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DO FINANCIAL ANALYSTS PREDICT STOCK PRICE CRASHES?

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ABSTRACT

This study examines whether analysts' recommendations can predict stock price crashes, and whether this predictability is different during good and bad macroeconomic periods. Recent literature suggests that investors rely on analysts more during bad times, when there is a larger degree of uncertainty. We examine analysts' consensus recommendation changes prior to stock price crashes in recessionary economic conditions and in normal conditions. We examine a sample of 11,903 observations in the US stock market, from 1995 to 2013, collected from the Institutional Broker Estimation System (IBES) database. We employ a cross sectional regression methodology for this study. Using two different proxies of stock price crash, we find that analysts' downgrades are followed by a larger possibility of a crash in normal macro conditions, and a smaller possibility of a crash in unfavourable periods. We use four different definitions for good and bad macroeconomic conditions. We find statistically significant evidence to suggest that analysts' recommendations are able to predict crashes in normal macroeconomic conditions, however we do not find empirical evidence for this notion during bad macroeconomic conditions.

Keywords: Investment Decisions, Information and Financial Efficiency, Portfolio Choice

1. Introduction

Analysts' main role is to disseminate information in the form of their recommendations, be it a 'buy' recommendation or a 'sell' recommendation. Analysts are likely to play a more significant role in the dissemination of bad news (Frankel, Kothari & Weber 2006). The existing literature is quiet about the type of recommendations, which are given by analysts before a firm experiences a stock price crash. Stock price crashes can be very detrimental to the portfolio of some of the retail investors. Therefore, we empirically analyse analysts' consensus recommendations prior to stock price crashes.

When accumulated hidden bad news by top level management reaches a peak, it bursts and results in a large-scale decline in stock price, namely, a stock price crash (Kim, Wang & Zhang 2015). In such a situation of deliberate hiding of negative information, it's hard for analysts to predict stock prices. Therefore, it may not be easy for analysts to give negative recommendations- say 'sell' or 'strong sell' by analysing what is on the surface. But if in such a situation, analysts give a 'buy' recommendation then one starts casting doubt on analysts' ability to recommend.

Investors depend on analysts' recommendations and more so when existing economic conditions are experiencing recession (Loh and Stulz, 2018). However, analysts are also likely to face the most difficulty when predicting stock prices, during bad macroeconomic conditions, which are inherently more uncertain (Jacob, 1997; Chopra,1998). Therefore, the question arises of the ability of analysts to give more accurate recommendations, especially of anticipated crash risk in good or bad macro conditions. During a recession, the end of the tunnel appears to be never ending, due to the greater macro uncertainty, possible outcomes can be more extreme and, consequently can have a greater impact on firms in bad times. Therefore, reliance on analyst output increases, which helps investors in sorting out the impact of the ongoing recession on their portfolio holdings (Loh and Stulz, 2018).

If skill contributes to investment returns, individual investors are obviously at a disadvantage, especially when they trade against professionals like fund managers, institutional investors etc, (Barber, Lee, Liu and Odean, 2009). These individual retail investors are the ones who depend more on analysts' recommendations compared to large institutional investors, who may have other sources for getting stock specific information as well as better resources to analyse industry-specific and other macro information. Retail investors not only trade more than large investors following upgrade and buy recommendations, but also trade more following upgrade and buy recommendations than they do following downgrade and hold/sell recommendations (Mikhail, Walther and Willis 2007). Literature has found that many individual investors tend to concentrate their portfolios in a small number of stocks (see Barber and Odean (2000); Goetzmann and Kumar (2008)). The reason behind such practice of lack of diversification could be prompted by behavioural biases such as familiarity (French and Poterba 1991) or overconfidence (Barber and Odean 2000) or even limited resources. When their investment is confined to only a small set of stocks, then their portfolio is more exposed to crash risk of even a single stock. Such a situation requires analysts to dig beneath the surface and bring some ex-ante indication of a crash, especially as retail investors have limited sources of information as well as resources. The findings of this study would be useful to understand whether the retail investor community can use analyst recommendations to avoid infrequent but extreme investment losses. Secondly, regulators who aim to protect investors from being misled by analyst recommendations would find this study useful in understanding whether investors misunderstand recommendations leading to large scale losses.

