The Impact of Information Uncertainty on Stock Performance During the 2008-2009 Financial Crisis

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We investigate the impact of information uncertainty on stock performance during the 2008-2009 financial crisis. We document that firms with more information uncertainty suffered a greater stock price drop during the period of market-wide price declines. In contrast, the negative effect of information uncertainty on stock returns was absent during the market-reversal or pseudo-drop period. In addition, during the reversal period, firms with forecast dispersion in the top tercile (or quartile) had more positive returns than those with lower forecast dispersion. We contribute to the literature by testing the relationship between information uncertainty and firm returns in the special setting of the most recent financial crisis and providing initial evidence that firm-specific information uncertainty amplified stock price fluctuations during the financial crisis.

Keywords: financial crisis, information uncertainty, forecast dispersion

INTRODUCTION

Uncertainty played a central role in the 2008-2009 financial crisis, both amplifying the financial distress and slowing down the recovery from the crisis (Blanchard 2009; Bloom et al. 2016; Straub and Ulbricht 2023).[1] The crisis was characterized by unusually high levels of macro-level uncertainty (e.g., Basu and Bundick 2016; Jo and Sekkel 2019). Such uncertainties were exacerbated by ambiguities about economic policies the government would potentially implement to contain the crisis (Benati 2014) and other macroeconomic uncertainties (e.g., the financial crisis that was unfolding in other parts of the world). There was also uncertainty about the severity of the crisis itself (Hosono et al. 2016).

During episodes of environmental upheaval, such as the most recent financial crisis, many assumptions about industry and firm value are challenged (Fralich and Papadopoulos 2018).[2] Previous literature has documented that information uncertainty affects future stock returns beyond the impact of firms' fundamentals (e.g., Johnson 2004; Erickson et al. 2012). Literature has also shown that macro-environmental conditions can interact with firm-specific characteristics to affect existing economic relationships. For example, Byrne et al. (2016) find that for a sample of UK firms, firm-level uncertainty had a greater impact on firm survival during the financial crisis compared to non-crisis periods. Similarly, Lang and Maffett (2011) find that the link between information transparency and liquidity uncertainty is higher during the financial crisis. In this study, we examine how the macro-level uncertainty brought upon by the 2008-2009 global financial crisis (GFC) affected the relationship between firm-level information uncertainty and firm stock returns.

Building on previous literature, we expect firm-level information uncertainty, proxied by analyst forecast dispersion, to have a more negative relationship with stock returns during the downturn period of the financial crisis. Our central rationale is that the GFC impaired investors' ability to learn about firms' fundamentals, reduced firms' ability to obtain funding, and imposed greater financial constraints on firms. These factors would be expected to reduce returns for all firms, but critically, these factors were amplified for firms with a higher level of information uncertainty (Byrne et al. 2016; Straub and Ulbricht 2023).

Following prior literature, we measure firm-level information uncertainty as the dispersion of analysts' earnings forecasts (e.g., Johnson 2004; Zhang 2006; Erickson et al. 2012). Consistent with Cella et al. (2013), we define the "drop period" as ten weeks before to eight weeks after the Lehman bankruptcy. Stock market indices declined precipitously during the drop period. We define the "reversal period" as Week 9 to Week 25 after the bankruptcy. Mean abnormal returns were positive (10.4%) for our sample during the reversal period. Our "pseudo-drop" period covers the same period as the drop period but is outside the GFC. Our results show that analyst forecast dispersion negatively impacted stock returns during the period of market decline, and the effect of information uncertainty on stock returns was more negative surrounding the Lehman Brothers' collapse (i.e., during the drop period) than during the pseudo-drop period. Thus, macroeconomic uncertainty magnifies the negative effect of firm-level uncertainty on firm value during the market-wide downturn.

Additionally, we find that during the reversal period, firms with top tercile (or quartile) forecast dispersion experienced more positive returns, although these firms experienced more negative returns during the drop period, consistent with Zhang (2006)'s argument that due to investors' behavioral bias (such as overconfidence in private information or underreaction to public signals), the relationship between information uncertainty and future returns is conditional on positive or negative news. The difference is that Zhang (2006) uses firm-specific news, and we show that the impact of information uncertainty is also conditional on macroeconomic news. Thus, although we rely on economic theory to motivate our hypothesis, we do not rule out the possibility that investors' behavioral bias plays a role in strengthening the negative relationship between information uncertainty and stock returns during the drop period, especially considering our findings for the reversal period.

Our study contributes to the literature studying firms' stock performance during the GFC. Literature has shown that CEO overconfidence (Ho et al. 2016) or financial leverage (Hossain and Nguyen 2016) affected stock performance during the financial crisis. Further, institutional investors with short-term trading horizons amplified the market-wide negative returns experienced by a firm during the GFC (Cella et al. 2013). We add to this line of research by documenting that firm-level information uncertainty also amplified the negative returns during the crisis.

Second, although previous studies have examined the association between forecast dispersion and future returns (Johnson 2004; Zhang 2006), we test this relationship in the special setting of the GFC, a period marked by heightened macro-environmental uncertainty. Our findings indicate that in the market reversal and non-crisis pseudo-drop periods, this relationship does not hold. Thus, our study contributes to this stream of research by documenting under what circumstances the negative relationship is more likely to exist.

Lastly, we provide some evidence that information uncertainty amplified stock price fluctuations during the financial crisis, suggesting that higher information uncertainty is more likely to drive stock prices to temporarily deviate from their fundamental values (Cella et al. 2013) and magnify the market turmoil for high uncertainty firms.

Our study has both theoretical and practical implications. First, we find that the negative relationship between forecast dispersion and future returns is more likely to exist during highly uncertain times. This result may have implications for theories about the relationship between forecast dispersion and future returns, as well as how tests of these theories should be constructed in future research. Further, our findings imply that investors wishing to take advantage of the dispersion-returns anomaly should carefully consider the macro-economic environment.[3] In particular, excess returns from a portfolio of high forecast dispersion stocks are likely to be strongly and negatively affected by financial crisis. Lastly, to the extent firms can mitigate firm-specific information uncertainty through various channels of corporate disclosure (Sengupta 1998; Barrios et al. 2021; Aman and Moriyasu 2022), our study points to the important role of financial disclosure in firm valuation, especially during periods of market turmoil. For example, better disclosure mitigates information uncertainty, which in turn may mitigate the effect of market-wide negative shocks on individual stock's returns and reduce the effect of wide market swings on stock price fluctuations (to the extent managers have relevant information to disclose).

