11) | | (11.10) | | (11.06) | | (11.19) |
| LFR | | 0.002*** | | 0.002*** | | 0.002*** | | 0.002*** |
| | | (13.23) | | (13.04) | | (13.12) | | (13.09) |
| Star Analyst | | 0.002 | | 0.002 | | 0.002 | | 0.001 |
| | | (1.28) | | (1.54) | | (1.40) | | (0.65) |
| Relative Experience | | -0.000*** | | -0.000*** | | -0.000*** | | -0.000*** |
| | | (13.83) | | (13.89) | | (13.94) | | (13.63) |
| Accuracy Quintile | | 0.021*** | | 0.021*** | | 0.021*** | | 0.021*** |
| | | (23.97) | | (23.98) | | (24.10) | | (24.02) |
| Log Days toAnnc | | -0.021*** | | -0.021*** | | -0.021*** | | -0.021*** |
| | | (19.71) | | (19.76) | | (19.71) | | (19.59) |
| Mutiple Forecast Day | | -0.053*** | | -0.053*** | | -0.053*** | | -0.052*** |
| | | (32.46) | | (32.78) | | (33.06) | | (32.06) |
| Log Broker Size | | 0.009*** | | 0.009*** | | 0.009*** | | 0.009*** |
| | | (13.21) | | (13.17) | | (12.84) | | (13.28) |
| Log # Analysts | | 0.081*** | | 0.081*** | | 0.080*** | | 0.080*** |
| | | (34.18) | | (34.21) | | (34.45) | | (33.72) |
| Log Size | | -0.002** | | -0.002** | | -0.002*** | | -0.001* |
| | | (2.47) | | (2.53) | | (2.59) | | (1.92) |
| Log BM | | 0.006*** | | 0.005*** | | 0.006*** | | 0.006*** |
| | | (4.86) | | (4.73) | | (6.17) | | (5.18) |
| Momentum | | -0.010*** | | -0.010*** | | -0.008*** | | -0.011*** |
| | | (7.16) | | (7.07) | | (6.14) | | (7.08) |
| Dispersion | | 0.018*** | | 0.018*** | | 0.018*** | | 0.019*** |
| | | (14.71) | | (14.64) | | (14.73) | | (15.22) |
| Intercept | 0.623*** | 0.695*** | 0.622*** | 0.697*** | 0.620*** | 0.696*** | 0.614*** | 0.690*** |
| | (214.61) | (70.71) | (219.76) | (70.99) | (211.74) | (71.56) | (140.03) | (69.16) |
| Observations | 1602593 | 760692 | 1602593 | 760692 | 1602593 | 760692 | 1602593 | 760692 |
| Adj R-sq | 0.0028 | 0.1017 | 0.0042 | 0.1021 | 0.0042 | 0.1032 | 0.0015 | 0.1009 |
| Industry fixed effects | No | Yes | No | Yes | No | Yes | No | Yes |

**Figure 1: Impact of recommendation changes in bad times**

The figure plots the mean 2-day CAR and the influential probability of recommendation changes (in percent). The sample is from 1993-2011. Recommendation changes are based on the individual analyst's prior outstanding recommendation (i.e., initiations are excluded) and changes made on earnings announcement days, earnings guidance days, and multiple-recommendation days are excluded. A recommendation is influential when its CAR reaction is in same direction as the change and 1.96 times more than expected based on the stock's prior idiosyncratic volatility (as in Loh and Stulz (2011)). Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *Down Market* is when the prior 3-month buy-and-hold market return is negative.



# Figure 2: Impact of earnings forecast revisions in bad times

The figure plots the mean 2-day CAR and the influential probability of earnings forecast revisions (in percent). The sample is from 1983-2011. Earnings forecast revisions are based on the individual analyst's prior outstanding forecast (i.e., initiations are excluded). Revisions made on earnings announcement days, earnings guidance days, and multiple-forecasts days are excluded. A revision is influential when its CAR reaction is in same direction as the change and 1.96 times more than expected based on the stock's prior idiosyncratic volatility (as in Loh and Stulz (2011)). Bad times definitions are as follows: *Crisis:* Sep-Nov 1987 (1987 crisis), Aug-Dec 1998 (LTCM), or Jul 2007-Mar 2009 (*Credit Crisis*). *Recession* represents NBER recessions, namely: Jul 1990-Mar 1991, Mar 2001-Nov 2001, and Dec 2007-Jun 2009. *Down Market* is when the prior 3-month buy-and-hold market return is negative.