Our main independent variable is the change in consensus recommendation prior to the fiscal year when the crash takes place. We consider two main variables that indicate a crash. The NCSKEW (negative skewness) and DUVOL (down up volatility). We examine the results using four alternative definitions for bad times, namely Recession, Crisis, Credit Crisis and Contraction. Our results indicate that analysts' downgrades are followed by a larger possibility of a crash in good times, and a smaller possibility of a crash in bad times. Our multivariate results suggest that the recommendation changes have a negative relationship with crashes, but the statistical evidence is weak.

The rest of the study is organized as follows. Section 2 summarizes the related literature. Section 3 describes our sample and methodology, In Section 4, we examine our main results. Section 5 concludes.

2. Related Literature

Analysts' recommendations serve as a useful source of information for a vast majority of investors. (Boni and Womack, 2006). In most of the cases, stock favouring recommendations by analysts are more in quantity as compared to stock dis-favouring (Butler & Lang (1991), Brous & Kini (1993), Francis & Philbrick (1993), Easterwood & Nutt, (1999)). Hong, Kubik, & Solomon (2000) argue that management has stronger incentives to highlight good news than bad news, and therefore in the absence of financial analysts, bad news is expected to propagate through prices more slowly. Thus, analysts are likely to play a more significant role in the dissemination of bad news (Frankel, Kothari and Weber, 2006). In a recent study, Loh & Stulz (2018) contributed to the literature by suggesting that investors rely more on analyst recommendations during bad times than good times. Loh & Stulz (2018) suggests that investors rely on analysts for investment guidance during bad times, when the information environment is more uncertain and hazy.

Bad news gets accumulated due to deliberate non-disclosure by the management and ultimately may lead to a drastic decline in stock prices after the negative information comes to light, which is named as a "stock price crash" (Kim, Wang & Zhang 2015). Kim, Wang & Zhang (2015) reported that firms with overconfident CEOs are more prone to stock price crash. Callen and Fang (2015) found that Short interest is a predictor of crash risk. In another paper, Callen &

Fang (2015) reported that religiosity and crash risk are negatively related. An & Zhang (2013) found that institutional ownership and crash risk are negatively related. Kim, Li & Zhang (2011) reported that corporate tax avoidance and crash risk are positively related. Xu, Jiang, Chan & Zhihong (2013) analyse coverage, analyst optimism and stock price crashes.

To the best of our knowledge this study is the first study to examine whether on average, analysts are able to predict firm specific stock price crashes. Therefore, we contribute to the stock price crash literature by examining whether investors could rely on analysts to predict stock price crashes during more uncertain bad times in the market. We also extend Loh and Stulz (2018) by examining whether analysts are able to forecast stock price declines during bad times, in which investors rely on them more. Our study is distinguishable from Loh and Stulz (2018), since they examine whether investors rely on analysts during bad times using immediate market returns after the revision of the recommendation, whereas we examine whether analysts are able to predict stock price crashes which would occur in the longer-term (within one year). Furthermore, we examine whether analysts can predict very infrequent but extreme stock price changes that would have a lasting impact rather than the predictability of average stock price changes examined in past studies (see: Asquith, Mikhail & Au (2005); Barber, Lehavy, McNichols & Truman (2006); Loh & Stulz (2010); Loh and Stulz (2018)).