The rest of the article is organized as follows. Section II contains the literature review and hypothesis development, section III discusses the data and research methodology, section IV analyzes and discusses the results, and section V provides a discussion and conclusions.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Information Uncertainty and Stock Returns

At the firm level, information uncertainty is the "ambiguity with respect to the implications of new information for a firm's value, which potentially stems from two sources: the volatility of a firm's underlying fundamentals and poor information" (Zhang 2006, 105). Because investors are risk-averse and information uncertainty is one component of risk, standard economic models predict that investors of firms with higher information uncertainty should be compensated for the higher risk, which would result in higher future stock returns for higher information uncertainty firms. However, prior research has found that information uncertainty is negatively related to future returns (e.g., Diether et al. 2002; Jiang et al. 2005; Bandyopadhyay et al. 2017).

To explain this negative relationship, some researchers suggest that information uncertainty raises cost of capital and discount rate, thereby lowering future stock returns. Literature has provided evidence corroborating this argument. Chen (2013) shows that income smoothing through total accruals and discretionary accruals is associated with lower information uncertainty and thus higher abnormal returns around earnings announcement. Erickson et al. (2012) find that mergers and acquisitions increase acquiring firms' information uncertainty, contributing to acquirers' long-term stock underperformance. In this study, we will motivate our hypothesis using the cost-of-capital point of view.

We use analyst forecast dispersion to proxy for firm-level uncertainty. Analyst forecast dispersion is a widely used measure of uncertainty in the valuation of individual firm stock (e.g., Zhang 2006; Sadka and Scherbina 2007; Manconi et al. 2018). Theoretically, forecast dispersion reveals both uncertainty and information asymmetry (Barry and Jennings 1992; Abarbanell et al.1995; Barron et al. 1998; Barron and Stuerke 1998). Consistent with dispersion measuring uncertainty, prior research has shown that earnings announcements reduce dispersion (e.g., Brownand Han 1992; Taylor and Koo 2015). Barron et al. (2009) decompose forecast dispersion into uncertainty and information asymmetry. They conclude that "levels of dispersion reflect levels of uncertainty prior to earnings announcements" (p. 353). Erickson et al. (2012, 921) also provide a review of the studies using forecast dispersion as a proxy for information uncertainty.

The Financial Crisis and Information Uncertainty

The global financial crisis (GFC) was a time of high macro-uncertainty. Analysts and investors were especially uncertain about macro-variables such as future inflation, interest rates, GDP growth, retail sales, and employment (Baetje and Friedrici 2016; Jo and Sekkel 2019). Part of the uncertainty stemmed from the inherent unpredictability of the government's policy response to contain the crisis (Benati 2014; Basu and Bundick 2016). Nagar et al. (2018) find that uncertainty about government economic policy was particularly high during the financial crisis, and that the financial crisis increased investor information asymmetry. Environmental shocks also create uncertainty in how organizational strategies will change (Meyer 1982; Meyer et al. 1990). Further, the financial crisis impaired investors' ability to understand firms' financial situation (e.g., Straub and Ulbricht 2023).

Similar to firm-level uncertainty being proxied with the dispersion of earnings forecasts, prior research often proxies macro-uncertainty with dispersion of forecasts of macro-economic factors such as unemployment, inflation, GDP growth, and consumption (e.g., Baetje and Friedrici 2016; Sheen and Wang 2021). The dispersion of macro-forecasts was significantly elevated during the GFC (e.g., Jo and Sekkel 2019; Sheen and Wang 2021).

More sophisticated investors were more likely to sell during the GFC, thereby amplifying the effect of macro-level uncertainty on the uncertainty in stock valuation. Stock sales during the GFC was concentrated in hedge funds (Ben-David et al. 2012) and institutional investors, especially those with short trading horizons (Cella et al. 2013).[4] Consistent with the high level of macro-uncertainty, exit of more sophisticated investors, and impaired investor ability to acquire information during the GFC, Kim and Na (2016) found that earnings forecast dispersion peaked in 2008-2009.

Hypothesis

For firms with higher information uncertainty, an extreme economic event like the financial crisis will cause a more severe impact. For example, Byrne et al. (2016) argue that nonpublic firms, due to their high information asymmetry and uncertainty, are more likely to become financially constrained. Thus, the effect of information uncertainty is stronger for nonpublic firms than for public firms during extreme economic events. Corroborating this predication, they find nonpublic banks had a higher failure rate than public firms during the financial crisis. We make a similar argument. In particular, firms with high information uncertainty will become more financially constrained during the financial crisis compared to low uncertainty firms, causing a larger increase in the cost of capital and larger declines in stock price.

In an analytical model, Straub and Ulbricht (2023) also suggest that due to investors' impaired ability to learn about a firm's fundamental value during the crisis, higher uncertainty firms will have more difficulty obtaining funding, which in turn, will hamper investors' ability to assess the firm's true profitability and further increase the firm's uncertainty. Thus, The GFC increased information uncertainty, especially for opaque firms and firms in opaque information environments. Because the GFC increased information uncertainty more for high uncertainty firms, we expect high uncertainty firms to have a larger increase in their cost of capital, thereby strengthening the negative relationship between information uncertainty and stock returns.

Consistent with Cella et al. (2013), we define our drop period as Week -10 to Week 8 around the Lehman bankruptcy. The drop period starts ten weeks before the Lehman bankruptcy because it covers the period of Lehman's several failed attempts to find a partner or buyer, raising the prospect of another high-profile bankruptcy after the collapse of New Century Financial Corporation and Bear Stearns. The drop period ends eight weeks after the Lehman bankruptcy because the cumulative abnormal returns for the sample firms reached the most negative level. Starting from Week 9, stock returns became less negative and started to rebound. To test the negative relationship between forecast dispersion and future returns, we will focus on the drop period. We make this decision because uncertainty is associated with worry and anxiety (Panarello and Bukowski 2021), which would more suitably describe how investors feel in a market-wide decline than in a market recovery. We will analyze the reversal period within the GFC in additional analysis. We thus state our hypothesis as follows:

H1: *Analyst forecast dispersion is negatively related to stock returns and this relationship is more negative during the market-wide drop period of the financial crisis than during periods outside the GFC.*

Our study is the first to focus on whether the GFC had a significant effect on the relationship between information uncertainty (forecast dispersion in particular) and stock returns. Our results will shed light on when the negative relationship between information uncertainty and stock returns is strongest, which will highlight the differential impact of information uncertainty on stock performance during different periods.

Additional Analysis: The Reversal Period

Consistent with Cella et al. (2013), we define the reversal period as Week 9 to Week 25 after the bankruptcy. Cella et al. (2013) found that during the drop period, short-term institutional investors tended to liquidate a larger portion of their holdings than long-term institutional investors. These liquidations are likely to be related to the level of uncertainty, and therefore, may affect both the decline and recovery of stock price during the GFC.

In our sample, mean *CAR* during the drop period was negative (-9.31%) but positive (10.4%, untabulated) during the reversal period. These price reversals indicate a rebound in investor confidence. If investor confidence has returned to normal during the reversal period, high dispersion stocks should have positive abnormal returns in the reversal period to offset the drop period's negative abnormal returns. As a result, we expect that analyst forecast dispersion is positively related to stock returns during the reversal period.

DATA AND RESEARCH METHODOLOGY

Data

We use publicly available data in our analyses. We obtain data on firm characteristics from Compustat, stock price data from CRSP, analyst forecast data used to compute the information uncertainty measure from I/B/E/S, and institutional data from Thomson Reuters's Institutional Managers (13f) Holdings. Our final sample spans the period from 2004 to 2012.

Models for Hypothesis Testing

We first confirm the negative relationship between information uncertainty (proxied by analysts' forecast dispersion) and firm returns during the market-wide downturn. We use the following model:

$$\begin{aligned} CAR\_DROP \quad = \quad & \alpha1 + \alpha2*DISPERSION + \alpha3*SIZE + \alpha4*BM + \alpha5*LEV + \alpha6*ROA \\ & + \alpha7*RATING + \alpha8*MOMEN\_M3M1 + \alpha9*MOMEN\_M12M4 \\ & + \alpha10*VOLATILITY + \alpha11*LIQUIDITY + \alpha12*IOR + error \end{aligned} \tag{1}$$

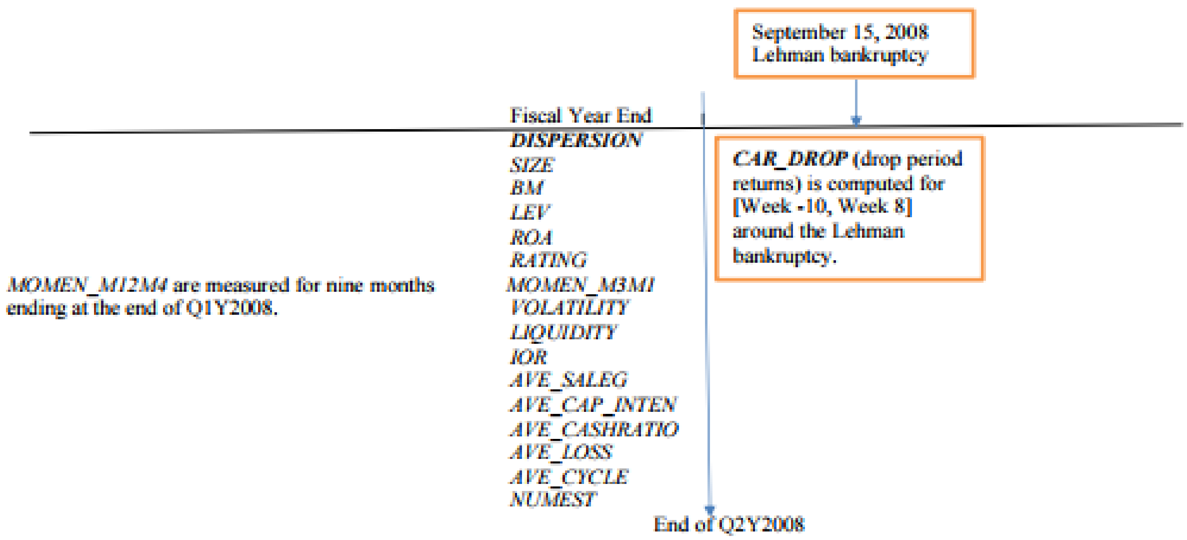
CAR_DROP is the cumulative abnormal returns for the market drop period. Following Cella et al. (2013), we define the market-drop period as ten weeks before to eight weeks after the week of the Lehman Brothers bankruptcy ([Week -10, Week 8]).[5] To compute *CAR_DROP*, we first estimate a benchmark CAPM, where the dependent variable is the weekly compounded returns from the beginning of 2003 to March 31, 2008, adjusted for the risk-free rate, and the independent variable is S&P500 weekly compounded returns, also adjusted for the risk-free rate. We then use the estimated parameters to compute cumulative abnormal returns for the drop *(CAR_DROP)* period.

DISPERSION is the standard deviation of the last annual earnings forecast by each analyst for the most recent fiscal year ending before or at the end of second quarter of 2008, scaled by price at the beginning of the fiscal year. Higher values of this variable reflect higher information uncertainty. We require each firm to be followed by a minimum of three analysts. In model [1], a negative coefficient on *DISPERSION* will indicate a negative impact of information uncertainty on drop period returns.

Following Cella et al. (2013), we control for firm characteristics, including firm size (*SIZE*), book-to-market ratio (*BM*), leverage (*LEV*), firm profitability (*ROA*), and credit rating (*RATING*).[6] We also control for stock market-related measures, including momentum of shares for the second quarter of 2008 (*MOMEN_M3M1*), momentum for the nine-month period ending at the end of the first quarter of 2008 (*MOMEN_M12M4*), volatility of stock returns (*VOLATILITY*), liquidity (*LIQUIDITY*), and institutional ownership ratio (*IOR*). The Appendix contains detailed variable definitions.

Firm characteristics, e.g., *BM*, *SIZE*, are measured annually and are computed for the most recent fiscal year ending on or prior to June 30, 2008. Stock market-related variables, e.g., *VOLATILITY*, *LIQUIDITY*, are measured on a quarterly basis and are computed for the quarter ending on June 30, 2008. We depict the timing for variable measurements in Figure 1.

FIGURE 1
TIMELINE OF VARIABLES FOR TESTING THE EFFECT OF ANALYST FORECAST DISPERSION ON DROP PERIOD RETURNS



In H1, we examine whether the impact of analysts' forecast dispersion on drop period returns was different from that for the non-drop period. We estimate the following model [2]:

$$
\begin{aligned}
CAR\_DROP = \; & \alpha 1 + \alpha 2*DISPERSION*DROP2008 + \alpha 3*DISPERSION + \alpha 4*DROP2008 \\
& + \alpha 5*SIZE + \alpha 6*BM + \alpha 7*LEV + \alpha 8*ROA + \alpha 9*RATING \\
& + \alpha 10*MOMEN\_M3M1 + \alpha 11*MOMEN\_M12M4 + \alpha 12*VOLATILITY \\
& + \alpha 13*LIQUIDITY + \alpha 14*IOR + error
\end{aligned} \tag{2}
$$

DROP2008 is a dummy variable that equals one for the drop period in 2008, and zero for the non-drop period. In model [2], a significant and negative coefficient on *DISPERSION*DROP2008* (i.e., *a2*) implies that analysts' forecast dispersion had a more negative impact on firm returns during the drop period, compared to the non-drop period. We define the non-drop period as [Week -10, Week 8] around the week of September 15 in 2004-2007 and 2009-2012, called the pseudo-drop period in our paper.