3. Data, Variables and Methodology

We collect CRSP daily stock return data to estimate the firm-specific crash measures. We also collect the analyst consensus and individual analyst recommendation data from IBES, available for the US equity markets. We use all the consensus recommendations available on the IBES database, which is available from 1996 to 2013. We restrict our sample to share codes 10 and 11, so that we confine to common stocks, consistent with prior literature. We exclude stocks in the Financial and Utilities industries using the SIC codes. Our final sample consists of 11,903 firm-years.

A. Analysts' Data

We collect the consensus analyst data between 1994 and 2013 from IBES database. IBES records the analyst ratings as 1 (Strong Buy); 2 (Buy); 3 (Hold); 4 (Underperform) and 5 (Sell). The monthly consensus file reports the mean, median, standard deviation and the cumulative number of ratings. We reverse the rating as Strong Buy (5); 4 (Buy); 3 (Hold); 2 (Underperform) and 1 (Sell). We then calculate the change in ratings prior to the financial year of the crash variables (i.e. We subtract the January rating from the December rating of the same year). The consensus rating changes are uniformly distributed across the years. We use consensus recommendation changes consistent with Jagadeesh, Kim, Krische & Lee (2004), which, the paper finds, is a robust predictor of stock returns[‡].

B. Measures of Stock Price Crash Risk

We use several measures to capture stock price crash risk. Following Chen, Hong & Stein (2001), Jin & Myers (2006) and Hutton, Marcus & Tehranian (2009), we employ (i) NCSKEW (the negative skewness coefficient of daily firm-specific returns) (ii) DUVOL (the down-to-up volatility of daily firm-specific returns).

C. Good and Bad Time Definitions

We collect the recession index from the National Burau of Economic Research (NBER) in order to identify Recessions. We define Crisis and Credit Crisis periods using Loh & Stulz (2018).

We define Contraction periods based on the CFNAI-MA3 index data collected from the Federal Reserve Bank of Chicago.

D. Control Variables

Following Chen et al. (2001), Hutton et al. (2009), and Kim et al. (2011a, 2011b), we include a number of control variables: DTURNt-1, SIGMAt-1, RETt-1, LMVEt-1, MTBt-1, LEVt-1, and ROAt. The variable DTURNt-1 is the detrended average monthly stock turnover in year t-1, which captures differences of opinion among investors; SIGMAt-1 is the standard deviation of weekly stock returns over the fiscal year t - 1; RETt-1 is the average firm-specific weekly return over the fiscal year t - 1; LMVEt-1 is the log of the market value of equity; MTBt-1, a proxy for growth, is measured as the market value of equity divided by the book value of equity; LEVt-1 is a ratio of long-term debt to total assets; and ROAt is income before extraordinary items to total assets in year t.

4. Empirical Findings

In this section, we address the question of whether analysts have asymmetric predictions prior to crashes in good and bad times. We are of the opinion that analysts who downgrade prior to crashes are somehow sensing the sudden and steep downfall in the stock prices of concerned firms. Following Jagadeesh, Kim, Krische and Lee (2004) we use the changes in consensus recommendations of all analysts for our analyses. Our main independent variable is the change in consensus recommendation prior to the fiscal year when the crash took place.

[‡] We also examine our hypothesis using the detailed individual recommendations sample collected from IBES. We find that our results are even more supportive of the hypothesis when individual recommendation changes are used. We report only results estimated using the consensus recommendation changes sample, for brevity.

A negative (positive) change in the consensus is considered a downgrade (an upgrade).

We consider two main variables that indicate a crash. The NCSKEW (negative skewness), and DUVOL (down up volatility), which indicates the possibility of a crash taking place. Panel A of Table 1 reports our main result, indicating the mean crash variables across good and bad macro environment, when analysts downgrade their recommendations. We examine the results using four alternative definitions for bad times, namely Recession, Crisis, Credit Crisis and Contraction. Crisis and Credit crisis are in the similar spirit of Loh & Stulz (2018). The means for bad and good times as well as the difference(s) in the averages are reported, based on standard errors clustered by firm and calendar year.