RESULTS AND ANALYSIS

Descriptive Statistics

Table 1 contains descriptive statistics for the market drop period. *DISPERSION* has an average value of 0.0081. The average returns that firms experienced during the drop period, defined as the period beginning ten weeks before and ending eight weeks after the Lehman bankruptcy, were -9.31%.

Table 2 shows the Pearson correlations for the variables during the market drop period. Information uncertainty (*DISPERSION*) is negatively correlated with drop period returns (-0.120, p-value < 1%), consistent with our expectation and previous literature's finding that analyst forecast dispersion is negatively related to future stock returns.

TABLE 1
DESCRIPTIVE STATISTICS FOR THE MARKET-DROP PERIOD (N = 2,571)

Variable Name	Mean	Std. Dev.	Minimum	25th percentile	Median	75th percentile	Maximum
CAR_DROP	-0.0931	0.4545	-1.4305	-0.3484	-0.0453	0.1852	1.0506
DISPERSION	0.0081	0.0140	0.0002	0.0014	0.0033	0.0086	0.0959
SIZE	7.1587	1.7417	3.7618	5.8847	7.0023	8.2626	11.8405
BM	0.4647	0.3470	-0.2539	0.2352	0.3946	0.6163	1.8296
LEV	0.2065	0.2066	0	0.0078	0.1694	0.3281	0.9261
ROA	0.0154	0.1662	-0.7540	0.0017	0.0514	0.0948	0.2918
RATING	0.2405	0.3265	0	0	0	0.6931	0.6931
MOMEN_M3M1	-0.1206	0.1879	-0.6061	-0.2348	-0.1122	-0.0052	0.3750
MOMEN_M12M4	0.0027	0.3913	-0.7023	-0.2619	-0.0390	0.1932	1.4104
VOLATILITY	0.0297	0.0131	0.0101	0.0210	0.0270	0.0350	0.0821
LIQUIDITY	6.1847	0.8501	3.4479	5.7966	6.4093	6.7637	7.5160
IOR	0.7316	0.2472	0.0703	0.5823	0.7906	0.9415	1
AVE_SALEG	0.3375	0.6906	-0.2030	0.0795	0.1620	0.3135	4.9965
AVE_CAP_INTEN	0.2718	0.2406	0.0103	0.0785	0.1825	0.4196	0.8969
AVE_CASHRATIO	0.9635	1.3300	0.0144	0.2044	0.4953	1.1303	7.9648
AVE_LOSS	0.2510	0.3429	0	0	0	0.4	1
AVE_CYCLE	0.3490	0.3838	0.0151	0.1660	0.2624	0.4076	3.1626
NUMEST	11.4823	7.5515	3	6	9	15	37

The market-drop period is the period starting ten weeks before and ending eight weeks after the week when Lehman Brothers filed for bankruptcy on September 15, 2008. The sample is winsorized at the 1st and 99th percentiles.

TABLE 2
CORRELATIONS FOR THE MARKET-DROP PERIOD (N = 2,571)

	CAR_DROP	*DISPERSION*	*SIZE*	*BM*	*LEV*	*ROA*	*RATING*	*MOMEN_M3M1*	*MOMEN_M12M4*	*VOLATILITY*	*LIQUIDITY*
CAR_DROP	1										
DISPERSION	-0.120***	1									
SIZE	-0.028	-0.244***	1								
BM	-0.030	0.110***	-0.301***	1							
LEV	-0.106***	0.113***	0.096***	-0.113***	1						
ROA	0.015	-0.345***	0.427***	-0.071***	-0.040**	1					
RATING	-0.045**	-0.155***	0.578***	-0.024	0.299***	0.207***	1				
MOMEN_M3M1	-0.034*	-0.071***	0.129***	0.046**	0.015	0.150***	0.117***	1			
MOMEN_M12M4	-0.133***	-0.123***	0.386***	-0.410***	-0.074***	0.288***	0.088***	-0.041**	1		
VOLATILITY	-0.033*	0.333***	-0.491***	0.148***	-0.013	-0.447***	-0.315***	-0.335***	-0.221***	1	
LIQUIDITY	0.053***	-0.348***	0.789***	-0.254***	0.072***	0.536***	0.440***	0.258***	0.372***	-0.584***	1
IOR	0.060***	-0.209***	0.276***	-0.015	0.060***	0.303***	0.167***	0.119***	0.096***	-0.213***	0.528***
AVE_SALEG	-0.084***	0.139***	-0.129***	-0.088***	-0.040**	-0.260***	-0.172***	-0.112***	0.001	0.248***	-0.196***
AVE_CAP_INTEN	-0.192***	0.007	0.222***	0.040**	0.340***	0.141***	0.214***	0.192***	0.071***	-0.128***	0.164***
AVE_CASHRATIO	0.057***	0.113***	-0.261***	-0.077***	-0.229***	-0.297***	-0.313***	-0.144***	-0.011	0.236***	-0.270***
AVE_LOSS	-0.052***	0.403***	-0.452***	-0.002	0.034*	-0.694***	-0.321***	-0.195***	-0.196***	0.489***	-0.544***
AVE_CYCLE	0.005	0.137***	-0.097***	-0.051***	-0.068***	-0.218***	-0.096***	-0.074***	-0.035*	0.150***	-0.165***
NUMEST	-0.002	-0.129***	0.583***	-0.181***	0.008	0.209***	0.301***	0.047**	0.114***	-0.190***	0.495***

(Table 2 Continued)

	IOR	*AVE_SALEG*	*AVE_CAP_INTEN*	*AVE_CASHRATIO*	*AVE_LOSS*	*AVE_CYCLE*	*NUMEST*
IOR	1						
AVE_SALEG	-0.210***	1					
AVE_CAP_INTEN	-0.057***	-0.041**	1				
AVE_CASHRATIO	-0.201***	0.282***	-0.235***	1			
AVE_LOSS	-0.264***	0.283***	-0.181***	0.329***	1		
AVE_CYCLE	-0.103***	0.282***	-0.207***	0.239***	0.240***	1	
NUMEST	0.256***	-0.036*	0.055***	-0.083***	-0.210***	-0.082***	1

The sample is winsorized at the 1^{st} and 99^{th} percentiles. Significance level is two-tailed, with * denoting $p < 0.1$, ** $p < .05$, and *** $p < .01$.

Results From Hypothesis Testing

We first estimate the effect of forecast dispersion on stock returns using model [1] and present the results in Table 3. We find that for the market drop period (Column 1), the coefficienton *DISPERSION* is negatively related to *CAR_DROP* (coefficient = -2.6356, t-stat = -3.04), suggesting that higher forecast dispersion is related to lower returns during the drop period.

Economically, a standard-deviation increase in forecast dispersion is associated with a decrease of 3.7% in stock returns, which accounts for almost 40% of the absolute mean of stock returns during the drop period.[7] Furthermore, momentum and leverage are negatively associated with market drop period returns, which is consistent with Cella et al. (2013) and provides assurance about our empirical measures.

TABLE 3
THE EFFECT OF ANALYST FORECAST DISPERSION ON STOCK RETURNS DURING THE DROP AND PSEUDO-DROP PERIODS

Independent Variables	Drop Period (1)	Pseudo-Drop Period (2)
DISPERSION	-2.6356***	-0.0512
	(-3.04)	(-0.45)
SIZE	-0.0297***	0.0122***
	(-3.22)	(6.57)
BM	-0.1270***	0.0679***
	(-3.79)	(10.72)
LEV	-0.2382***	-0.0088
	(-4.58)	(-0.74)
ROA	0.0519	-0.0153
	(0.69)	(-0.80)
RATING	-0.0567	0.0186***
	(-1.62)	(2.69)
MOMEN_M3M1	-0.0925*	-0.0619***
	(-1.70)	(-5.59)
MOMEN_M12M4	-0.2259***	-0.0275***
	(-8.12)	(-5.89)
VOLATILITY	-0.0099	-1.0298***
	(-0.01)	(-4.61)
LIQUIDITY	0.1090***	-0.0075**
	(4.74)	(-2.30)
IOR	-0.0108	-0.0080
	(-0.23)	(-0.83)
INTERCEPT	-0.0501	-0.1236***
	(-0.35)	(-3.74)
Industry FE	Yes	Yes
F-statistics	16.89	17.21
Prob F	0.0000	0.0000
Adj R-Sq	0.1666	0.0300
N	2,571	19,179

The market-drop period is ten weeks before to eight weeks after ([Week -10, Week 8]) the week of Lehman bankruptcy. The pseudo-drop period is [Week -10, Week 8] around the week of September 15 each year in 2004-2007 and 2009-2012.
The sample is winsorized at the 1st and 99th percentiles. T-statistics are in parentheses. In Column (2), t-statistics are based on standard errors clustered by firm. Significance of coefficients is two-tailed, with * denoting p < 0.1, ** *p* < .05, and *** *p* < .01.

For comparison, we also estimate model [1] for the pseudo-drop period. In Column 2, *DISPERSION* is not significant, suggesting that the negative association between forecast dispersion, a proxy of information uncertainty and stock returns, is more likely to be present during a market downturn.

Next, we estimate model [2] and conduct formal analysis to evaluate whether the observed effect of forecast dispersion on returns during the drop period of 2008 differs from the effect during the pseudo-drop period. We present the results in Table 4.

TABLE 4
COMPARING THE EFFECT OF FORECAST DISPERSION ON STOCK RETURNS BETWEEN THE DROP AND PSEUDO-DROP PERIODS

Independent Variables	Coefficients
*DISPERSION*DROP2008*	-2.7060***
	(-4.80)
DISPERSION	0.0849
	(0.74)
DROP2008	-0.0076
	(-0.81)
SIZE	0.0065***
	(3.35)
BM	0.0533***
	(8.18)
LEV	-0.0315***
	(-2.61)
ROA	-0.0082
	(-0.44)
RATING	0.0118
	(1.63)
MOMEN_M3M1	-0.0719***
	(-6.48)
MOMEN_M12M4	-0.0440***
	(-9.54)
VOLATILITY	-0.8798***
	(-3.84)
LIQUIDITY	0.0034
	(1.03)
IOR	-0.0069
	(-0.70)
INTERCEPT	-0.1283***

	(-3.79)
Industry FE	Yes
F-statistics	18.00
Prob F	0.0000
Adj R-Sq	0.0296
N	21,750

DROP2008 is a dummy variable, equal to one for the drop period in 2008, and zero for the pseudo-drop period. The sample is winsorized at the 1st and 99th percentiles. T-statistics are reported in parentheses and are based on standard errors clustered by firm. Significance of coefficients is two-tailed, with * denoting $p < 0.1$, ** $p < .05$, and *** $p < .01$.

The main variable of interest is *DISPERSION*DROP2008*. We find that when the drop period is combined with the pseudo-drop period, the coefficient on *DISPERSION*DROP2008* is negative and highly significant (coefficient = -2.7060, t-stat = -4.80), suggesting that *DISPERSION* is more negatively associated with stock returns during the 2008 drop period compared with the pseudo-drop period in other years. If forecast dispersion increases by one standard deviation, the change in stock returns during the market drop period would be 3.8% lower (or more negative) than the change in stock returns during the pseudo-drop period.[8]

Addressing the Endogeneity of Forecast Dispersion

We measure forecast dispersion (*DISPERSION*) before the period for which we measure drop period returns so that we are more assured that *DISPERSION* influences stock returns, instead of the reverse. However, if forecast dispersion is serially correlated, then we cannot rule out the possibility that the relationship between pre-crisis forecast dispersion and market-drop period returns is a contemporaneous one. As a result, it is still possible that our findings are a manifestation of stock returns' effect on forecast dispersion. To address this issue, we employ the approach of instrumental variables and two-stage least squares.

Ng (2011) identifies five innate determinants of information quality[9] which he measures as accrual quality as well as analyst forecast dispersion. The five determinants include annual sales growth (*AVE_SALEG*), capital intensity (*AVE_CAP_INTEN*), cash holdings (*AVE_CASHRATIO*), loss *(AVE_LOSS)*, and working capital cycle (*AVE_CYCLE*), averaged over the most recent five years. Following Ng (2011), we employ these five determinants as instruments for forecast dispersion. We additionally include number of analysts (*NUMEST)* to consider the effect of analyst following on forecast dispersion.

We estimate model [1] using the two-stage least squares and present the results in Table 5 Panel A. In the first stage, we obtain a predicted value of *DISPERSION* by regressing the observed value of forecast dispersion on the instruments of *DISPERSION* and other independent variables in model [1]. In the second stage, we estimate model [1] by regressing stock returns on the predicted value of *DISPERSION* and remaining independent variables. Our instruments are sufficiently strong, as indicated by the Kleibergen-Paap rk Wald test (F statistic = 7.822, p-value = 0.00). In Column 2, we find that predicted value of *DISPERSION* remains significantly negative.