Panel A shows that there are visible differences between the crash variables in good and bad times. For instance, the negative skewness is -7.5% for recessions and 7.5% in non-recessions, which indicate that downgrades precede significantly larger negative skewness only in good times. The same can be stated for down-up-volatility, where the possibility of a crash is larger when analysts downgrade their recommendations prior to a good time, across all the scenarios of a bad economic environment. These observations indicate that analysts' downgrades are followed by a larger possibility of a crash in good times, and a smaller possibility of a crash in bad times. This finding supports the notion that analysts' downgrades during a good economic environment has predictability of stock price crash but same cannot be said for downgrade recommendations during bad economic environment.

Panel B presents the averages and the differences in crash variables during good and bad times, when analysts issue upgrades. We find that analysts issue more upgrades prior to crashes in bad times, whereas they issue less upgrades prior to crashes in good times. This pattern is consistent across both the crash variables. For instance, we find that when an analyst issues an upgrade, the negative skewness is 14% during bad times and -3% during good times, which leads to a strongly significant difference of 17%. Similarly, we find that there is a statistically significant difference of 5.3% between Good and Bad times under down-up-volatility as a crash proxy during recession. Our findings are qualitatively similar when we use other proxies of recessionary or similar conditions, which are Crisis, Credit Crisis and Contraction for crash risk.

Table 1: Univariate Analysis

Panel A: Downgrades

	NSKEW			DUVOL		
	Bad Times	Good Times	Diff	Bad Times	Good Times	Diff
Recession	-0.075*** (-4.31)	0.074*** (6.44)	-0.149*** (-7.08)	-0.102*** (-14.05)	-0.05*** (-8.75)	-0.053*** (-6.30)
Crisis	-0.061** (-2.43)	0.074*** (5.92)	-0.135*** (-4.95)	-0.094*** (-8.50)	-0.05*** (-8.50)	-0.045*** (-3.72)
Credit Crisis	-0.084*** (-3.67)	0.067*** (5.45)	-0.151*** (-5.95)	-0.106*** (-12.50)	-0.05** (-9.02)	-0.056*** (-5.81)
Contraction	-0.084*** (-4.06)	0.073*** (5.20)	0.157*** (-6.37)	-0.099*** (-11.93)	-0.051*** (-8.55)	-0.047*** (-4.85)

Panel B: Upgrades

Rec Changes	NSKEW			DUVOL		
	Bad Times	Good Times	Diff	Bad Times	Good Times	Diff
Recession	0.14*** (3.40)	-0.03 (-1.21)	0.17*** (3.45)	-0.036** (-2.42)	-0.089*** (-7.70)	0.053*** (2.98)
Crisis	0.13*** (2.92)	-0.0356 (-1.27)	0.165*** (3.14)	-0.040** (-2.48)	-0.090*** (-7.60)	0.050*** (2.57)
Credit Crisis	0.18*** (14.01)	-0.03 (-1.17)	0.21*** (7.00)	-0.019** (-2.55)	-0.089*** (-8.10)	0.07*** (5.29)
Contraction	0.130** (2.45)	-0.02 (-0.85)	0.150** (2.53)	-0.036* (-1.89)	-0.086*** (-7.70)	0.050** (2.40)

Table 1 presents the univariate results for crash variables across good and bad times. Panel A presents the downgrades sample. Panel B presents the upgrades sample. NCSKEW is the negative skewness of the firm specific daily results across the fiscal year. DUVOL is the log of the ratio of standard deviation of firm specific daily returns for the "down-day" sample to the standard deviation of the "up-day" sample over the fiscal year. The mean(s) are reported for each crash variable across different measures of good and bad time period measures. Recession represents the NBER recession index. Crisis represents the LTCM (1998) and *CreditCrisis* (2007-2009). Contraction represents the years where the business cycle experiences a contraction as indicated by the Chicago Federal National Activity Index (CFNAI). The average crash variables and the differences are reported. Standard errors are clustered by firm and year. Symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2 presents our main results using a multivariate model. Panel A reports the findings using Recession as the proxy for bad times. We use NSKEW and DUVOL as crash variables in a similar way to univariate analysis which we have shown in Table 1. First, we examine whether on average analysts are able to align their predictions to crashes via their recommendation changes or not.