Next, we apply the two-stage least squares procedure to model [2]. In model [2], we have two endogenous variables: *DISPERSION* and the interaction term *DISPERSION*DROP2008*.[10] The instruments for *DISPERSION* are the six variables discussed above. The instruments for the interaction term are the products between each of the six instruments for *DISPERSION* and *DROP2008*. In the first stage, we obtain the predicted values of *DISPERSION* and *DISPERSION*DROP2008* which we will use in the second stage regression. For brevity, we include only the second-stage results in Table 5 Panel B. As shown in Panel B, the interaction terms remain negative and significant.

TABLE 5
CORRECTING THE ENDOGENEITY OF FORECAST DISPERSION

Panel A Two-Stage Least Square Results for The Drop Period

Independent Variables	First Stage	Second Stage
DISPERSION, predicted		-10.1537**
		(-2.45)
SIZE	0.0007**	-0.0230**
	(2.19)	(-2.34)
BM	0.0045***	-0.0972**
	(4.05)	(-2.53)
LEV	0.0090***	-0.1562**
	(4.16)	(-2.27)
ROA	-0.0050	-0.0586
	(-1.28)	(-0.58)
RATING	-0.0025***	-0.0838**
	(-2.76)	(-2.28)
MOMEN_M3M1	0.0039**	-0.0618
	(2.05)	(-1.06)
MOMEN_M12M4	0.0019*	-0.2112***
	(1.92)	(-7.16)
VOLATILITY	0.1349***	1.2806
	(3.79)	(0.98)
LIQUIDITY	-0.0026***	0.0840***
	(-3.23)	(3.17)
IOR	-0.0029*	-0.0301
	(-1.84)	(-0.62)
AVE_SALEG	-0.0001	
	(-0.20)	
AVE_CAP_INTEN	0.0025	
	(1.37)	
AVE_CASHRATIO	-0.0003	
	(-1.02)	
AVE_LOSS	0.0097***	
	(6.29)	
AVE_CYCLE	0.0020	
	(1.43)	
NUMEST	0.0000	
	(0.97)	
INTERCEPT	0.0112**	0.0815
	(1.99)	(0.49)
Industry FE	Yes	Yes
F-statistics	10.69	15.44

Prob F	0.0000	0.0000
Adj R-Sq	0.2530	
N	2,571	2,571
Weak identification test (Kleibergen-Paap rkWald F statistic):		7.822 (p-value = 0.00)

Panel B Second Stage Results for the Combined Sample of Drop and Pseudo-Drop Period

Independent Variables	Drop Period Combined with Pseudo-Drop period
*DISPERSION*DROP2008, predicted*	-4.8624***
	(-3.28)
DISPERSION, predicted	-2.4173***
	(-3.65)
DROP2008	0.0030
	(0.22)
SIZE	0.0093***
	(4.39)
BM	0.0771***
	(8.60)
LEV	0.0148
	(0.86)
ROA	-0.0819***
	(-2.87)
RATING	-0.0019
	(-0.24)
MOMEN_M3M1	-0.0543***
	(-4.44)
MOMEN_M12M4	-0.0185**
	(-2.28)
VOLATILITY	-0.3012
	(-1.08)
LIQUIDITY	-0.0056
	(-1.35)
IOR	-0.0249**
	(-2.30)
INTERCEPT	-0.0812**
	(-2.44)
Industry FE	Yes
F-statistics	16.89
Prob F	0.0000
N	21,750

Weak identification test (Kleibergen-Paap rk Wald F Statistic):	17.994 (p-value = 0.00)

The sample is winsorized at the 1st and 99th percentiles. Standard errors are clustered by firm and t-statistics are reported in parentheses. Significance of coefficients is two-tailed, with * denoting p < 0.1, ** p < .05, and *** p < .01.

Results From the Additional Analysis: The Reversal Period

Our primary analysis focused on the relationship between dispersion and returns in periods outside the GFC as well as our drop period, the 18 weeks surrounding the Lehman bankruptcy. In this section, we examine the relationship between forecast dispersion and returns for the reversal period. Our sample firms experienced positive abnormal returns in the reversal period (10.4%, untabulated), indicating a rebound in investor confidence. As a result, we expect that the negative abnormal returns experienced by high dispersion stocks during the drop period should start to reverse during the reversal period. Univariate correlation suggests forecast dispersion is positively correlated with stock returns for the reversal period (correlation = 0.04966, p-value = 0.0129; untabulated), but the positive association disappears when we estimate model [1] (untabuluated). To further explore this issue, we code forecast dispersion as a dichotomous 0/1 variable and re- estimate model [1]. Table 6 contains the results.

TABLE 6
FORECAST DISPERSION AS A DICHOTOMOUS VARIABLE

Independent Variables	*DISPERSION* equals one when in top tercile		*DISPERSION* equals one when in top quartile	
	Drop (1)	Reversal (2)	Drop (3)	Reversal (4)
DISPERSION (1 for top tercile)	-0.0615*** (-2.82)	0.0598*** (2.92)		
DISPERSION (1 for top quartile)			-0.0760*** (-3.05)	0.0581** (2.49)
SIZE	-0.0298*** (-3.21)	0.0282*** (3.37)	-0.0301*** (-3.25)	0.0289*** (3.45)
BM	-0.1247*** (-3.73)	-0.0594* (-1.71)	-0.1240*** (-3.72)	-0.0576* (-1.66)
LEV	-0.2511*** (-4.87)	-0.1126** (-2.24)	-0.2514*** (-4.88)	-0.1110** (-2.20)
ROA	0.0579 (0.76)	-0.1826** (-2.35)	0.0476 (0.62)	-0.1819** (-2.34)
RATING	-0.0546 (-1.56)	-0.0091 (-0.29)	-0.0533 (-1.53)	-0.0121 (-0.39)
MOMEN_M3M1	-0.1037* (-1.91)	-0.2664*** (-5.13)	-0.1004* (-1.85)	-0.2699*** (-5.20)
MOMEN_M12M4	-0.2270*** (-8.11)	-0.0629*** (-2.60)	-0.2266*** (-8.11)	-0.0627*** (-2.58)
VOLATILITY	-0.1612 (-0.14)	3.8162*** (3.65)	-0.0879 (-0.08)	3.8199*** (3.66)
LIQUIDITY	0.1101*** (4.75)	-0.0020 (-0.09)	0.1110*** (4.78)	-0.0045 (-0.20)

IOR	-0.0112	0.0832**	-0.0143	0.0854**
	(-0.24)	(2.01)	(-0.31)	(2.08)
Intercept	-0.0456	-0.3774***	-0.0430	-0.3670***
	(-0.31)	(-2.90)	(-0.29)	(-2.82)
Industry FE	Yes	Yes	Yes	Yes
F-statistics	16.76	6.69	17.14	6.59
Prob F	0.0000	0.0000	0.0000	0.0000
Adj R-Sq	0.1645	0.0888	0.1655	0.0881
N	2,571	2,505	2,571	2,505

The sample is winsorized at the 1st and 99th percentiles. Standard errors are clustered by firm and t-statistics are reported in parentheses. Significance of coefficients is two-tailed, with * denoting $p < 0.1$, ** $p < .05$, and *** $p < .01$.

In Columns (1) and (2*), DISPERSION* equals one when its value is in the top tercile of the sample. We find that the coefficient on *DISPERSION* is negative during the market-drop period and is positive during the reversal period, indicating firms in the top third of forecast dispersion experienced a larger price drop during the market downturn but also experienced a larger price rebound in the reversal period. In terms of economic significance, the returns for firms with top-third forecast dispersion were 6.15% lower during the drop period and 5.98% higher during the reversal period, compared to the firms in the lower terciles of forecast dispersion. Columns (3) and (4) present similar findings when *DISPERSION* equals one if its value is in the top quartile. The returns for firms in top-quartile forecast dispersion were 7.6% lower in the market-drop period and 5.81% higher in the reversal period, compared to firms with forecast dispersion in lower quartiles. Together, the evidence suggests that firms in the top tercile (or quartile) of forecast dispersion experienced larger-magnitude price declines and recovery. Thus, pre-crisis information uncertainty may have magnified the turmoil experienced by a firm's stock during the financial crisis.

The evidence for the dichotomous dispersion variable is consistent with Cella et al.'s (2013) finding for institutional investors with short-term trading horizons. Fearing stock prices and market demand would decline further in the near future, short-term institutional investors tended to sell a larger portion of their holdings in the drop period, compared to long-term institutional investors. This trading pattern of short-term investors will drive down the stock price from the firms' fundamental values to a greater extent. The larger decline from the firm fundamental value is temporary, only to be reversed when the overall market condition improves (i.e., during the reversal period). As a result, stock price recovers to a greater extent during the reversal period for firms held mostly by short-horizon investors. In our study, stock prices declined to a greater extent for firms with top tercile/quartile forecast dispersion but also rebounded with a greater magnitude during the reversal period, suggesting a role of firm-level information uncertainty in amplifying the market turmoil during the financial crisis, similar to the role of short-term investors documented by Cella et al. (2013).

Another view that can potentially explain our findings is proposed by Zhang (2006). Combining the arguments that (1) psychological biases may be magnified when there is high information uncertainty and (2) short-term stock price continuation can be attributed to behavioral biases (such as overconfidence in private information and underreaction to new and public signals), Zhang (2006) hypothesizes that firms with higher information uncertainty will have higher returns following good news and lower returns following bad news, compared to stocks with lower information uncertainty.

In our study, if the market-wide downturn (reversal) serves as a continuous stream of macroeconomic bad (good) news,[11] then according to the argument by Zhang (2006), we should find stock returns are lower for top tercile/quartile uncertainty firms during the drop period and higher during the reversal period, relative to the firms in lower terciles/quartiles of uncertainty. That is exactly what we find. However, we acknowledge that the relation of our study to Cella etal. (2013) and Zhang (2006) holds only when forecast dispersion is defined as a dichotomous variable.[12]

CONCLUSION AND DISCUSSION

Financial crises are periods with heightened uncertainties. The 2008-2009 financial crisis was no exception (Straub and Ulbricht 2023). Since information uncertainty was one of the uncertainties that characterized the most recent financial crisis, in this study, we investigate the economic consequences of information uncertainty. Information uncertainty has two levels: market- and firm-level. The heightened information uncertainty at the macroeconomic level could exacerbate the effect of firm-level uncertainty during the financial crisis, with firms that were already suffering from higher firm-level information uncertainty affected the most.

We use analysts' forecast dispersion to proxy for firm-level information uncertainty and relate it to stock returns during the crisis. Our primary finding is that higher information uncertainty leads to larger stock market losses during the market-wide downturn in the crisis and that this relationship is stronger compared to periods outside the crisis. Therefore, our study highlights the consequence of information uncertainty, especially during times of market-wide negative shocks.

Global financial markets have been roiled by periodic crises, the latest being the COVID-19 related crisis. Therefore, insights on how the factors we study can mitigate or compound the adverse effects of crises will be of interest. To the extent that information uncertainty can be mitigated by financial disclosure and managers have information to disclose, a firm may have some control over the extent to which stock prices are negatively affected by market downturn.

Consistent with our primary analysis, we find that during the most uncertain portion of the financial crisis, the period surrounding the Lehman bankruptcy (the drop period), sample firms with top tercile (quartile) of forecast dispersion suffered lower returns. We also examined the sixteen weeks subsequent to the drop period. This reversal period is within the financial crisis, but it is subsequent to the most uncertain period of the crisis. We find that sample firms with top tercile (quartile) of forecast dispersion experienced more positive returns in the reversal period. Thus, the more negative abnormal returns experienced by high dispersion stocks during the drop period appear to be reversing even before the crisis has ended.

This provides preliminary evidence that information uncertainty (specifically, analyst forecast dispersion) amplified the wide swings of the stock market during the financial crisis, although we did not find this amplification effect for the continuous measure of forecast dispersion. This evidence is consistent with Zhang (2006) who argues that due to investors' behavioral biases such as overconfidence and underreaction, stock returns should be more negative after the bad news and more positive after the good news for higher uncertainty firms, compared to lower uncertainty firms. This evidence also suggests that stock prices of firms with higher information uncertainty are more likely to deviate from the fundamental value during market turmoil. Therefore, if a firm can take measures to mitigate information uncertainty, for example, by disclosing relevant information on a more timely basis (and if managers have such information to disclose), it may reduce the market tumult the firm experiences during the crisis.