Although, we find that the recommendation changes have a negative relationship with crashes, the statistical evidence is weak in NSKEW case. For instance, in column (1) we find that analysts' recommendation changes are negatively related to negative skewness, however the coefficient (-0.0284) is insignificant. Column (3) shows the same relationship using the down-up-volatility crash variable. Though the coefficient is significant here but not that strongly, it takes the value -0.0115 at 10%, only for down-up-volatility.

In Panel A, columns (2) and (4), we include interactions between recommendation changes and Recession as bad-time proxies. We find that when there is an upgrade NSKEW is smaller but insignificant when we do not include the time dimension. We find that recommendation changes are positively related to crash variables in recessions. The *RecChange×Recession* coefficient(s) are 0.177 and 0.0591 when dependent variables, NSKEW and DUVOL are used. These coefficients are significant at 1% level of significance across the panel. This evidence suggests that analysts' upgrades (downgrades) are followed by larger (smaller) possibilities of crashes in bad times. Further, coefficient *ReChange* in column (2) and (4) are -0.0599 and -0.0220 and statistically significant, which signifies that when we do not take economic conditions into consideration, then when there is an upgrade, the crash variable becomes small, whereas when there is a downgrade crash variable is larger. These results are consistent with the notion that analysts on average do not upgrade their recommendations prior to a stock price crash, in good times. We find that the evidence is consistent across Panels B, C and D, where alternative bad-time definitions are used as our interaction variable of Recommendation change*Recession is positive and statistically significant using Crisis, Credit Crisis and Contraction as alternative proxies[§].

5. Conclusion

We use a large sample of analyst consensus recommendation changes from 1995 to 2013, to examine whether analysts can predict stock prices crashes during good and bad macroeconomic conditions. We use two measures for crashes and four different definitions for good and bad times. We find no significant evidence to suggest that analysts downgrade or upgrade stocks prior to the stock price crashes, when the time of recommendation is not considered. We find evidence to state that analysts tend to downgrade a firm prior to the firm experiencing a stock price crash, during good (normal) macro-economic conditions. Whereas, analysts tend to upgrade a firm prior to the firm experiencing a stock price crash during bad macroeconomic conditions. The previous literature shows that investors rely on analysts for information during bad economic conditions. Our study shows that analysts are not able to forecast

[§] Detailed results are available on request.

stock price crashes during bad economic conditions, when investors rely on them most.

Table 2: Multivariate Analysis

Panel A: Recession

	(1) NSKEW	(2) NSKEW	(3) DUVOL	(4) DUVOL
RecChange	-0.0284	-0.0599***	-0.0115*	-0.0220***
	(-1.43)	(-3.47)	(-1.72)	(-3.81)
Recession	-0.0570***	-0.0377***	-0.0247***	-0.0182***
	(-3.94)	(-2.77)	(-5.34)	(-4.56)
RecChange× Recession		0.177***		0.0591***
		(6.71)		(6.93)
lag_dturn	0.0553	0.0643	-0.00137	0.00165
	(0.61)	(0.71)	(-0.03)	(0.04)
lag_nskew	0.0724***	0.0730***	-0.0326***	-0.0323***
	(2.97)	(3.01)	(-3.06)	(-3.05)
lag_duvol	-0.00372	-0.00443	0.158***	0.158***
	(-0.07)	(-0.09)	(6.46)	(6.47)
lag_sigma	-1.340***	-1.330***	-0.800***	-0.797***
	(-5.53)	(-5.53)	(-9.62)	(-9.65)
lag_ret	0.0731***	0.0730***	0.0248***	0.0248***
	(6.35)	(6.39)	(4.94)	(4.97)
lag_MB	0.00916**	0.00906**	0.00384***	0.00381***
	(2.50)	(2.44)	(2.99)	(2.91)
lag_size	-0.00250	-0.00211	-0.00200	-0.00187
	(-0.38)	(-0.32)	(-0.82)	(-0.77)
lag_lev	-0.0605	-0.0600	-0.00331	-0.00314
	(-0.91)	(-0.90)	(-0.14)	(-0.13)
lag_roa	-0.120	-0.124	-0.0265	-0.0278
	(-1.23)	(-1.27)	(-0.61)	(-0.64)
lag_opaque_noint	-0.00885	-0.00407	-0.00470	-0.00310
	(-0.17)	(-0.08)	(-0.24)	(-0.16)
_cons	0.366	0.347	0.137*	0.131
	(1.58)	(1.41)	(1.82)	(1.63)
N	11903	11903	11903	11903
Adj. R^2	0.010	0.012	0.026	0.029
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Panel B: Crisis