ENDNOTES

1. See Straub and Ulbricht (2023) Footnotes 1 and 2 for a more comprehensive review of studies on the role of uncertainty during the recent financial crisis.
2. In contrast with the earlier findings that more powerful bidder CEOs tend to offer higher premiums for the targets in mergers and acquisitions, Fralich and Papadopoulos (2018) document that at the onset of the financial crisis, more powerful CEOs curbed the premiums due to their superior ability to steer the firm through information uncertainty during the crisis.
3. Chen et al. (2018) provide evidence that investors allocate attention to macroeconomic news when trying to absorb firm-specific news, such as earnings announcements.
4. Similarly, Hoopes et al. (2022) found that individuals' stock sales immediately after the Lehman bankruptcy

were concentrated in the more sophisticated individual investors as measured by the top 1% and top 0.1% of the overall income distribution.

5. Lehman Brothers declared bankruptcy on September 15, 2008. This was the largest bankruptcy in terms of assets to date ($639 billion in assets). The subsequent turmoil in the capital markets wiped out $10 trillion from the global equity markets (Choudhry and Landuyt 2010, 25), including a 22.5% decline in the S&P500 index. Therefore, the period after the Lehman bankruptcy was a period of extreme turmoil in the stock markets.
6. Doron et al. (2009) find that the probability of finding a negative relationship between dispersion and returns is the highest for the lowest-rated firms.
7. Calculated as the standard deviation of forecast dispersion (0.0140) multiplied by the estimated coefficient for *DISPERSION* (-2.6356) divided by the mean of drop period returns (-0.0931 in absolute value).
8. Calculated as the standard deviation of forecast dispersion (0.0140) multiplied with the coefficient (-2.7060) for the interaction between forecast dispersion and *DROP2008*.
9. Information quality, according to Zhang's (2006) definition, is one of the two sources contributing to information uncertainty.
10. https://www.statalist.org/forums/forum/general-stata-discussion/general/1628022-2sls-regression-with-interaction- between-endogenous-and-exogenous-variables.
11. Prior studies have used stock returns to define good or bad news (e.g., Marks and Nam 2018).
12. Barron et al. (1998) develop two measures, uncertainty and consensus, calculated using forecast dispersion, error in the mean forecast, and the number of forecasts. With Barron et al.'s (1998) measure of uncertainty, we obtain similar results to those presented in the paper for the continuous value of information uncertainty (i.e., for the drop period), but the results for the dichotomous variable (i.e., for the reversal period) using Barron et al.'s (1998) measure become insignificant. We decide to report results using analyst forecast dispersion for the following reasons. First, most studies we cite use analyst forecast dispersion as a proxy for information uncertainty (Diether et al. 2002; Jiang et al. 2005; Zhang 2006; Erickson et al. 2012; Bandyopadhyay et al. 2017, among others). Second, analysts' behavioral biases may cause Barron et al.'s (1998) measure of uncertainty and consensus to lose some of the construct validity. For example, analyst herding will cloud the distinction between public and private information, and analysts' tendency to issue optimistic or pessimistic forecasts can also confound the validity of the measures (Barron et al. 1998). Given that we focus on the 2008-2009 financial crisis, a period when many environmental changes occurred, and that changes in analysts' herding behavior or optimism/pessimism biases are hard to gauge during that period, we use the original value of analyst forecast dispersion.

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APPENDIX: VARIABLE DEFINITIONS

Major variables

DISPERSION	Standard deviation of the last annual earnings forecast by each analyst for the most recent fiscal year that ends prior to the end of the second quarter in 2008 (2004-2007 and 2009-2012 for the pseudo-drop period). We require at least three analyst forecasts. We scale this measure by share price at the beginning of the fiscal year.
CAR_DROP	Cumulative weekly abnormal returns for the drop period. We estimate a benchmark CAPM where the dependent variable is firms' weekly returns (adjusted for risk-free rate) from the beginning of 2003 to March 31, 2008, and the independent variable is S&P500 weekly returns (also adjusted for risk-free rate). We use the estimated parameters to compute abnormal returns for the drop period, which is [Week -10, Week 8] around the week of Lehman Brothers bankruptcy on Sept. 15, 2008. For the pseudo-drop period, we use weekly returns spanning a five-year period ending on March 31 each year during 2004-2007 and 2009-2012 to estimate CAPM parameters. We then compute *CAR* for [Week -10, Week 8] around the week of Sept. 15 each year for 2004-2007 and 2009-2012.
DROP2008	A dummy variable that equals one for the drop period in 2008, and zero for the non-drop period.

Control variables

SIZE	Natural log of market value of stockholders' equity (in millions) for the fiscal year ending on or before June 30, 2008.
BM	Ratio of book value to market value of stockholders' equity for the fiscal year ending on or before June 30, 2008.
LEV	Sum of long-term debt and long-term debt due in one year, divided by total assets, for the fiscal year ending on or before June 30, 2008.
ROA	Income before extraordinary items divided by average total assets for the fiscal year ending on or before June 30, 2008.
RATING	Average of monthly S&P domestic long term issuer credit rating over the 12 month-period of the fiscal year ending on or before June 30, 2008. A rating is assigned 1 if the rating is B+ or better, and zero otherwise. To normalize the average, we use the natural log of (1+average rating). (For the pseudo-drop period, the above variables are for the fiscal year ending on or before June 30 each year during 2004-2007 and 2009-2012.)
MOMEN_M3M1	Daily compounded returns for the three-month period ending on June 30, 2008.
MOMEN_M12M4	Daily compounded returns for the nine-month period ending on March 31, 2008.
VOLATILITY	Standard deviation of daily returns in the quarter ended June 30, 2008.
LIQUIDITY	Daily bid-ask spread, (ask – bid) / [(ask + bid)/2)], averaged over the quarter ended June 30, 2008. We take the log form and multiply the value by minus one.
IOR	Institutional ownership ratio on June 30, 2008, computed as number of shares held by institutional investors scaled by number of shares outstanding June 30, 2008. (For the pseudo-drop period, the above variables are for the quarter ending on June 30 each year during 2004-2007 and 2009-2012.)

Instruments for *DISPERSION*

AVE_SALEG	Annual sales growth, averaged over the most recent five years.
AVE_CAP_INTEN	Net value of PPE scaled by total assets, averaged over the most recent five years.
AVE_CASHRATIO	Cash scaled by current liabilities, averaged over the most recent five years.
AVE_LOSS	Equal to one if income before extraordinary items is negative, and zero otherwise. The indicator variable is then averaged over the most recent five years.
AVE_CYCLE	Sum of average inventories divided by cost of goods sold and average receivables divided by sales. The sum is then averaged over the most recent five years.
NUMEST	Number of financial analysts for the most recent fiscal year ended on or before June 30, 2008.

Reversal period variables

All reversal period variables are computed in the same manner as drop period variables except for *CAR*. For the reversal period, *CAR* is measured for [Week 9, Week 25] after the week of Lehman bankruptcy on Sept. 15, 2008.