	(1) NSKEW	(2) NSKEW	(3) DUVOL	(4) DUVOL
RecChange	-0.0284	-0.0596***	-0.0115*	-0.0214***
	(-1.43)	(-3.39)	(-1.72)	(-3.53)
Crisis	-0.0570***	-0.0395***	-0.0247***	-0.0191***
	(-3.94)	(-2.82)	(-5.34)	(-4.37)
RecChange×Crisis		0.159***		0.0504***
		(4.69)		(4.09)
N	11903	11903	11903	11903
Adj. R^2	0.010	0.012	0.026	0.028
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel C: Credit Crisis

	(1) NSKEW	(2) NSKEW	(3) DUVOL	(4) DUVOL
RecChange	-0.0284	-0.0537***	-0.0115*	-0.0199***
	(-1.43)	(-3.09)	(-1.72)	(-3.39)
Credit_Crisis	-0.0570***	-0.0351**	-0.0247***	-0.0174***
	(-3.94)	(-2.50)	(-5.34)	(-4.09)
RecChange× Credit_crisis		0.187***		0.0621***
		(7.52)		(7.69)
N	11903	11903	11903	11903
Adj. R^2	0.010	0.012	0.026	0.028
Industry Fixed Effects	Yes	Yes	Yes	Yes
Yearly Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Panel D: Contractions

	(1) NSKEW	(2) NSKEW	(3) DUVOL	(4) DUVOL
RecChange	-0.0284	-0.0511***	-0.0115*	-0.0189***
	(-1.43)	(-2.83)	(-1.72)	(-3.09)
Contraction	-0.0570***	-0.0365***	-0.0247***	-0.0180***
	(-3.94)	(-2.66)	(-5.34)	(-4.57)
RecChange×		0.171***		0.0558***
Contraction		(5.16)		(5.27)
N	11903	11903	11903	11903
Adj. R^2	0.010	0.012	0.026	0.028
Industry Fixed Effects	Yes	Yes	Yes	Yes
Yearly Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table 2 presents the multivariate results for the relationship between recommendation changes and crashes in good and bad times. Panel A uses the NBER Recession index as the definition for bad times. Panel B uses the *Crisis* as bad times, *Crisis* represents the LTCM (1998) and Credit.Crisis (2007-2009). Panel C uses CreditCrisis (2007-09) as the definition for bad times. Panel D uses *Contraction* to represent the years where the business cycle experiences a contraction as indicated by the Chicago Federal National Activity Index (CFNAI). *RecChange* represents the change in consensus rating during the lagged fiscal year, where the rating is calculated as the last consensus rating minus the first in the fiscal year. The sample covers firm-year observations with non-missing values for all variables for the period 1994 to 2013. *t*-statistics reported in parentheses are based on standard errors corrected for clustering by firm and year. Year and industry fixed effects are included. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in the Appendix

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